Decarbonization and defossilization of the German transport sector

Electric vehicle charging, clean fuel supply options and energy system impact

Zur Erlangung des akademischen Grades eines Doktors der Ingenieurswissenschaften

(Dr.-Ing.)

von der KIT-Fakultät für Wirtschaftswissenschaften des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

M.Sc. Niklas Wulff

Tag der mündlichen Prüfung:	03. Dezember 2025
Hauptreferent:	Prof. Dr. Patrick Jochem
Korreferent:	Prof. Dr. Kay Mitusch

Karlsruhe, 2026

License & Copyright Information

© 2026 Niklas Wulff.

This work is licensed under Creative Commons Attribution 4.0 International License (CC BY 4.0).

Abstract

A decade after the Paris Agreement, the German transport sector CO_2-emissions are not sufficiently decreasing. Transport sector emission reduction is among the hardest challenges of the energy transition and requires a fundamental transformation of transport demand and energy supply. Within this thesis, methods of adequately representing electric vehicle charging, transport fuel demand and respective energy supply transformations towards emission-free energy supply are assessed. By applying a set of methods from energy system modeling and transport research, medium-term electric vehicle representation and long-term electricity and fuel supply options are assessed.

A method for adequately describing electric vehicle fleet charging and its flexibility is presented in the first part of the thesis. The approach is based on today's detailed driving behavior to represent controlled and uncontrolled charging of future electric vehicle fleets. All interfaces and code are made available in an Open Source repository to adapt the approach to specific needs.

The thesis then assesses medium-term impacts of decarbonization modeling. A technical demand flexibility potential is compared to a more user-constrained one, showing large differences in resulting demand-side flexibility and respective annual shifted loads in a 2030 German case study. The energy system impacts of this reduction are higher in wind rich regions such as northern Germany and limited in southern Germany, where electric vehicle charging follows diurnal patterns. If only controlled charging is assumed (no feeding-back to the grid), cost-optimal energy infrastructure and operation is found to be generally more sensitive to the variation of other model inputs such as emission restrictions, weather years, and wind and solar power plant cost assumptions than to intra-annual electric vehicle fleet charging representation.

For long-term energy transition, the prominent role of solar and wind power plant expansion until 2040 for transport sector defossilization is confirmed. Imports of electricity, clean hydrogen and clean liquid fuels to Germany are needed in all demand scenarios, however to a larger degree if demand follows higher conversion depth scenarios. Biomass availability for transport from waste and agricultural crops - comparable to today's volumes -, may limit necessary 2030 renewable energy capacity expansion, hydrogen infrastructure build-up needed in 2040, and reduce clean fuel import dependence. This is specifically important if road passenger vehicle users are unwilling or incapable of purchasing battery electric vehicles implying high fuel demands until 2040 (high conversion depth).

Acknowledgement

This thesis is not only my product but the product of my environment, continuously challenging me, discussing, refining, supporting and inspiring the thoughts that are documented in the following.

Thank you, Patrick Jochem for not only leading the DLR department for energy systems analysis but also in organizing the exchange between Ph.D. students in an open, constructive and inspiring way. The thesis strongly profited from your strong background in battery electric vehicle and transport modeling. Hans Christian is probably the person that coined the content of the individual Papers the most aside me. In leading the energy system modeling group, he shaped the direct relationships, research foci and methodological developments during the course of my thesis. I always valued the relatively democratic strategic decision-making in the group and the great level of trust towards us in project development. Thank you to both of you for intensive discussions of the thesis, especially in the late stages.

Benjamin Fuchs and Tobias Junne were the two persons, why I started at DLR, the former because of his prominent role as software teacher, the latter as a project partner, co-author and later friend at the soccer table in our office. Thanks to you, Ben, I am now able to write function annotations in Python and venco.py would most likely not have been published in the current form if it wasn't for you.

Thank you Farzad Sarfarazi, for sharing a range of perspectives and interests especially outside our research field and thus being a continuous source of inspiration and social comfort around DLR. The same is true for Jens Schmugge, whom I had already known from TU Darmstadt and who I shared my passion for running, leading to a shared marathon in Kassel. Thank you, Fabia Miorelli for countless hours of conceptualizing, planning, coding and writing venco.py. I'm faithful, that with you, the tool is in the best hands. Thank you Ben Fuchs, Marc-Andre Triebel and Jens Schmugge for your invaluable reviews in the last months before handing in.

I'm grateful for the meeting and everyday-work with Karl-Kiên Cao, Eugenio Arellano, Stefan Kronshage, Hedda Gardian, Andreas Meurer, Jonas Eschmann, Christoph Schimeczek, Johannes Kochems, Thomas Pregger, Manuel Wetzel, Shima Sasanpour, Oriol Raventos Morera, Kristina Nienhaus, Maria Camila Villaraga Diaz, Kai von Krbek, Yvonne Scholz, Carsten Hoyer-Klick, Madhura Yeligeti, Jürgen Kern, Jan Buschmann, Julian Bartels, Wenxuan Hu, Francesco Witte, Wided Medjroubi, Susanne Le Bihan, Evelyn Sperber and many other DLR colleagues. You all significantly contributed to the inspiring atmosphere that I painfully missed during the pandemic.

Aside my everyday DLR-colleagues, thank you to all my co-authors, Danial Esmaeili Aliabadi, Felix Steck, Samuel Hasselwander, Markus Millinger, Wolfgang Grimme, Matthias Jordan, John Anderson, Bent van den Adel, Marlin Arnz and Juri Horst. I always enjoyed the interdisciplinary mode of collaboration in my own

style of intensive exchange, physical meetings and mutual understanding of each others perspectives, concepts, language and methodological approaches. I learned a lot about user preferences, transportation, biomass and aviation. Without the level of openness and trust you showed, the quality of this work would have not been possible.

Thanks to Parth Butte, Eugenio Arellano, Niklas Steinman, Lisa Wegner and Saikat Mitra for contributing by writing your theses with DLR.

Thank you to my project collaborators in the projects EVer, BEniVer and Drive2X; Juliane Prause, Moritz Bergfeld, Andrea Amri-Henkel, Patrick Matschoss, Ralph-Uwe Dietrich, Moritz Raab, Ines Österle, Simon Pichlmaier, André Brosowski, Özcan Deniz, Sofia Haas, Eva Hauser, Manfred Aigner and numerous others. I learned a lot in the steering committee discussions about group research organization that I will draw from in my future project work to come. Especially the conversations with Andrea Amri-Henkel on societal responsibility of engineering-based research and postcolonial trade-relationships opened a critical perspective, that will only increase in importance in the years to come.

A warm thank you also goes out to the members of the openmod community, namely Francesco Sanvito Davide, Robbie Morrison, Tom Brown, Stefan Pfenninger, Ian Staffell, Carlos Gaete, Marta Victoria and others. Thank you for organizing the workshops in Frankfurt, Aarhus and Berlin which I had the honour to participate in. The spirit of collaboration and openness formed my ideal-benchmark of research and deepened my opposition to commercialized research and competition that still unfolds as part of economization of research and knowledge. My decision, not to stay in research would have been different, if energy systems analysis groups would broadly share this spirit.

I wouldn't be the person I am without my family, that shaped my curiosity and enabled so many experiences growing up. Especially my resilience and motivation would not be the same without you. Thank you Claudia and Michael, Mirjam and Jonas and Troy for the safe space in which and open discussions by which I still grow today. I will always carry you in my heart.

Collecting ourselves in the vast nothingness of the world, word-to-word, means everything to me, Sophie. Nelly and you form the nucleus of my social identity. I am grateful for the mental load and endless care work that enabled these last six years of my research, the quality of the supportive, inspiring, and loving bonds that connect us. Countless attempts to break down research in what I perceived as your way of thinking provided a layer of reflection hidden to others. Thank you for implicitly and explicitly shaping this research in so many ways.

Contents

Abstract ii

Acknowledgement ii

List of Figures vii

List of Tables viii

List of abbreviations viii

Nomenclature xi

1. Introduction 1
- 1.1. Objective and research questions . . . 2
- 1.2. Structure of the thesis . . . 3

2. Background 5
- 2.1. Energy system modeling as evidence base for energy planning . . . 6
  - 2.1.1. Energy system planning in Germany . . . 6
  - 2.1.2. The last ten years of energy systems analysis in Germany . . . 7
  - 2.1.3. Current challenges and trends in energy systems analysis . . . 11
- 2.2. Electric mobility . . . 16
  - 2.2.1. Vehicle fleets . . . 16
  - 2.2.2. Battery electric vehicle charging patterns . . . 17
  - 2.2.3. The role of PEVs on energy system model results . . . 19
- 2.3. Clean fuels for low-emission transportation . . . 20
  - 2.3.1. The role of clean fuels for transport sector emission reduction 21
  - 2.3.2. *RFNBO* domestically produced in Germany . . . 22
  - 2.3.3. *RFNBO* imported to Germany . . . 24
  - 2.3.4. Biofuels . . . 26
- 2.4. Summary and research gap . . . 28

3. Methodology 30
- 3.1. Energy system modeling . . . 32
  - 3.1.1. Intermittent renewable energy model . . . 37
  - 3.1.2. Plug-in electric vehicle model . . . 37
  - 3.1.3. Electrolysis model . . . 40
  - 3.1.4. Synthetic fuel conversion model . . . 40
  - 3.1.5. Synthetic fuel import model . . . 42

3.2. Transport modeling approaches 42
3.2.1. Vehicle fleet modeling 43
3.2.2. User-driven charging decisions 43
3.3. *Model coupling*, interfaces and harmonization of model scope 44
3.3.1. Electric mobility *model coupling* 44
3.3.2. Fuel demand *model coupling* 47
3.4. Scenarios of energy system transformation pathways 53

4. Summary of Paper and results **56**
4.1. Paper I 56
4.2. Paper II 57
4.3. Paper III 58

5. Critical reflection and discussion **60**
5.1. Discussion of Paper I 60
5.2. Discussion of Paper II 62
5.3. Discussion of Paper III 63
5.4. Critical reflection on the general approach 64

6. Conclusion and outlook **69**

Bibliography **72**

A. List of author's publications **91**
A.1. Peer-reviewed journal articles 91
A.2. Conference Papers and technical articles 92
A.3. Book chapters 92

B. Papers of the thesis **93**
B.1. Paper I 93
B.2. Paper II 117
B.3. Paper III 159

List of Figures

1.1. Overview of the thesis' Papers differentiated by transport applications and time dimension. 4

2.1. Schematic depiction of fundamental strategies of transport sector Carbon dioxide (CO_2) emission reductions, types of fuels and scope of this thesis. 5
2.2. Energy system infrastructure and annual energy flow diagram resulting from the 85%-scenario of Henning & Palzer (Henning and Palzer, 2015). 8

3.1. Schematic depiction of the scopes of the Papers I-III part of this thesis. 32
3.2. Schematic depiction of data harmonization techniques for *model coupling*. 45

5.1. German cumulative CO_2 emissions up to 2050 for various literature studies. 65

List of Tables

3.1. Overview of recent energy system studies modeling a low-emission German energy supply considering transport in some detail. 31
3.2. Dimensions, main variable categories and objective function of Renewable Energy Mix linear Optimization Model (*REMix-OptiMo*). 34
3.3. Variables of the electric mobility module of the energy system model framework. 38
3.4. Techno-economic assumptions of electrolysis technologies assumed in Paper III. 40
3.5. Overview of models used in this work and harmonization techniques. 46
3.6. Model dimensionality of VECTOR21 and harmonization with REMix-OptiMo scope. 48
3.7. Model dimensionality of 4DRACE and harmonization with REMix-OptiMo scope. 49
3.8. Model dimensionality of SZEM and harmonization with REMix-OptiMo scope. 50
3.9. Model dimensionality of BENOPTex and REMix-OptiMo with respective harmonization techniques. 51
3.10. Most important model inputs into REMix-OptiMo and categorization to background model, sensitivity variation and scenario. 55

List of abbreviations

4DRACE	Aviation Energy Consumption Model
AEL	Alkaline Electrolysis
BDC	Bi-Directional Charging
BEniVer	Evaluatory research for the initiative Energy Transition in Transport (German: Begleitforschung Energiewende im Verkehr)
BENOPT	BioENergy OPTimization Model
BENOPTex	Extended BioENergy OPTimization Model
BEV	Battery Electric Vehicle
BtL	Biomass-To-Liquid
CAPEX	Capital Expenditure
CCS	Carbon Capture and Storage
CCU	Carbon Capture and Utilization
CGE	Computational General Equilibrium
CH_4	Methane
CHP	Combined Heat and Power
CO_2	Carbon dioxide
CURRENT	Charging Infrastructure for Electric Vehicles Analysis Tool
DAC	Direct Air Capture
emobpy	Electric Mobility in Python
e-H_2	Hydrogen based on Electricity from RES
EU	European Union
EV	Electric vehicle
EVSE	Electric Vehicle Supply Equipment
FCEV	Fuel Cell Electric Vehicle
FCI	Fix Capital Investment
FT	Fischer Tropsch
H_2	Hydrogen
HEV	Hybrid Electric Vehicle
HHV	Higher Heating Value

HVO	Hydrogenated Vegetable Oil
ICE	Internal Combustion Engine
LCA	Life Cycle Assessment
LHV	Lower Heating Value
LNG	Liquified Natural Gas
LOHC	Liquid Organic Hydrogen Carrier
MENA	Middle East and North Africa
MGA	Modeling to Generate Alternatives
MiD	Mobility in Germany (German: Mobilität in Deutschland)
OEM	Original Equipment Manufacturer
OM	Operation and Maintenance
OPEX	Operational Expenditure
PBtL	Power-Biomass-To-Liquid
PEM	Proton Exchange Membrane
PEV	Plug-in Electric Vehicle
PHEV	Plugin Hybrid Electric Vehicle
PtL	Power-To-Liquid
PV	Photovoltaic
REMix-OptiMo	Renewable Energy Mix linear Optimization Model
RES	Renewable Energy Sources
RFNBO	Renewable Fuels of Non-Biological Origin
SAF	Sustainable Aviation Fuel
SOC	State-Of-Charge
SYN	Synthetic Fuel Scenario
SZEM	Scenario energy accounting model
TEPET	Techno Economic Process Evaluation Tool
VECTOR21	Market Analysis Model for the Vehicle Market
venco.py	Vehicle Energy Consumption in Python

Nomenclature

Δt	Temporal resolution
μ	Dual variable of electricity balance equation
Ξ	Objective function, total system costs

Parameters and input

η	Chemical conversion efficiency
$\eta_{charge}, \eta_{discharge}$	Plug-in Electric Vehicle (PEV) charge, discharge efficiency
μ_{DE}	Approximated German wholesale electricity price
$C_{av,veh}$	Average PEV battery size
$c_{elec,DE}$	Annual weighted German electricity price
$C_{unc,in}$	Uncontrolled charging input profile
C_{unc}	Uncontrolled charging profile
D^{elec}	Electricity demand
D^{f}_{fix}	Fuel demand
D_{ann}	Annual PEV fleet demand
$e_{SFC,in}$	Input fuel share, LHV
$e_{SFC,out}$	Output fuel share, LHV
F	Spatial disaggregation factor
$L_{max,in}$	Maximum fleet battery input profile
L_{max}	Maximum fleet battery profile
$L_{min,in}$	Minimum fleet battery input profile
L_{min}	Minimum fleet battery profile
$P_{av,veh}$	Average rated power of charging per vehicle

$P_{charge,avail}$	Fleet grid connection capacity profile
$P_{charge,in}$	Fleet grid connection capacity input profile
$P_{curt,DE}$	Annual curtailed electricity
$P_{drive,in}$	Fleet energy drain input profile
P_{drive}	Fleet energy drain profile
$P_{ely,DE}$	Annual electricity demand for H_2 production
s_{CC}, s_{BDC}	Fleet share capable of controlled and bidirectional charging
V_{veh}	Vehicle fleet size

Sets and dimensions

c	Technology
e	Electric vehicle technology, PEV
f, f_{in}, f_{out}	Fuel, input fuel, output fuel
j	Transport sub-sector
k	Fuel demand type set
l	Electrolysis technology
p	Renewable power plant technology
r	Model region
s	Scenario
t	Timestep
v	Synthetic fuel conversion technology
y	Year

Variables

Λ	Fleet battery level
ν	Intermittent renewable energy power curtailment
Ω	Technology capacity
Φ	Electricity from Battery Electric Vehicle (BEV) fleet fed back to the grid
π	Intermittent renewable energy production timeseries

Ψ	PEV fleet charging
ρ	Shifted load of PEV fleet
σ	Fleet share capable of controlled / bidirectional charging
$\xi^{elec}, \xi^{heat}, \xi^{f}$	Technology operation
$\xi_{EG,imp}$	Imported electricity
$\xi_{GG,imp}$	Imported gaseous fuel
$\zeta^{elec}, \zeta^{heat}, \zeta^{f}$	Electricity, heat and fuel demand
$\zeta_{EG,exp}$	Electricity export
$\zeta_{GG,exp}$	Gaseous fuel export
C^{CAPEX}	Capital expenditure
$C^{OPEX,fix}$	Fix operational expenditure
$C^{OPEX,var}$	Variable operational expenditure
m_{DE}	Annual German gross electricity production
$m_{PP,DE}$	Annual German electricity mix

1. Introduction

The IPCC's Assessment Report 6 reports a lack of ambition between global climate targets and what would be needed to keep global warming well below 2°C (IPCC, 2023a). However, while climate change is a global phenomenon, emissions occur locally, shaped by regional, national, and local policies. In order to understand underlying dynamics leading to CO_2 emissions and options for emission reductions, it is inevitable to study the specific social, economic and technical preconditions, interdependence and energy system implications of transport sector CO_2 emission reduction measures.

While the transport sector accounts for only 15% of global CO_2 emissions (IPCC, 2023b), transport is attributed to around 30% of energy consumption, globally (Laura Cozzi et al., 2024). For Germany, the transport final energy demand amounts to 30% of total energy consumption (AGEB, 2024) and around 20% of 2022 German emissions in t CO_2 equivalents (UBA, 2024). Despite a general consensus to transform energy supply to CO_2 neutral forms of energy supply, transport sector transformation strategies are still controversially discussed.

Three strategies are generally suggested: Reducing demand increase by *modal shift* and *demand avoidance*, motor *efficiency increases* and *fuel switching* (Creutzig et al., 2015). Limiting transport demand increases through *avoidance* and *modal shift* are still under-researched (Arnz et al., 2024), especially in its impacts on energy system planning. Shared mobility, public transport and active modes - walking and cycling - may have significant alleviating potential for breaking the historic trend of ever-increasing car-based individual mobility. The last timeseries report of the German national travel surveys shows increased distance traveled by car from 1.5 to 1.8 bn. km per day between 2002 and 2017 despite slight decreases in the number of absolute daily trips (Nobis et al., 2019). Thus, the majority of transported passengers and goods requires motorized individual vehicles and motorized trucks. Autonomously driving vehicles may significantly change future property structures of the vehicle fleet towards municipal, shared or commercially owned fleets (Pruckner and Eckhoff, 2020). However, a shift towards autonomous vehicles may have opposing effects on energy demand. If used in a ride-sharing manner, energy demand can be reduced but if individually taken trips are only to be replaced by autonomous vehicles, energy demand may even slightly increase due to feeder routes.

With the clear goal of climate neutrality and high responsibility for global climate change of industrialized countries, efficiency improvements can at most be a bridge towards emission-free transport. This is true on a vehicle-level (motor-efficiency) but less so on a system level (*fuel switching*). Thus, for now, the most relevant strategy remains *fuel switching*.

Generally, there are two different approaches to reducing CO_2 emissions through *fuel switching*. *Decarbonization* aims at replacing hydrocarbons as energy carrier

by electricity from batteries - often also referred to as *direct electrification*. *Decarbonization* may also comprise replacing hydrocarbons by hydrogen - as long as it is produced without the emission of CO_2. However, hydrogen lost its perceived value as a final energy carrier due to lower efficiency and higher costs compared to electric driving as well as evidence that future energy systems will likely be highly flexible, yielding limited excess electricity. The second *fuel switching* strategy, *defossilization*, refers to the replacement of fossil hydrocarbons by non-fossil hydrocarbons using an alternative source of carbon, e.g. biomass or Direct Air Capture (DAC). *Decarbonization* and *defossilization* mark the poles within the strategy of *fuel switching*. Switching to hydrogen as an intermediate technological option and non-fossil hydrocarbons are subsumed under the term *indirect electrification*. Figure 2.1 summarizes the strategies, terms and gives exemplary end-use and conversion technologies.

Fuel switching requires electricity from Renewable Energy Sources (RES) and has various second-order impacts on future energy systems. While electricity demand is expected to grow - final electricity demand for *direct electrification*, secondary electricity demand for *indirect electrification* - these strategies bring about some potential for solving another long discussed problem - balancing of intermittent RES - namely solar and wind power. BEV require batteries with a capacity of 30-100 kWh, a mobile battery storage, and potentially long connection times to the electricity grid. This flexibility, might not only complement diurnal fluctuations of solar power but also, to some degree, fluctuating wind power feed-in.

Indirect electrification on the other hand requires the conversion of electricity to hydrogen via electrolysis and potentially further chemical processing to synthetic fuels. Because hydrogen is a relatively stable gas, the demand-driven build-up of hydrogen electrolysis and gas storage facilities may act as a seasonal flexibility, capable of energy storage capacity for weeks and months.

All three categories of drivetrain design - BEV, Fuel Cell Electric Vehicle (FCEV) and Internal Combustion Engine (ICE) burning clean fuels - are also related to different implications for end-users. *Direct electrification* requires households and companies to purchase new, more expensive cars containing batteries and electric motors, with reduced costs for both maintenance and fuel. However, vehicle model availability of BEV is still not comparable to that of ICE vehicles - especially in smaller segments - and prices are still significantly higher. Replacing a fossil fuel, such as diesel, with a synthetic alternative based on hydrogen from RES may not require households to switch their end-use technology or to build up costly new infrastructure - through electric and hydrogen distribution grids as well as refueling and charging stations. On the other side, hydrogen and *synthetic fuels* are likely to be significantly more expensive than electricity due to energy losses during conversion.

1.1. Objective and research questions

As transport sector energy demand is likely to increasingly shift to electricity as a form of primary energy, possible energy system impacts need to be assessed. However, differentiated knowledge of transport sector electricity and fuel demand as well

as the respective supply systems' flexibility in high temporal and spatial resolution are required to assess sector-coupling impacts on future energy systems. The necessity of energy system wide CO_2 neutrality implies drastic transformations of demand and supply energy infrastructure for the German transport sector.

The previous section thus motivates the thesis' overarching research question: What techno-economic measures are required on an energy system level to reach CO_2 neutrality of the German transport sector by 2045 and what impacts do they imply? In this work, this research question is specified by the following sub-questions:

- How can charging of future fleets of BEV and its flexibility adequately be modeled?
- What are energy system impacts of different approaches of modeling BEV fleet energy demands?
- What are optimal energy system transformation pathways assuming different end-use demand scenarios varying in the degree of *direct* and *indirect electrification*?

1.2. Structure of the thesis

As shown in Figure 1.1, the first sub-question, answered in Paper I, focuses on using historic travel patterns for BEV modeling. Paper II answers the second sub-question for prospective, medium-term energy systems. Paper III then relaxes the scope to various transport sector energy demands for a sector-coupled energy system transforming to CO_2 neutrality for answering the third sub-question.

Clean energy supply scenarios of the transport sector need to be assessed with methods capable of grasping the manifold complex relationships of energy systems with high shares of wind and solar power. This requires tools to quantify and translate transport sector electricity and fuel demands into high resolution energy demands to be assessed in energy system models. A challenge is that other sectors likewise will replace fossil energy carriers by electricity and that electricity supply systems will increasingly be interconnected in Europe. This implies that energy system models must - at least in a simplified manner - take other sectors' electricity demands and respective flexibilities into account.

The thesis is structured as follows. In the next Section 2, a review of relevant research at the interface of energy systems analysis and transport research is described, focusing on studies aiming at a transition towards CO_2 neutral transport. Section 3 then introduces the key methodological novelties of the work. Thereafter, Section 4 summarizes the three studies. Section 5 then critically discusses the individual parts and the overarching approach of the research. Concluding, Section 6 summarizes the key findings and formulates an outlook for future research.

Throughout the thesis, technical terms and those specific to the research field are used. To increase readability for various audiences, these terms are written in *italic*. Numbers are usually rounded to 10 GW and 10 TWh unless below 10 GW or

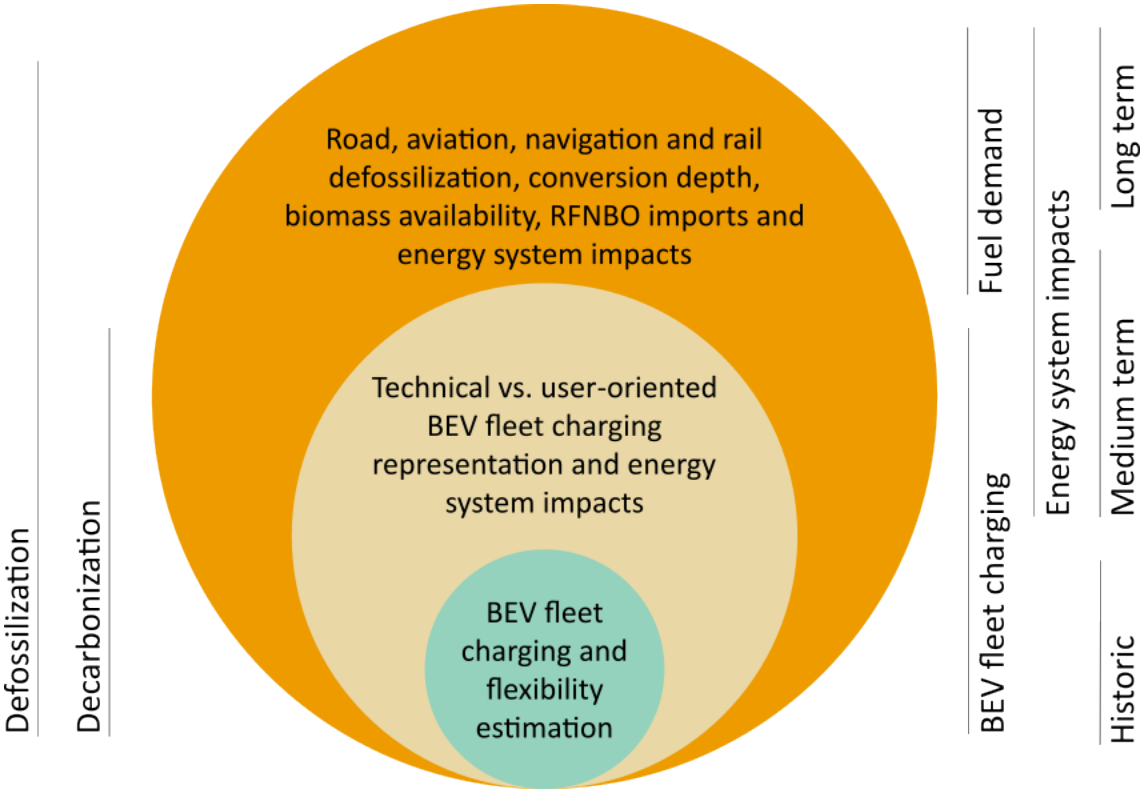


Figure 1.1.: Overview of the thesis' Papers differentiated by transport applications and time dimension.

TWh. *Fuels* from RES-based electricity are referred to as Renewable Fuels of Non-Biological Origin (*RFNBO*), and biomass-based fuels as *biofuels*. Both form the category referred to as *clean fuels*. The abbreviated form of *electrofuels* is only used for hydrogen (Hydrogen based on Electricity from RES (e-H_2)) and its derivatives (e.g. e-diesel). A sufficiently precise terminology for *energy carriers* is given at the beginning of Section 2.3. When referring to electric vehicles, usually the two categories of BEV - vehicles with a battery and an electric motor - and PEV - the former together with Plugin Hybrid Electric Vehicle (PHEV) are used. Hybrid Electric Vehicle (HEV) are not part of the analysis and FCEV are only relevant in the description of the *model coupling*.

2. Background

The following Chapter summarizes relevant studies from the fields of energy systems analysis, BEV integration and *clean fuel* supply research. Focusing on German techno-economic energy system studies, publications from other fields or regions are included where they provide defining underpinnings, motivate central quantitative or qualitative assumptions of this research or from other scopes where they introduced methods relevant to this work.

This chapter follows a logic of increasing thematic granularity of the thesis' topic, starting with a localisation and central terms to this thesis. Section 2.1 presents a short chronology of energy system research since the Paris Agreement in 2015 (UNFCCC, 2015), followed by a review of latest insights, and concluded in a more abstract discussion of scenario modeling. The chapter then deep-dives into recent studies on *decarbonization* of road transport in Section 2.2 with relevance to energy systems analysis and continues with a review of techno-economic studies on *clean fuel* supply for transport sector CO_2 emission reduction in Section 2.3. The chapter concludes with a summary and the formulation of research gaps.

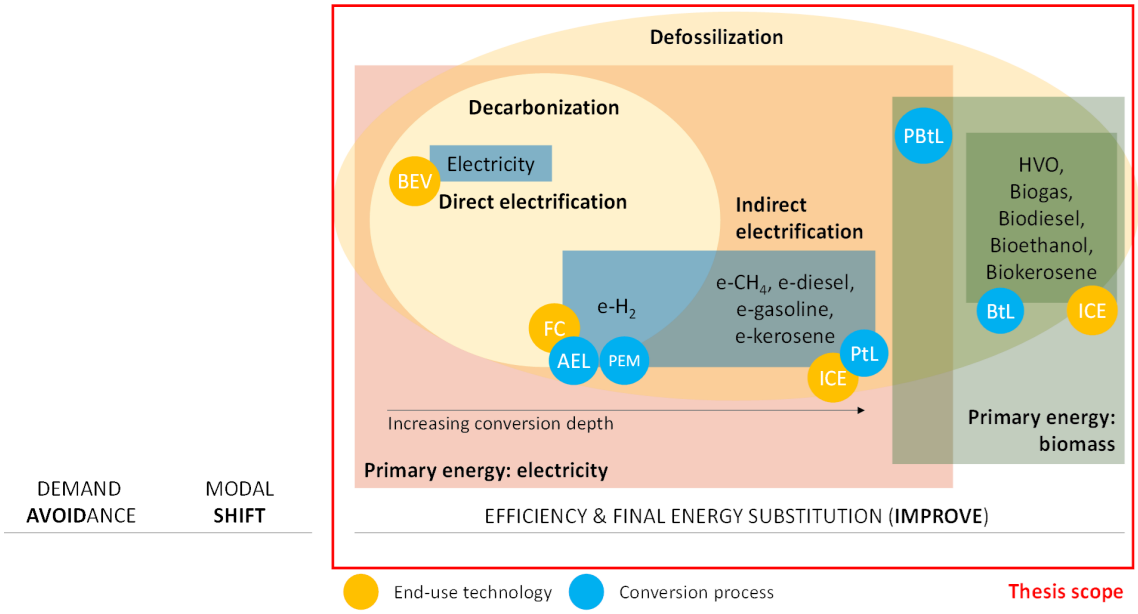


Figure 2.1.: Schematic depiction of fundamental strategies of transport sector CO_2 emission reductions, types of fuels and scope of this thesis. Abbreviations: AEL - alcalic electrolysis, BEV - battery electric vehicle, BtL - biomass to liquid, FC - fuel cell, HVO - hydrogenated vegetable oil, ICE - internal combustion engine, PBtL - power biomass to liquid, PEM - proton exchange membrane (electrolysis), PtL - power to liquid.

The two pairs of *decarbonization-defossilization* on the one hand and *direct-indirect electrification*, central to the research design of thesis, are shown on the right side of Figure 2.1 and associated with exemplary end-use technologies in orange as well as fuel supply concepts in blue.

The schema visualizes the term *conversion depth* relevant to long-term energy supply scenarios. Increasing *conversion depth* relates to higher conversion losses. Hypothetical *all-electric* scenarios have the lowest *conversion depth*. A scenario with *e-H_2* replacing final electric demand has a higher *conversion depth* even surpassed by a scenario assuming hydrocarbons replacing either final electric or final hydrogen demand.

The use of biomass as primary energy is part of this thesis as an option to alleviate strong electricity demand increases and related extension of electricity and *clean fuel* supply infrastructure. Despite its controversial role - high land area requirements, discussions on energy vs. nutrition crops, and competition with base-chemicals - this thesis strengthens the evidence base on biofuel availability's impacts on energy system transformation pathways.

End-user driven *modal shift* and systemic strategies of transport demand *avoidance* as well as other efficiency improvement strategies such as motor efficiency improvements or vehicle shape optimizations (not shown) are outside the scope of this thesis.

Figure 2.1 shows the layer of secondary and final energy, serving as lay-of-the-land from a transport sector side. However, at the methodological core of this thesis are developments and applications of energy system models and their capability of modeling necessary energy supply, transmission and storage infrastructure for energy systems with large shares of intermittent RES, which will be described in the following.

2.1. Energy system modeling as evidence base for energy planning

This section introduces energy planning processes in Germany (Section 2.1.1), gives an overview about the development of energy systems research (Section 2.1.2), and summarizes current challenges in the research field (Section 2.1.3).

2.1.1. Energy system planning in Germany

Energy system planning describes the decision-making related to the future supply, distribution, storage, and consumption of energy. It comprises designing rule sets at the interface between non-energy socio-ecologic-economic systems such as environmental protection groups, industry associations, consumer groups, or resident initiatives and energy system's entities such as transmission grid operation companies, power plant operating companies, and operators of flexibility - both industrial and that of households.

Energy policies - a large part of energy system planning - create the legislative framework on the background of which stakeholders act. They form the central

instrument of governments on the EU, German, federal state and municipal level. Energy system planning has been defined by various studies but for the purpose of this thesis, it suffices to separate two types of energy planning: *Strategic energy transition planning* provides a solid evidence base for medium- to long-term decision making. On the other hand, *procedural and administrative advice* points towards structuring processes. This thesis aims at the former part of energy planning, providing evidence for long-term decision making.

Two main studies form the evidence basis for energy planning in Germany today - the Grid Development Plan of the four German transmission system operators (Bartos et al., 2024) and the Long-Term Scenarios developed for the Federal Ministry of Economic and Climate Action (Sensfuß et al., 2022b). Both are not static documents but dynamic processes that develop over time and adapt to changing boundary conditions and legislation. While the Grid Development Plan follows a fixed procedure between the Federal Grid Agency, the four German transmission grid operators and external stakeholders, the Long-Term Scenarios are a service currently provided by Fraunhofer Institute for Systems and Innovation Research ISI, Consentec GmbH, the ifeu-Institute for Energy and Environmental Research gGmbH and TU Berlin to the federal Ministry without a participatory process for external stakeholders. Both processes were strongly affected by the German Supreme Court's ruling to significantly increase climate protection ambition in order to safeguard the interests of future generations (BVerfG, 2021).

The Grid Development Plan is the central biannual process for planning the extension of transmission grid infrastructure. It is not transparent, how the Federal Ministry of Economic Affairs and Climate Action uses the Long-Term Scenarios but they are among the most advanced energy system scenarios existing today and act as a benchmark in the field (see Table 3 in Section 3).

2.1.2. The last ten years of energy systems analysis in Germany

The energy systems analysis community and its topics are largely influenced by political discourse. While the adequate modeling of BEV and heat pumps were a focus of the years 2015-2020, modeling of hydrogen infrastructure and synthetic fuel scenarios became more important in the consecutive years on the background of political debate.

As one of the first studies, Henning and Palzer assessed the costs of a fully sector-coupled energy system (Henning and Palzer, 2015). What today is considered medium CO_2 reduction ambition of 85% vs. 1990 emission levels, was still "the goal of Energiewende" in 2015 (Federal German Governement, 2014). Already in pre-2021 studies, authors showed that raising ambition from 80% to 95% CO_2 emission reduction and beyond would encompass progressively increasing transformation efforts. This can be shown in Henning and Palzer's energy balance shown in Figure 2.2, serving as a benchmark to explain recent trends in transport sector *decarbonization* and *defossilization* scenarios since then.

Henning and Palzer give a final energy demand of 490 TWh/a for the transport

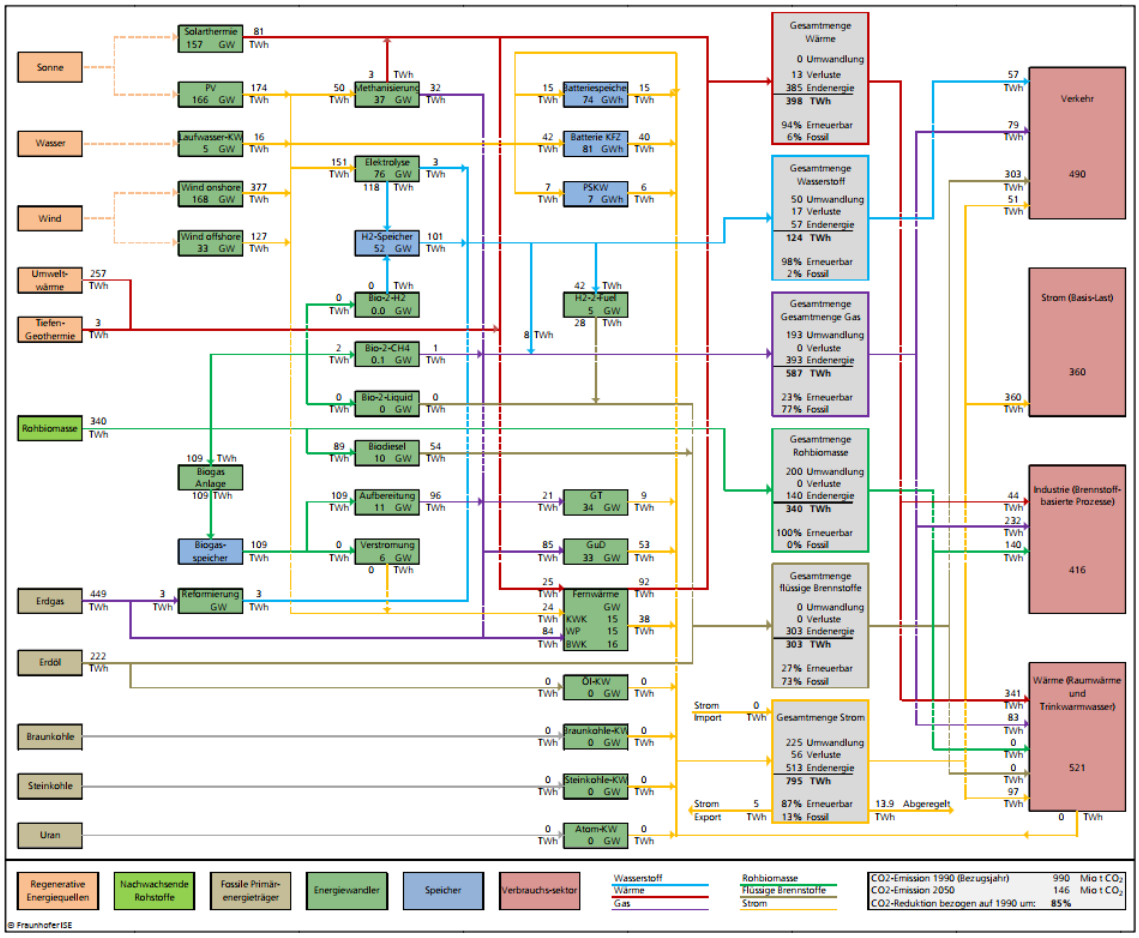


Figure 2.2.: Energy system infrastructure and annual energy flow diagram resulting from the 85%-scenario of Henning & Palzer (Henning and Palzer, 2015).

sector in their target year 2050, supplied by 50 TWh of electricity, 60 TWh of Hydrogen (H_2), 80 TWh of gas, and 300 TWh of liquid fuels - the latter two consisting of 77% and 73% of fossil gas and liquids respectively. They find 80 GW of electrolysis capacity, 40 GW of *methanation* and 5 GW of a "H_2-to-fuel" blackbox - supposedly inspired by a *Fischer-Tropsch* process. In their scenario, intermittent RES capacity of 170 GW of Photovoltaic (PV), 170 GW of onshore wind and 30 GW of offshore wind power plants are installed.

Especially the high share of fossil gaseous and liquid energy carriers in the transport sector under their 85% reduction scenario demonstrates the lack of addressing the feasibility of a fully sector-coupled net-zero energy system by the middle of the century. It also shows two additional shortcomings of energy research. First, in 2015 it was already widely known that climate change can only be kept in boundaries, persistently enabling human life, by providing useful energy without burning fossil fuel. However, the scenarios were mostly guided by then current policies rather than scientific underpinnings of what would be needed for successfully overcoming societies' dependence on fossil fuel. Secondly, the motivating narrative in that time rather seemed to be proving the technical and economic feasibility of a far-stretching

transformation as well as assigning a price-tag to this transformation rather than achieving consistency with climate targets.

Studies published between 2015 and 2021 show some variation in scenario design e.g. (Ruhnau et al., 2019). In spite of general consensus that wind and solar would become the main sources of primary energy in Germany, large uncertainties persisted as exemplified by Nacken et al. showing a range of 100% between minimum and maximum cumulative intermittent RES capacity of 300-600 GW in a target system (Nacken et al., 2019).

Two literature reviews summarize findings and research trends during that time period. Wiese et al. conducted a broad review of energy scenarios describing an at least 95% reduction of CO_2 emissions of the German energy system with the four sectors energy, transport, industry, and buildings (Wiese et al., 2022). Secondly, Ruhnau et al. reviewed trends with additional focus on transport and heat sectors (Ruhnau et al., 2019), assessing the two strategies of *direct* and *indirect electrification*.

The review by Wiese et al. compares 20 scenarios from 8 publications that were all published between 2018 and 2021 (Wiese et al., 2022). They support large variations in primary energy demand independent of CO_2 emission reduction beyond 95% with 600-1300 TWh/a of electricity generation from wind and solar power plants across the analyzed studies. Most scenarios comprise imports of electricity and *clean fuels*. One study (Hansen et al., 2019) compensates a lack of imports by the use of biomass. Seven out of eight studies assume the use of biomass for energy supply with the study by the Federal Environmental Agency being the only exception (Purr et al., 2019). Around half of the 20 scenarios assume fossil energy carriers still being present by 2050.

Generally the highest quantitative deviations across the scenarios were found for demand reduction measures, RES required abroad for the import of electricity and fuels and the import of *clean fuels*. They show that final energy demand is a key driver for other scenario outcomes, both for the installed intermittent RES capacity and the cumulative import of energy. However, ranges of 300 GW intermittent RES capacity and around 900 TWh of energy imports persist in the scenarios showing medium final energy demand of 1300-1600 TWh/a. The authors also argument that while this range is large, all scenarios show far lower total imports compared to the 2018 level of 3400 TWh/a of mostly fossil energy carriers (Wiese et al., 2022).

Turning to the transport sector, Wiese et al. show large variations of final transport energy demands between 200-750 TWh/a. All but one scenario on persisting lifestyles (Brandes et al., 2020) ex-ante assume transport sector lifestyle changes leading to between 30 to beyond 70% reduction of final transport energy demand. More than half of the scenarios presume more than 50% of final energy demand reductions in transport. This is also signified by an assumed reduction of transport sector useful energy from an around 80% share of car-use of total person-km to 51-54%. This assumption is not backed by recent trends in person transport. Car transport shares in passenger transport have been stable between 1982 and 2017 at around 74%, although large absolute increases in pkm and some changes from co-drivers to drivers can be observed (Nobis et al., 2019). Thus, all scenarios assessed by Wiese et al. (Wiese et al., 2022) assume disruptive changes in mobility trends and

most of them to a large degree. Despite their valuable work on harmonizing scenario assumptions and filling persistent data gaps, the authors do not describe varying degrees of sector-coupling, especially in the transport sector. The comparison of domestic infrastructure to produce *clean fuels* is out-of-scope of the study.

From the second review study by Ruhnau et al. (Ruhnau et al., 2019), three insights are relevant for this research. The authors call for the awareness of technological uncertainty in the transport sector mainly related to the degree of electrification driven by the CO_2 reduction ambition but especially pronounced by uncertainty in road freight transport. Generally the authors raise awareness for disrupting technologies that are not yet included in scenario creation, such as post-lithium batteries or new conversion technologies from electricity to hydrogen or hydrogen to hydrocarbons. Thirdly, the authors call for increased transparency in energy system scenarios to increase transparency and comparability (Ruhnau et al., 2019).

Both review-studies (Wiese et al., 2022; Ruhnau et al., 2019) formulate the need of data and code transparency as well as model openness. A sub community of energy system researchers has formed, propelling the ideas of open-source models and open data to increase the transparency of energy system modeling (Pfenninger et al., 2018). Despite this effort, a multitude of models exist covering a broad variety of temporal scopes, spatial scopes, sectoral scopes, technological details and agent behavior. No real benchmark model or data set has been accepted by the community thus far, although the communities around the models PyPSA (Hörsch et al., 2018), CALLIOPE (Tröndle et al., 2020) and OSEMOSYS (Howells et al., 2011) as well as the open energy platform seem to be the most influential ones. Still, large energy modeling tool heterogeneity can be observed showing the lack of forming a shared research modeling infrastructure.

The year 2021 marks an important cornerstone for energy systems analysis research in Germany - again driven by decisions shaping the German energy-political landscape. On March 24, 2021 the German Federal Constitutional Court ruled that the German government had to increase its climate policy ambitions beyond 2030 and to introduce sectoral climate targets together with traceable intermediary targets up to 2030 (BVerfG, 2021). In reaction, the German government changed the Climate Protection Act to aim at climate neutrality in 2045 and more ambitious sectoral and intermediary CO_2 reduction targets. This strongly affected the energy scenario studies being published from then on as the emission reduction target of 80-95% reduction vs. 1990 levels still assumed by Henning and Palzer now were surpassed by the amendment to the German Climate Protection Act (Henning and Palzer, 2015).

A range of studies was published in the second half of 2021 updating the previous ambition of 80-95% of CO_2 emission reduction compared to 1990 to climate neutrality in 2045 and in the wake of the German parliamentary elections. One of them was a study performed by Brandes et al., mentioning that the updated target can only be achieved when investments are almost entirely allocated to target-consistent technologies (Brandes et al., 2021). This implies if one accepts the 2045 target, it is irrational to invest in technology burning fossil fuel. Energy policy-making should reflect this fact especially for subsidies still in place for fossil-fuel burning end-use technologies.

2.1.3. Current challenges and trends in energy systems analysis

Three recent methodological developments can be observed. First, modelers increasingly model scenarios with little residual emissions in the energy system - a trend that unfolded after the German federal constitutional court's ruling in 2021 (BVerfG, 2021). Secondly, models increase in scope comprising the coupling of electricity systems to transport, heat and industry sectors. Due to the complexity of energy system models and related computational costs, this is mostly done by using multiple different models for supply and demand modeling to grasp sector specific aspects while at the same time broadening the scope (Robinius et al., 2017). Thirdly, the modeling of transformation pathways - bridging the gap between nowadays fossil-based energy systems and future net-zero energy systems - gained increasing importance since the feasibility of target energy systems with large amounts of intermittent RES had already been shown as early as 2015 (Henning and Palzer, 2015). This third trend overcame the limitation of scenarios being abstract, far away and seemingly disconnected from nowadays energy policy making.

A *model scope* differs from its input parameters and output results as it defines the model. Mathematically speaking, the scope defines the number of sets in each of the model *dimensions*. It is comparable to a mathematical problem's independent variables as it defines the structure of the problem, not the problem itself - the latter is done by the quantities of the input parameters. The main structural *dimensions* of energy system models are time, space, technology and sector. This is not a classification system for energy system model comparison as layed out e.g. in (Dekker et al., 2023).

Recently, there has been a multitude of studies extending existing energy system models to study the role of specific emerging technologies or sectors. There is a distinct relationship between *model scope* and scenarios which usually describe developments outside of the system boundary. In recent years, studies have been published analyzing the trade-offs between multiple scope-relevant *dimensions* e.g. synergies between transmission expansion and sector-coupling (Brown et al., 2018b) or emerging technologies, e.g. repurposing of gas infrastructure for hydrogen (Wetzel et al., 2023).

On a global scale, Teske et al. develop normative scenarios for achieving global 2 °C and 1.5 °C emission pathways. They find that significant electrification of transport sector final energy demand in the range of 3-35% has to be achieved before 2030 in order to keep warming below 1.5 °C and argue against including Carbon Capture and Storage (*CCS*) in energy scenarios for compensating future emissions as *CCS* potentials are needed to compensate for historic emissions. Bogdanov et al. present a detailed global analysis using hourly resolution load series for 145 regions of the world. They show large variability in energy system structures driven by locally available RES. Despite modeling in high temporal detail, the analysis lacks sectoral scope, i.e. the integration of electrified transport sector demand (Bogdanov et al., 2019).

On a European scale, Wetzel et al. show the robust capacities and operation of European energy infrastructure depending on constrained electricity and gas trans-

mission between European countries. The authors calculate energy system structure and operation for two overarching storylines - Continental Europe Sovereignty and Energy Partnerships to Neighboring Countries - and for three constraining sensitivities. They interpret their results as proving feasibility with additional political and technical degrees of freedom. They show that offshore wind power generation and $e\text{-}H_2$ imports are significantly lower when unlimited transmission extension is allowed for. The authors do not explicitly discuss implications for transport sector demand (Wetzel et al., 2023). Turning to various scopes for German energy system studies, three developments can be described: Increasing Germany-internal spatial resolution, differentiating recommendations by short-term, medium-term, and long-term, and increasing the sectoral integration.

In the following, we dive into three of four cluster topics, identified for research by Fodstad et al. (2022): Temporal and spatial resolution, multi-energy systems and sectoral coupling, and uncertainty. The fourth cluster topic, energy behavior will be referred to in Section 2.2.

Spatial scope and resolution

Several studies motivate the increasing importance to consider spatial distributions of energy infrastructure in energy systems analysis (Ulrich et al., 2022). Lohr et al. raise awareness for the concentration of intermittent RES capacity in spatially resolved models. To illustrate the differences, results for the three states Baden-Württemberg, Lower Saxony and Hesse are given as three states with various supply and demand characteristics, situated in northern, middle and southern Germany. Frystacki et al. assess the impact of spatial model resolution on system costs and installed capacity (Frysztacki et al., 2021). They argue that spatial resolution needs to be incorporated since capacity factors can vary especially in large spatial horizons (such as Europe). They also show, that high resolution can lead to concentration at best sites and that onshore wind replaces offshore wind in higher-resolution models. While their general insight holds true, its transferability to fully sector-coupled energy systems is limited as their trade-offs between onshore wind and solar capacity on the one hand side and offshore wind on the other does not apply.

One of the early studies, assessing a German climate neutral scenario including both, the European context and an intra-national spatial resolution together with a fully sector-coupled energy system is Bartholdsen et al. (Bartholdsen et al., 2019). The authors only provide two short paragraphs on the changes in transport sector energy supply, but they are insightful for showing a general shortcoming of energy systems analysis when modeling transport energy demand. The authors write "Unlike freight transport, passenger transport will have a stagnating volume over the years, with an increasing share of traffic handled by rail. In absolute numbers, the volume of passenger kilometers handled by rail increases from 87.2 billion person-kilometers (GPkm) per year to 291.5 GPkm.". They neither motivate this more than threefold increase in rail passenger transport nor do they show, what these drastic increases imply for railway infrastructure planning. As recent rail infrastructure is planned to keep current volumes or only slightly increase (see e.g. Hansen (2017) for the case of Stuttgart21), this assumption either undermines the scenario's

relevance or motivates calls for stronger rail passenger infrastructure reinforcements. Comparable assumptions are common and partly explain the drastic car use share reductions shown already for pre-2021 studies (Wiese et al., 2022). The authors find PEV shares of 62% in 2050 with the remaining third being supplied by *biofuels*. Baden-Württembergs, Hesse and Lower Saxonys power production is found to consist of around 50%, 75%, and 20% of onshore wind power and around 40%, 25%, and 15% solar PV, respectively. Lower-saxony is supplied by around two thirds of electricity from offshore wind. The authors do not disclose the data but as far as can be seen from the plots, the regional distribution is not strongly affected by their scenarios on the political will, questioning the choice of combination of spatial resolution and scenarios.

Thelen et al. (2024) updated the 2021-study by Brandes et al. (2021) with regional detail in Germany, differentiating the federal states and assessing the four scenarios *Technology Openness*, *Efficiency*, *Incumbent* and *Robustness*. The renewable energy capacity in Baden-Württemberg, Hesse and Lower-Saxony is estimated at around 70%, 65% and 30% for solar PV and 20%, 30% and 30% for onshore wind capacity respectively, with slightly more than one third of offshore wind supplying Lower-Saxony. Electricity production shifts to northern federal states for wind power but is still considerable in Baden-Württemberg, Bavaria, and North Rhine-Westphalia due to almost half of electricity production from solar PV. These three states are also marked by electricity imports whereas northern and eastern nodes do not show any electricity imports. This contradicts findings from European studies (Wetzel et al., 2023) that import of electricity, *e-H_2*, and methane from northern Europe to Germany is robust across all scenarios (Wetzel et al., 2023). The authors find around 60 GW of interconnection capacities between Germany and its neighboring countries.

Temporal scope, resolution and transition modeling

Two structural differentiations are commonly made on the temporal dimension: Horizon and resolution. Both can be used to differentiate times of investment decisions (e.g. 2030 vs. 2040) or infrastructure operation (e.g. H_2 production during day or night). They are intertwined as e.g. higher storage capacity investment motivate a different storage operation. Although infrastructure operation needs to be considered to account for renewable energy variability, it rarely directly motivates policy recommendations. This is due to high uncertainty in stochastic weather patterns (Pfenninger, 2017), increasingly shaping the German energy system and the coarse resolutions of energy system models in other *dimensions* e.g. space or technology.

Lopez et al. show that transition modeling is beneficial vs. target year modeling as legacy energy infrastructure can be considered. In target year optimizations, costs tend to be underestimated (Lopez et al., 2022). Various example of pathway modeling exist answering to more short-term policy advice. Luderer et al. show what energy infrastructure is needed until 2030 for a transition to net zero in 2045 in a multi-model comparison (Luderer et al., 2021).

On a European scale, Victoria et al. show cost benefits of increased CO_2 emission reduction speed arriving at fairly similar target systems (Victoria et al., 2020). This

shows that incorporating intermediary years may encompass larger uncertainty than the target system itself. However, this assessment is only carried out on a European scale not focusing on different speeds of German transport *defossilization*.

Esmaeili Aliabadi et al. (2023) give policy recommendations on two temporal horizons. They recommend rapid electrification of vehicles in the short term and increased research efforts for new technologies in commercial transport in the long term. The latter point also corroborates findings by Ruhnau et al. that policy makers have to be aware of transport sector technological uncertainty (Ruhnau et al., 2019).

Luderer et al. show that energy transformation evolves in phases. While supply-side measures are important in the short-term, necessitating limited build-up of gas power plants (Thelen et al., 2024) and replacement of fossil final energy carriers become relevant only from 2035 onwards. This in part explains current lack of interest in *e-H_2* projects as electricity supply still is far from being entirely RES-based.

A study by Van Ouwerkerk combines inner-German resolution with cross-model comparison of five open source models for the target year 2030 in order to identify robust short-term policy implications (van Ouwerkerk et al., 2022). The model comparison experiment reveals strong relationships between Germany-internal transmission grid and offshore wind and high variability between 100-150 GW of internal transmission. The authors also argue that increasing intermittent RES to 80% does not suffice to reach climate policy targets and further investments in transmission and storage are needed.

A question immanently tied to the temporal *dimension* is, if energy system transformation scenarios will achieve sufficient CO_2 emission reductions fast enough to stay in line with global climate targets of keeping global warming below 2 °C.

Sectoral scope and integration

As shown by Göke et al., the contribution of flexible electrolysis operation to peak load reduction is larger than for flexible BEV charging (Göke et al., 2023). This explains that excess, i.e. curtailed renewable energy is largely reduced in studies assuming CO_2 neutrality and modeling fully sector-coupled energy systems. Supply and demand infrastructure in such systems are characterized by two phenomena: Large demands for electricity, hydrogen, heat, and hydrocarbons based on RES, and on the other hand flexibilities in demand and supply of hydrogen through cavern and tank storage capacity. However, there is a contradiction between the modeled long-term role of e-H_2 in fossil-free energy systems globally (Breyer et al., 2024), and doubts of large-scale market roll-out of hydrogen infrastructure, specifically electrolyzers (Odenweller et al., 2022). This is not only due to a lack of costs of hydrogen supply equipment but also due to a lagging wind and solar PV expansion.

Soft-coupling of models - using model output data as input for other models - is one reaction to increasing computational burden of large-scale models and increasing complexity through higher demand sector detail. It was suggested by Robinius et al. (2017) for modeling sector-coupled energy systems with the benefit of grasping both, large scale effects and sub-sector specifics. Most often, models are coupled

unilaterally where e.g. a demand model provides data for an energy system model. An example of an unilateral soft-coupling is Ulrich et al., coupling an energy system model and a Computational General Equilibrium (CGE) model to assess socio-economic impacts of energy transformations such as employment and GDP (Ulrich et al., 2022). Arnz et al. couple the modal choice model Quetzal (Arnz, 2022) with the energy system model from Göke et al. (Göke et al., 2023) to assess energy system implications of *avoiding*, *shifting* or *improving* transport demand (Arnz et al., 2024). They show that even combining all demand reduction and *modal shift* measures, target energy systems are similar in structure. Improvement strategies are more effective in reducing necessary energy supply infrastructure than *avoid* and *shift* strategies. However, all strategies combined yield the smallest and thus least costly system.

Uncertainty

The assessment of energy system model uncertainty has been a research topic from the beginning of energy systems analysis. Here, we refrain from comprehensively describing uncertainty studies, but focus on the category of "knowledge or epistemic uncertainty" proposed by Mirakyan and De Guio (Mirakyan and de Guio, 2015). They suggest the following sub-categories

- Context and framing uncertainty,
- model inputs and parameters,
- model structure uncertainty,
- model technical uncertainties, and
- model output uncertainty.

From those, we will describe the first and the third type in greater detail here. Input and output uncertainty are assessed in Paper II for a medium-term energy system setup, technical uncertainty is not assessed in this thesis.

Context and framing uncertainty is generally tackled by analyzing scenarios, assessing climate ambition (Wiese et al., 2022), the choice of secondary and final energy carriers (Luderer et al., 2021), the role of imports (Luderer et al., 2021; Bartos et al., 2024; Sensfuß et al., 2022a), the degree of European cooperation (Wetzel et al., 2023) and end-user behavior (Rodrigues et al., 2022; Brandes et al., 2021; Thelen et al., 2024). Some studies develop coherent storylines as done in the latest scenario frame for the German Grid Development Plan (Bartos et al., 2024) or for general trends in climate politics and the economy - e.g. survival-of-the-fittest vs. green-democracy (Bartholdsen et al., 2019). This technique has been criticized as ineffective and creating false biases (Morgan and Keith, 2008).

Model structure uncertainty stems from model-inherent resolutions or mathematical implementations. The range of results across models is usually greater than across scenarios from the same model (Wiese et al., 2022). Pfenninger shows the

energy system model sensitivity of hourly wind and PV feed-in timeseries in an example for UK (Pfenninger, 2017). While the model is sensitive in 90% renewable energy systems, he shows that this sensitivity is reduced by introduction of storage. Schyska et al. show the model sensitivity to various temporal resolutions and recommend choosing the timeseries resolution based on the cycle of storage technologies e.g. below 6 hours for battery storages (Schyska et al., 2021).

2.2. Electric mobility

Direct electrification plays a crucial role in reducing transport sector CO_2 emissions. This strategy implies using electricity stored in electric batteries as source for propulsion energy through the use of electric motors. The strategy of *indirect electrification* through the use of *e-H_2* or hydrocarbons is discussed in Chapter 2.3.

For *direct electrification* to comprehensively reduce emissions to zero during operation, two preconditions have to be fulfilled: First, vehicles must be fully electric and secondly, electricity generation for charging must not emit CO_2. In the following, literature on vehicle fleet modeling is described before the development of reproducible profiles for charging flexibility in high temporal resolution is introduced. This section concludes with a review of energy system analyses' results of BEV charging in high RES energy systems.

2.2.1. Vehicle fleets

Of the 49.1 Mio. vehicles registered in Germany in 2024 (KBA, 2024), the number of BEV increased from 2021 at 300,000 to 1.4 Mio. vehicles in 2024. With a growing fleet of BEV, increasing electricity demand at household wallboxes or public charging facilities is observed.

Energy system researchers have been modeling electricity demand of future BEV fleets for some time. One of the first instances of incorporating BEV fleets and their charging behavior into an energy system model was done by Pehnt et al. (Pehnt et al., 2011) with Heinrichs developing a fully integrated model framework for modeling BEV diffusion and energy system impacts. This was further expanded to the incorporation of FCEV, biodirectional charging and a detailed trip pattern modeling by Luca di Tena (Diego Luca de Tena Costales, 2014). He describes using results from the fleet model Market Analysis Model for the Vehicle Market (*VECTOR21*) for his analysis based on previous work (Mock, 2010).

In a model-comparison, Yeh et al. find large variations between energy consumption across four transport sector models for a global 2°C-scenario (Yeh et al., 2017). In their results, the use of electricity is low compared to that of clean fuels and modal shifts, showing the high sensitivity of the form of energy demand to modeling approach and the lack of detail in early integrated transport and energy demand modeling.

In recent literature, five different approaches can be observed to model fleet diffusion in the context of energy systems analysis:

- Assume specific fleets in a topdown-manner (Bartos et al., 2024),

- to use scenarios to assess the impact of various drive-train technologies (Brown et al., 2018b),
- to calculate vehicle diffusion assuming exogenous sales numbers implying specific fleet diffusions (Arnz et al., 2024),
- let a central planner optimize fleet developments by choosing from discrete drivetrain designs (Thelen et al., 2024), and
- to use detailed transport sector models to quantify the fleet development. Then set the respective energy demands as constraints for energy system models (Luderer et al., 2021; Sensfuß et al., 2022b).

Further approaches are described in the literature especially between economic and transport-research (Jochem et al., 2015), such as discrete-choice models, agent-based simulations (both bottom-up) and econometric vehicle stock, system dynamics and computational general equilibrium models (all three top-down).

Especially when modeling energy transition pathways, the availability of a detailed fleet scenario is crucial as one of the greatest challenges of transport sector CO_2 emission reductions lie in the high inertia of vehicle fleets. Luderer et al. show that this leads to only marginal emission reductions even in case of high BEV sales in the short term (Luderer et al., 2021).

2.2.2. Battery electric vehicle charging patterns

With increasing shares of intermittent RES in total electricity production and increasing BEV shares, researchers have been developing tools to grasp respective charging load increase and flexibility in high temporal resolution. While increasing BEV shares imply a challenge through higher demand, this demand may play a role in balancing fluctuating solar PV and wind electricity feed-in. In the following, individual vehicle charging is explained before methods of aggregating BEV loads and flexibility are described.

On a fundamental level, two types of charging can be distinguished: Uncontrolled charging and controlled charging. Fischer et al. define uncontrolled charging as "no exertion of influence on the charging process at all, so that it just results from the driving behaviour and the connection decision of the electric vehicle user" (Fischer et al., 2019). Uncontrolled charging is the dominant charging strategy today, where vehicle users charge as quick as possible as fast as possible.

Various ways of controlling the individual charging process have been suggested. Powell et al. describe three types of controlled charging - Load shifting, load modulation, and driver-focused control - and explain that, if charging is controlled, mostly hybrid forms of all three strategies are applied (Powell et al., 2022).

Generally, two approaches dominate the modeling of future BEV fleet loads: Bottom-up modeling based on individual mobility patterns and empirically based on measured charging patterns. There are other approaches as well, such as purely theoretical approaches and technical load-flow simulations, with the former too coarse and the latter too specific for the context of this thesis.

Examples of empirically measured vehicle data comprise data from south-western commercial vehicle fleets (Schäuble et al., 2017), 22 vehicles from a commercial fleet in the health sector and energy providers (Figgener et al., 2022). An early EV field trial by BMW and Vattenfall in 2013 in Berlin is documented by Franke and Krems (Franke and Krems, 2013). The largest set of real vehicle fleet data was collected by Märtz for a fleet of BMW i3 vehicles all over Germany (Märtz et al., 2022). Weiss et al. describe a dataset collected via the Central Data Management of NOW GmbH between 2013 and 2020 (Weiß et al., 2022).

Charging station data are collected by Fischer et al. from park and ride stations in the metropolitan area of Munich (Fischer et al., 2022) and by publicly available occupation status for the case of Hamburg (Adenaw and Krapf, 2022) and all publicly available German charging stations (Hecht et al., 2022). For the case of the Netherlands, the association of distribution grid operators - ElaadNL - collects high resolution charging station data. It has been used to quantify demand-response potential of BEV charging (Develder et al., 2016) and to fit a stochastic model of Dutch charging distributions by Flammini et al. (Flammini et al., 2019). However, the dataset only comprises public charging stations and Dutch trip distributions and respective charging behavior cannot be easily transferred to Germany.

Additionally, even if empirically sourced charging data is available, this approach is limited to the specific use case the data was gathered for, e.g. the data type, work place charging, public charging, fast-charging etc. Most importantly, BEV owners are early-adopters and generally live in detached or semi-detached houses in small towns and are medium-age males (Trommer et al., 2015).

Since vehicle usage data is highly sensitive, the profiles can hardly be reproduced, and it is hard to estimate load flexibility. In the following, the second approach is described, bottom-up modeling BEV charging based on mobility behavior.

The challenge of adequately modeling BEV load profiles for large fleets lies in the interlacing *dimensions* of technical, spatial, behavioral and economic factors (Fischer et al., 2019). Determining start and end time even of uncontrolled charging depends on the following technical factors: Vehicle battery size, the maximum charging rate of the battery management system, the maximum charging rate of the charging station, and the State-Of-Charge (SOC) at beginning and end of the charging activity. The latter one is determined by a range of intertwined socio-spatial factors such as trip distance, trip purpose, driving behavior, e.g. speed and parking time, but also by behavioral factors such as the decision to connect a vehicle and the choice of a specific charging location.

The technical factors described above are usually assumed in scenarios. Together with the assumption that mobility patterns are similar for owners of BEV as for ICE vehicles, socio-spatial data is available from national travel surveys such as Mobility in Germany (German: Mobilität in Deutschland) (MiD) (Nobis and Kuhnimhof, 2019) or the Mobilitätspanel (Ecke et al., 2023). From such travel surveys providing detailed trip and purpose data with spatial and temporal reference.

Different approaches have been developed to estimate charging of BEV fleets and their load flexibility based on today's detailed driving patterns. Luca di Tena develops travel diaries and suggests to calculate individual vehicle drain, connection, and uncontrolled charging profiles in conjunction with availability-based minimum

and maximum SOC constraints (Diego Luca de Tena Costales, 2014). However, the methods and tools were never published. One of the first open source formulations of BEV modeling taking a similar approach was Electric Mobility in Python (*emobpy*) published and described in Gaete-Morales et al. (2021). There, publicly available probability density functions for the distribution of trip distance, departure time and arrival time are used in order to estimate a drain profile, a connection profile, and a profile for uncontrolled charging. Then, exogenous charging strategies can be defined in order to determine the load shifting, load modulation, or driver-focused control. Mangipinto et al. describe a way of modeling charging patterns based on mobility data available on country level for all European countries based on stochastic sampling (Mangipinto et al., 2022) embedded in a tool for household electricity demand modeling - RAMP.

Flexibility itself can be categorized into temporal, durational, locational and quantitative flexibility (Gutiérrez-Lopez and Möst, 2023). Ried et al. showed that a mathematically precise aggregation of a large number of timesteps is infeasible even for medium-sized fleet sizes (Ried et al., 2020).

Both topics, *aggregation* of individual profiles to fleet profiles and characterization of charging flexibility are topics that are still actively researched, especially as Bi-Directional Charging (BDC) gains increasing attention among energy system research.

2.2.3. The role of PEVs on energy system model results

The following section summarizes electric-mobility-related findings from energy systems analysis studies. Luderer et al. show the seasonality of flexible BEV fleet charging as it complements diurnal solar PV feed-in patterns in spring, summer and fall months (Luderer et al., 2021). However, while showing a larger flexibility supply by battery storages than by synthetic fuels and heat storage, they do not disclose, if BEV are part of this category.

Arnz et al. show that BEV will require between 120-290 TWh/a in a fully emission free energy system, showing the large impact that *avoidance* and *modal shift* measures can potentially have - at least for limiting electricity demand increase by BEV fleets (Arnz et al., 2024). BEV fleets contribute more to flexibly provided energy than thermal, hydrogen, and hydro storage combined. However, the authors do not assume full fuel coverage e.g. do not assume synthetic kerosene demands, that may change this picture. Bartholdsen et al. show a 62% BEV fleet share with the remainder covered by *biofuels* (Bartholdsen et al., 2019). Unfortunately, they do not show BEV fleet or charging details on *NUTS1* level (in Germany, NUTS1 - Nomenclature des Unités territoriales statistiques, level 1 - refers to the 16 federal states).

The important Grid Development Plan scenario frame assumes 24-40 Mio. BEV, a larger share of 70-95% in 2045. This significant variation translates into a range of electricity demand between 70-90 TWh/a.

Taljegard et al. (2019a) conduct a study of all Scandinavian countries - Denmark, Finland, Norway and Sweden - connected to Germany and assess the role of different charging regimes on optimal energy system investment and power plant operation.

They find that demand increases based on increased BEV fleets are compensated mainly by additional wind power, smoothens the load curve, and reduces the value of solar power. They also find that BEV operated flexibly might increase fossil fuel power plant operating hours. In another study, they show that the complementarity between BEV and intermittent RES depends on the country with their specific mix of intermittent RES and demand characteristics (Taljegard et al., 2019b). BEV facilitate PV generation in countries aside Sweden. However, the model is limited as it cannot transfer energy over several days.

Another strand of publications assesses the impact of charging strategies on the specific CO_2 intensity of charged energy. Jochem et al. evaluate the impact of the accounting method and the charging strategy on CO_2 intensity of charged electricity in Germany in 2030. They find that controlled charging reduces the CO_2 intensity of charging in the two assessment schemes considering temporal resolution - time-dependent average mix, and marginal mix. Especially in the latter case, controlled charging significantly reduces specific CO_2 emissions by 30% (Jochem et al., 2015). In a study extending the energy system scenario to 2050 and including BDC into the assessment, Xu et al. find that uncontrolled and controlled charging may increase energy system emissions by 90 and 60 Mt CO_2-eq. while applying BDC may slightly reduce emissions. Emissions are accounted from an LCA perspectives and driven by supply-chain emissions of PV installations and gas power plants (Xu et al., 2020).

2.3. Clean fuels for low-emission transportation

Terminology of clean energy carriers so far has not converged, thus terms like *pink hydrogen* or *synfuels* have evolved. In the following, a clear terminology is proposed for the following descriptions. The section is largely taken from a book-chapter currently under review (Esmaeili Aliabadi et al., 2025).

The term *fuels* comprises all gaseous and liquid energy carriers primarily intended for end-use oxygenation in various applications; thus, Liquid Organic Hydrogen Carrier (*LOHC*) and ammonia are not considered in this group since they are intended to transport energy. They are an *energy carrier* but not a *fuel*.

Clean fuels comprise non-fossil fuels that are based on non-fossil primary energy, consisting of *RFNBO* and *biofuels* (and mixtures of the two), but not of blends between *fossil fuels* and *RFNBO* or *biofuels*. Those could be considered *grey fuels*. Sometimes, *RFNBO* are also referred to using the term *electrofuels* (Millinger et al., 2021) or - especially in public debate - as e-fuels. They consist of gases - mainly hydrogen and methane - and liquid fuels such as *e-kerosene*. In the following, the abbreviated form of *electrofuel* will only be used for specific derivatives such as *e-*H_2, but not for the category which will be referred to as *RFNBO*. So far, solid *RFNBO* are not being discussed but are technically possible, e.g. "renewable coal".

Biofuels describe gases, liquids, and solids based on biogenic primary energy, i.e. biomass. They can be based on a multitude of feedstocks. *Biofuels* based on *waste feedstocks* such as urban grass clippings, wood scrap, and manure from livestock are referred to as *advanced biofuels*. *First-generation biofuels* or *conventional biofuels* are usually based on agricultural energy crops, controversially discussed (tank

vs. plate debate) (Puttkammer and Grethe, 2015), and limited by EU policies also because of competing interests from non-energy sectors such as base chemical synthesis.

Operating synthesis of biogenic feedstocks including *e-H_2* as co-educt is referred to as *Power-Biomass-To-Liquid (PBtL)-fuel*. *Hydrocarbons* is a term based on fuels' chemical components and comprise *fossil hydrocarbons*, *hydrocarbons* based on *e-H_2*, and *biogenic hydrocarbons*. More end-use-application-oriented *fuels* such as *e-diesel*, *e-gasoline* and *e-kerosene* describe *fuels* that substitute fossil alternatives based on *e-H_2*.

Synthetic fuels or *synfuels* are fuels that are produced using a conversion step of chemical synthesis, usually in a catalytic synthesis reactor as e.g. in a *Fischer-Tropsch* conversion route (Meurer et al., 2024). *Synfuels* can be based on *e-H_2* via Power-To-Liquid (*PtL*), on *biomass* via Biomass-To-Liquid (*BtL*), or via a combination of both via *PBtL*. H_2 is not a *synfuel* but it is an *RFNBO*. *Synthetic fuels* form the basis of the term *defossilization* since they partly consist of carbon. *Hydrocarbons* can be gaseous, liquid or solid. All *synthetic fuels* require a source of hydrogen and an additional source of a hydrogen-carrying molecule - most commonly carbon or nitrogen. Carbon can again be fossil - e.g. via Carbon Capture and Utilization (*CCU*) from the exhaust gas stream of a fossil power plants, based on renewable electricity using *DAC* or bio-based - e.g. seperated from biogas through gas separation processes such as *pressure swing adsorption*. Carbon sources are not analyzed in detail in this thesis, for a detailed compilation of European carbon sources see e.g. Arellano Ruiz (Arellano Ruiz, 2021).

Sector-specific terms are e.g. *Sustainable Aviation Fuel (SAF)*. Jet fuel or Jet-A1 fuel is a synonym for kerosene and describes norm-conform fuel, independent of the primary energy source. The term *e-fuel* is colloquially used for liquid *RFNBO* for combustion in ICE-vehicles (Esmaeili Aliabadi et al., 2025). In this terminology, this lacks precision, as *e-H_2* is an *e-fuel* - a fuel based on electricity - but not a *synthetic fuel* - a fuel based on synthesis.

As mentioned above, hydrogen has been classified based on its origin by various colors, such as *green hydrogen* for *e-H_2* from RES-based electricity or *blue hydrogen* for H_2 from steam reformation using *CCS* technology to split CO_2 from the exhaust gas and store it underground. Beyond the term *green hydrogen* that will be used in the following due to brevity, the reader is referred to Incer-Valverde et al. for a detailed discussion of hydrogen "colors" (Incer-Valverde et al., 2023).

2.3.1. The role of clean fuels for transport sector emission reduction

As mentioned before, early energy systems analysis studies did not pay large attention to the transport sector as its transition did not fundamentally change under emission reduction goals of up to 80% (Henning and Palzer, 2015). The authors mostly limited sector coupling between energy and transport sector to integrating BEV as also done in (Brown et al., 2018b). With emphasizing the clear goal of CO_2 neutrality, requesting clearer climate targets beyond 2030, and a sectoral focus by

the German Federal Constitutional court in 2021, the transition to net-CO_2 free transport gained increasing attention.

While efforts in increasing PEV share in new car sales need to be significantly increased in order to reach the goal of 15 Mio. BEVs in 2030 (*decarbonization*), *defossilization* gains importance only from 2030-2035 onward under cost-optimality (Luderer et al., 2021).

There are multiple reasons to integrate demands for *clean fuels* into energy system models. Some modes of transport require the physico-chemical properties (mainly energy density and temperature stability) of hydrocarbons. These comprise kerosene for aviation, and diesel or ammonia for navigation. Domestic production of *RFNBO* in Germany is controversially discussed, however, it is likely that German demands will not only be imported (see below) but also produced in Germany. This has strong implications, as the production, storage, and transmission of hydrogen plays a vital role for inter-seasonal storage in most sector-coupled high-RES scenarios (Gils et al., 2021b). Thus, integrating the transport-induced demands for *clean fuels* is key. Here again - as for electric mobility - the challenge for the electricity system can be described as increasing demands for electricity that at the same time may provide relevant demand-side flexibility (Göke et al., 2023). Different from PEVs, hydrogen storage and grids may provide seasonal flexibility and has strong synergies with both the energy and heat sectors.

However, *e-H_2* is limited in Germany as well - 180-320 TWh/a of electricity for electrolysis in the scenario frame for the Grid Development Plant (Bartos et al., 2024) and 270-390 TWh/a in the Long-Term Scenarios (Sensfuß et al., 2022b) -, shifting the focus to the question of sources for *RFNBO* in other EU countries or to non-EU countries.

This section is ended with a thought from political science on international trade relationships as it has strong relevance for the topic of *RFNBO* fuels. De Souza et al. analyze on the background of a postcolonial theoretical framework, how "institutional orientalism" in European countries has hindered energy cooperation in the last decade since 2010 (de Souza et al., 2018). They argue that Middle East and North Africa (MENA) region risk is perceived as being greater than necessary in European energy planning and that energy cooperation is hindered by the lack of cooperation among European states under the argument of national sovereignty. Suggesting an "environmental space-time scale" as evaluation basis over geopolitical and economic considerations, energy cooperation projects should be mutually beneficial. They recommend fair transnational agreements, more knowledge and experience transfer and community administration of energy cooperation projects in order to avoid situations where project benefits are restricted to MENA elites only. Studies that assess imports of *RFNBO* to Germany need to be aware of historic relationships, power dynamics and the environmental space-time scale.

2.3.2. *RFNBO* domestically produced in Germany

Domestic production of *RFNBO* in Germany is widely discussed in energy systems analysis. As its role is uncertain (Bartos et al., 2024), researchers tend to model this uncertainty as scenarios or sub scenarios with high and low imports of *RFNBO* to

Germany, e.g. in the Long-Term Scenarios (Sensfuß et al., 2022b) or in Luderer et al. (Luderer et al., 2021).

As of July 2023, there were 19 so called power-to-liquid-projects in planning in Germany according to the PtX Lab Lausitz (PtX Lab Lausitz, 2023). With Solarbelt and NextGate there are two facilities in operation. The "Reallabor Westküste 100" canceled the decision to build the facility in Heide, Schleswig-Holstein at the end of 2023. Ineratec, a Karlsruhe-based company is installing a *PtL* -facility at Industriepark-Hoechst with a planned nominal capacity of 2500 t/a. Shell announced that they will transform one of their refinery plants in Wesseling to replace fossil crude oil by clean alternatives. However, for eight of the 19 projects, the start date for operation was undefined. As shown by Odenweller et al., *e-H_2* supply capacity in Europe remains scarce in the short-term and unclear in the long-term (Odenweller et al., 2022). They also show, that while there is significant electrolysis capacity announced in Europe up to 2030, the major share of this is in Spain and most projects overall are in the conceptualization or feasibility study phase.

There are multiple advantages of domestic production of transportation fuels in Germany. Germany's geopolitical dependency on fossil fuel imports showed in the aftermath of the Ukraine war in 2022. Higher energy sovereignty would mean lower dependence on world market developments. Secondly, it is questionable how fair trade relationships would be with countries of the global south and the exploitation of foreign countries' best RES resources for exportation has to be avoided. Thirdly, companies may want to gain experience with emerging technological systems and processes in a relatively stable political environment that they are familiar with before investing significant volumes abroad. In Germany, costs of capital are lower since risks of political collapse are perceived as lower than in many other countries. As a fourth advantage, the already planned build-up of hydrogen infrastructure - the German hydrogen grid and hydrogen storage facilities - secures the availability of a central and most important educt of *RFNBO* production.

However, there are several disadvantages to *RFNBO* production in Germany. Against the investment of companies in Germany stand the high energy costs - specifically electricity - combined with legal and bureaucratic complexity. The definition of *renewable hydrogen* in a Delegated Act of the European Union ties the label *renewable hydrogen* to the *additionality principle* as well as temporal and geographic proximity between electricity and hydrogen production (European Commission, 2024). Electricity for electrolysis may thus - from 2028 onwards - only stem from RES power plants that are additionally built for this purpose. This undermines electrolysis as a provider of flexibility interacting with the energy system and thus integrating potential of flexibly operated electrolysis plants for intermittent RES on a system level. There are further complicating rulesets defining taxes and levies that operators of electrolyzers have to take into account in a multitude of cases. Another argument against early electrolysis and *RFNBO* production capacities is the expected decrease of specific investments due to anticipated economies of scale. This may lead to the paradoxical situation that economies-of-scale may not be triggered because investments are kept back in expectation to economies-of-scale. In opposition to a self-fulfilling prophecy, this could be described as a *self inhibiting prophecy* and has to be alleviated by political subsidies - as can be observed to some

extent today.

2.3.3. *RFNBO* imported to Germany

Germany is - as all European countries except for Norway - a net energy importing country (Ikonnikova et al., 2023) which results from Germany's lack of sufficient and competitive coal, oil and gas resources to supply the demand. In spite of technical potential of RES being estimated at up to 3 TW, to what degrees these can be tapped is uncertain (Risch et al., 2022). Combining the lower-most estimate with the upper-most estimate for all four technologies - offshore, onshore wind, rooftop and open space PV - yields a still vast combined intermittent RES capacity potential range of 720-1550 GW (Risch et al., 2022). Assumed or resulting intermittent RES production in literature ranges from 600-1500 TWh/a (own analysis based on various recent studies).

In spite of high efficiency gains in the total energy balance due to high degrees of *direct electrification*, literature studies' final energy demand amounts to 1000-2200 TWh/a. As especially *RFNBO* synthesis comes with large conversion losses, these amounts are unlikely to be fulfilled by German RES sources alone. Hampp et al. suggest, that in all scenarios, import options are cheaper than domestic production (Hampp et al., 2023), although other studies suggest the opposite, at least for *e-H_2* (Göke et al., 2023). In sector-coupled energy system studies, energy imports in three forms play a relevant role. In almost all scenarios, electricity imports are described to various degrees. Hydrogen imports are most controversially discussed. While some studies find almost no *e-H_2* imports (Viebahn et al., 2022), others find *e-H_2* imports of around 60 TWh/a independent of transport sector *avoid*, *shift* and *improve* measures (Arnz et al., 2024), around 80 TWh/a for both models compared (Luderer et al., 2021), 100-250 TWh/a depending on targeted robustness or incumbent end-users (Thelen et al., 2024), around 190 TWh/a (Nesselhauf et al., 2024), 180-420 TWh/a depending on the demand focusing on electricity or hydrogen (Sensfuß et al., 2022b) or up to 400 TWh/a split up in around 200 TWh/a from EU countries and 200 TWh/a from non-EU countries (Gierkink et al., 2021). The scenario frame for the Grid Development Plan explicitly states these high uncertainties and varies the import of *e-H_2* in their scenarios between 50% and 70% of final hydrogen demand leading to 100-140 TWh/a of assumed *e-H_2* imports (Bartos et al., 2024).

The range of import shares of imported *clean fuels* is smaller as most authors show large imports of those energy carriers. However, assumed final demands and thus absolute hydrocarbon imports vary significantly. Most studies do not differentiate liquid energy carriers with the only exception of the Long Term Scenarios (Sensfuß et al., 2022b). The Grid Development Plan scenario frame assumes that all hydrocarbons are imported although it is not explicit, if domestic refineries hydrogen demands are part of their total hydrogen demand of 140-280 TWh/a (Bartos et al., 2024). Interestingly, maximum domestic fuel production of 200 TWh/a is shown in the reference+mix scenario developed by Arnz et al. where a minimum of *avoid*, *shift* and *improve* measures is assumed (Arnz et al., 2024).

A range of literature has assessed global production costs of electricity-based energy carriers. Lux et al. derive *e-H_2* and methane cost-potentials in the MENA

region. They find that minimum prices for substantial *e-H_2* and methane productions lie at 90 and 130 EUR/MWh in 2050 and conclude that imports are only competitive if transport costs are available at the lower end of current literature ranges and if interest rates are similar between the EU and MENA (Lux et al., 2021).

Pfennig et al. provide a comprehensive database of global *PtL* production plant sites and find production potential of 120 PWh/a of *e-H_2* and 90 PWh/a of clean fuels (Pfennig et al., 2023). They show production costs of around 45 EUR/MWh for *e-H_2* and around 80 EUR/MWh for *clean fuel*. As they state, they incorporate 40 socio-economic indices from the fields of politics, economy, society, technology and natural environment from "international organizations [...] and private firms" without providing further information. While it is a novel approach, to include other criteria than techno-economic and while the authors relativize their analysis by stating that they want it to be understood as on a "rough high level [that] does not have the scope of the techno-economic analysis", they continue by saying "It can serve as an initial orientation for the socio-economic assessment of countries and territories regarding their suitability for the development of a Power-to-X infrastructure." It seems, that their socio-economic analysis is mainly an instrument to refining export potentials in the interest of Germany rather than incorporating interests of social groups in foreign countries that may be culturally different from Germany. Even though this topic is not specifically part of the thesis, it is instrumental that energy system modelers are aware of the implications of such an analysis.

Hampp et al. find importing *e-H_2* by pipeline from Denmark, Spain, Western Asia and Northern Africa starting at 36-42 EUR/MWh. They also argue that for more complex energy carriers such as hydrocarbons, locations further away are more beneficial. Different from Runge et al. who argue for *e-H_2* import in the form of *LOHC* (Runge et al., 2023), they argue that for meeting *e-H_2* demands, direct import is more beneficial due to energetic losses of indirect routes (Hampp et al., 2023).

Recent energy system studies show various forms and detail of incorporating imports into their models. The simplest form is neglecting demand and supply. This may be reasonable if the analytical focus lies on other issues, such as on the influence of intermodal transport behavior in Arnz et al. (Arnz et al., 2024), neglecting kerosene demand within the model. Some studies use the scenario assumptions to exogenously define imports, as e.g. in the scenario frame of the Grid Development Plan (Bartos et al., 2024) and to our knowledge also for liquid fuels in the Long-Term Scenarios (Sensfuß et al., 2022b). The next detailed way of modeling imports is as sources with defined prices that may dynamically develop in case the study is a transformation study. Göke et al. assumes imports of *e-H_2* to Germany at costs of 110 EUR/MWh via shipping and of 70-80 EUR/MWh via pipeline from Morocco and Egypt (Göke et al., 2023). Other studies have shown that *e-H_2* import at higher costs than 30 EUR/MWh are not used, unless the German intermittent RES potential is fully exploited (Gils et al., 2021b). Göke et al. then also state in their results "Overall, domestic hydrogen production is cost-efficient and hydrogen imports from outside of Europe are negligible totaling 3.2 TWh imported by Italy and the UK." A similar approach is followed by Wetzel et al. assuming *e-H_2* imports

at 80 EUR/MWh and methane imports at 120 EUR/MWh (Wetzel et al., 2023).

An approach currently under development and under evaluation is assuming discrete steps of cost-potentials. Thelen et al. assume a similar approach with only one cost-potential step that develops over time (Thelen et al., 2024).

2.3.4. Biofuels

While the focus of this dissertation is not on biomass, a key novelty of the work is integrating *biofuels* into a bilateral *model coupling*. Thus, in the following, the role of biomass as primary energy carrier for clean transportation fuels is described. The analysis and discussion by Millinger et al. (2021), who first developed the fuel allocation model BioENergy OPTimization Model (*BENOPT*) (Millinger et al., 2022) serves as a basis.

The use of biomass for transport final energy needs to undergo multiple process steps, starting with available biogenic feedstocks. Those may be gathered from crops from agricultural land (*conventional* or *first generation biofuels*) or from biowaste streams (*advanced biofuels*). An extensive collection of 77 waste biomass streams has been compiled by the German Biomass Research Center and made available online via the Biomass Resource Monitor. The research center also publishes biomass potential data on the EU level (Deutsches Biomasseforschungszentrum, 2024). From this data base, Millinger et al. select the five biomass feedstocks with the highest relevance for fuel production (Krause et al., 2020): *Manure*, *biowaste*, *industrial residues*, *used cooking oil* and *straw*. They then complement these feedstocks with the five agricultural products of *silage maize*, *sugar beet*, *grains*, *rape seed* and *poplar*. These ten feedstocks are then used in ten conversion processes to produce the six fuels of hydrogen, methane - gaseous or liquified, ethanol, diesel and kerosene that supply the four transport subsectors. Additionally to the biogenic feedstocks, hydrogen is fed as co-educt to the processes of *Hydrogenated Vegetable Oil (HVO)* and *PBtL*. As biogenic feedstock prices are volatile and affected by a vast range of stochastic factors - such as weather (Brosowski et al., 2020), the authors assume three price categories of low, medium and high prices. They also add CO_2 emissions for transport, logistics and conversion. For crops, a range of available land of either 0 or 1 Mha is assumed, the latter being slightly lower than today's bioenergy crop land area. Crop plantation and *RFNBO* processes to use are then degrees-of-freedom of the model to supply the demands in the four transport sub-sectors.

Using a bi-optimization approach minimizing costs and maximizing CO_2 abatement, they find that in the medium term mainly beet-based ethanol is used for supplying gasoline demands for passenger ICE vehicles. Freight land and maritime transport are both supplied by large shares of H_2, liquefied methane and *PtL* fuel. In aviation, H_2 is used to the allowed maximum of around 10 TWh/a in 2050 and complemented by kerosene mainly from *BtL* and *PtL* fuel. Next to *sugar beet*, mainly *poplar* for *BtL* and *PBtL* production and *maize silage* for biomethane production are part of the optimal mix. A range of factors limit the insights of the analysis. As the authors mention, excess RES is assumed exogenously together with a fix price and specific CO_2 emission of the electricity mix. This neglects feedback effects of fuel allocation to the energy system as well as flexibility of BEV charging. A second

shortcoming is, that the authors only consider fuels for power and transport final demand but neglect interdependence with the heat-sector in a fully sector-integrated analysis.

This latter task is demonstrated in a few recent studies (Jordan et al., 2023, 2024; Meisel et al., 2024). As done in Millinger et al. (2021), fix end-use demands for transport combined with heat demands on various temperature levels and non-energy fuel demands are assumed. They aim at showing the consequences of a phase-out of biomass from energy use for the German energy transition in various sectors. Biomass phase-out is mainly compensated for by imported *e-H_2*, methane and *RFNBO* (Jordan et al., 2023), but also by a significant increase of 30% in electricity demand, however including electricity demand for fuel production abroad. They confirm an allocation of *synthetic fuels* (both *RFNBO* and *biofuels*) to the two hard-to-abate sectors shipping and aviation. In the biomass scarcity scenario around 35 TWh of kerosene, Liquified Natural Gas (*LNG*) and diesel are produced from imported *woody biomass*, imported and domestic *animal fats* and imported *digestible residues*. Compared to the scenarios from Luderer et al. (2021), the scenarios show an increase of *RFNBO* demands shifted from 2030-2035 to beyond 2040 when *biofuels* are taken into account.

In a follow-up analysis focusing on the coherence of short-term *biofuels* with long-term energy system scenarios, Jordan et al. show the impact of CO_2 quotas, CO_2 pricing, Ukraine-war-induced price effects and strong transport sector final energy reductions. They show that a biofuel quota in transport leads to much higher biofuel shares while pure CO_2 price increases lead to stronger *indirect electrification*. A quota may lead to significantly misallocations incoherent with long-term system optimality, because *biofuels* are increasingly used in road transport, whereas they should be allocated mainly to navigation and shipping in the long-term.

Especially of interest for this work is the result for a transport final energy demand reduction. The authors find that, by cutting final energy demand, an even increased quota of 35% (compared to 25% as of today) can be fulfilled by less biomass. This also leads to an introduction of *PtL* fuels in the late 2027. The respective scenario is also the one with the lowest transport sector emissions. This result shows the strong impact, that final energy demand reductions through *avoidance* and *modal shift* of transport demand can play, supporting findings by Arnz et al. (2024).

The study is one of the most comprehensive ones including biofuel modeling. However, some limitations persist. Despite modeling the explicit transport sector final energy demand reduction, the authors do not show vehicle fleet developments associated to their scenarios. As the study focuses on biofuel allocation, the electricity system is modeled with coarser detail, and *PtL* and *e-H_2* supply is assumed to be completely imported. Thus, energy system implications of the provided scenarios can only be derived with regards to CO_2 emissions and not to energy supply, transmission, and storage infrastructure.

2.4. Summary and research gap

In the following, recent publications will be summarized and the research gap described, that will be tackled in this thesis. Thereby, three of the four cluster topics for future energy system research mentioned by Fodstad et al. (2022) will be addressed; multi-energy systems, temporal and spatial resolution, and modeling energy behavior and energy transition.

Energy systems analysis studies in general show a large consensus that wind and solar power will have to provide the majority of Germany's future primary energy. With a range of 430 (Jugel et al., 2021) to 840 (Thelen et al., 2024) GW installed capacity, and 630 (Luderer et al., 2021) to 1600 (Thelen et al., 2024) TWh/a annual electricity production, the ranges across literature scenarios is still large. European and inner-German grid extension is shown to be among the cheapest options of spatial flexibility (Neumann and Brown, 2023) and authors have shown that currently planned internal and interconnection capacities are below cost-optimally found capacities (Neumann and Brown, 2023; Sensfuß et al., 2022b) with cost-optimal domestic transmission capacities of up to 100-150 GW (van Ouwerkerk et al., 2022).

Hydrogen seems less likely to play a major role as form of final energy. However, its role as a seasonal energy storage is seen as indispensable by most scholars in the long-term. Demand for liquid fuels has only recently been introduced into energy system modeling but studies show that their demand becomes relevant only beyond 2030 with electricity supply systems being largely renewable. Literature ranges for fuel imports are large, with limited excess renewable electricity in long-term sector-coupled energy systems at least on a national level if transmission grid extension is available as an option. Most studies assume demand decreases and drastic vehicle fleet transformations, sometimes to a degree that are not consistent with historic trends. Uncertainties persist on the role of imports of electricity, *e-H_2* and fuels.

The largest share of transport sector emissions stems from passenger road transport. The most efficient way of decreasing emissions is found to be *direct electrification* through the replacement of ICE by PEV. The increasing load of PEV fleets and its respective temporal flexibility has been a focus of research since around 20 years. However, open, reproducible tools for load and flexibility estimations are still rare and sometimes build on simple probability distributions or charging behavior of early adopters not representative for future BEV fleets. It is still unclear, how detailed the electric load of future fleets should be modeled and how the integration of user-choices, especially vehicle plugging and purchasing behavior, affect energy system model results. The share of *direct electrification*, i.e. the share of electricity in cumulated final energy demand, ranges between 30-70 % (Luderer et al., 2021) with the scenario frame for the Grid Development Plan at 31%.

With raising the ambition of German climate policy to CO_2 neutrality in 2045, the comprehensive *defossilization* of the transport sector becomes relevant for long-term energy systems analysis. While road and rail passenger transport final energy demand are likely to be *directly electrified*, aviation and navigation will continue to require hydrocarbons, necessitating a substitution of fossil crude oil with clean fuel alternatives. End-use specific fuels, such as diesel, gasoline and kerosene are rarely researched in the context of energy systems analysis.

The shares of imported *RFNBO* and domestic biomass vary in energy system scenarios. Recent evidence suggests that energy will most likely be imported in the form of hydrogen derivatives due to easier handling compared to hydrogen. The role of *e-H_2* imports itself is highly uncertain and likely to depend on political infrastructure extension decisions. The production of clean fuels outside the European Union (EU) has been assessed extensively showing vast potentials. However, future trade will depend on the specific combination of costs and potentials, motivating a detailed combined model description of mapped combinations of both.

Furthermore, there is evidence that energy system designs during their transformation - i.e. in the next 10-15 years show higher degrees of variation than long-term target systems, motivating an explicit modeling of intermediary years during the transformation. Specifically, the variation of *conversion depth* may be larger in the medium than in the long term with strong implications on energy system transformation pathways.

Energy transformation speeds - especially for the extension of intermittent RES and hydrogen infrastructure - are challenging. Biofuels - despite controversially discussed - have been shown to shift the introduction of *RFNBO* and related necessary energy system infrastructure extension, due to lowering transport sector final energy demand for clean fuels and unavoidable conversion losses. However, this is so far done for only one scenario with optimistic assumptions on vehicle fleet developemnts.

The role of biofuels in general has only been assessed as exogenous assumption - with a range of 190-740 TWh/a (Thelen et al., 2024) for post-2021 studies - or studies compromised on the detail of transport sector demand modeling. Thus, the question of trade-offs between domestic clean fuel production, clean fuel import and biofuels and respective energy system implications yet remains open.

An assessment of the cumulative CO_2 emissions along the considered energy system transformation pathways is not part of this thesis, but is discussed in Section 5.3.

3. Methodology

In this section, the contribution to the literature by improving on existing methods is described. Table 3 gives an overview on energy system studies including a CO_2 free transport sector and how their scope and approach relate to this study's scope.

Three relatively distinct types of publications exist. The first one are peer-reviewed scientific studies of universities and research centers. They can be described by a higher number of scenarios assessing the impact of various structural uncertainties such as the degree of political cooperation, the willingness to export fuel, and the willingness for lifestyle changes, but also quantitative - more modeling-related uncertainties such as the share of the BEV fleet capable of feeding-electricity back to the grid (Brown et al., 2018b), the upper limit of electricity and gas transmission capacity between European countries (Wetzel et al., 2023), and country-specific risks (Krüger et al., in review).

The second category of scenarios addresses decision-makers. Most of these publications are based on a scientific study but edited and interpreted for the target group, e.g. (Jugel et al., 2021) based on (Gierkink et al., 2021). They generally show in one scenario, how an energy system transformation to a system without CO_2 emissions is possible, also adding detail on intermediary years - at least 2030. With a broad scope of transport demand sectors, suitable sets of policy instruments are discussed on the short and medium term in order to achieve the target. Most of these studies do not disclose their model *scopes*, thus it is not possible to fully understand, prove or disprove the applied modeling logic. Most of the analyses are carried out without spatial detail, nevertheless assuming some sort of energy exchange with neighboring countries.

The third category are the scenario frame for the transmission Grid Development Plan (Bartos et al., 2024), the Long-Term Scenario (Sensfuß et al., 2022b), and a recent study by Thelen et al., adding a spatial resolution combined with a broad set of scenarios (Thelen et al., 2024). The latter study seems to be the only one that includes fuel imports as an option into their energy system model. Otherwise, the modeling detail of energy imports and *biofuels* strongly varies without a clear trend between the two categories.

In addition to the model dimensionality, transport sub-sector, fuel modeling detail, and scenarios analyzed above, the choice of technical detail of the components of the energy system and especially technologies at the interface between the energy system and transport energy demands are important. The technological and sectoral scope of models applied in the sub-studies of this thesis are depicted for the interface components between energy and transport sectors in Figure 3.1.

Reference	Years covered	Spatial res.	Transport sectors	N scens (fuels)	Imports	Biofuel
(Arnz et al., 2024)	-	*NUTS0*	Road,rail,air	8(3)	H2	x
(Bartholdsen et al., 2019)	20,30,50	*NUTS1*	Road,rail,air(n)	3(3)	Fossil	x(r/w)
(Bartos et al., 2024)	37,45	*NUTS1*	Road,rail; p/f	3(-)	-	-
(Wetzel et al., 2023)	45	*NUTS0*	Road	48(2)	gas	-
(Brown et al., 2018b)	-	*NUTS0*	Road,rail	18(2)	-	-
(Krüger et al., in review)	-	*NUTS0*	no res.*	1+3(8)	costpot	?
(Luderer et al., 2022)	25,30,35,40,45	*NUTS0*	Road,rail,air	6(4)	low	x(s/l/g)
(Nesselhauf et al., 2024)	25,30,35,40,45	-	Road,rail,air	1(2)	low	x(s/l/g)
(Burchardt et al., 2021)	30,45	-	Road,rail,air,nav	1(4)	low	x
(Jugel et al., 2021)	30,35,40,45,50	-	Road,rail,air,nav	1(5)	medium	(x)
(Thelen et al., 2024)	30,35,40,45	*NUTS1*	Road,rail,air	4(3)	costpot	-
(Sensfuß et al., 2022b)	25,30,35,40,45	high	Road,rail,nav,air	5(6)	?	x
This work (Paper III)	20,30,40,45	*NUTS1*	Road,rail,nav,air	8(5)	fossil,clean	x(a/r/w)

Table 3.1.: Overview of recent energy system studies modeling a low-emission German energy supply considering transport in some detail. Number of fuels does not contain electricity. Abbreviations: a=agriculture, costpot=cost-potentials of imports, f=freight, g=gaseous, l=liquid, n=national, N=Number, nav=navigation, p=passenger, r=residual, res.=resolution, s=solid, scens=scenarios, w=waste. *Full transport sector scope is assumed but only differentiated by fuel not by transport sub-sector, **

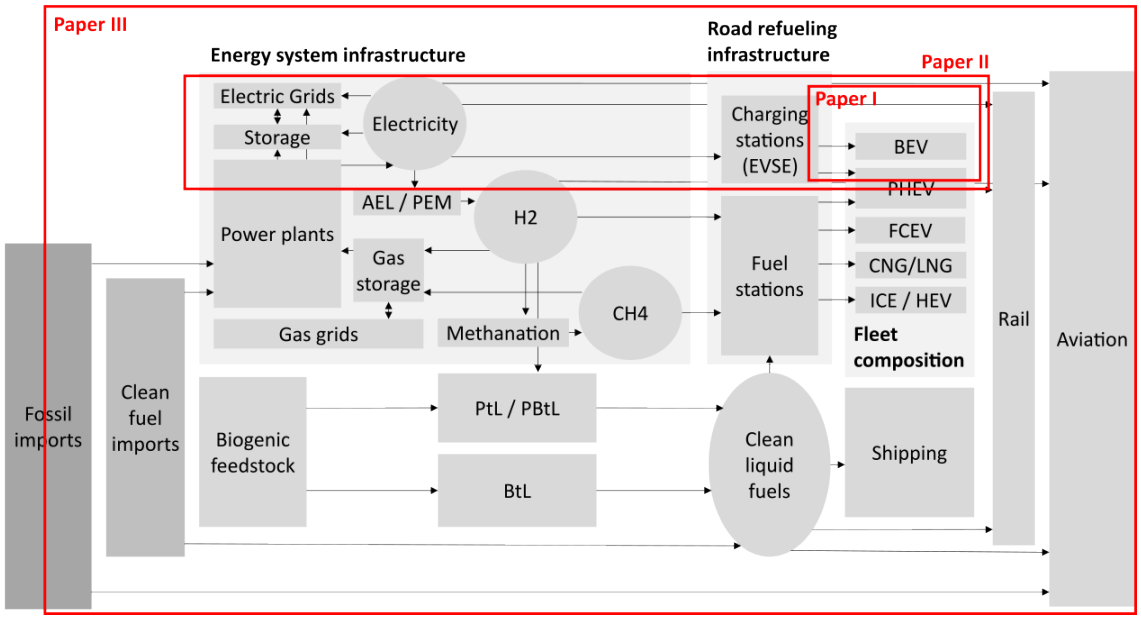


Figure 3.1.: Schematic depiction of the scopes of the Papers I-III part of this thesis. Abbreviations: AEL: Alcalyc electrolysis, BEV: Battery electric vehicles, BtL: Biomass-to-Liquid, CH4: Methane, CNG: Compressed Natural Gas, EVSE: Electric vehicle supply equipment, FCEV: Fuel Cell Electric Vehicle, H2: Hydrogen, HEV: Hybrid Electric Vehicle, ICE: Internal Combustion Engine, LNG: Liquefied Natural Gas, PEM: Proton exchange membrane (electrolysis), PBtL: Power-Biomass-to-Liquid, PHEV: Plugin-Hybrid Electric Vehicle, PtL: Power-to-Liquid.

The Section is structured as follows. First, an overview on the formal underpinnings of the energy system model *REMix-OptiMo* is given in Section 3.1. Then, the approach to BEV charging modeling is introduced in Section 3.2. Consecutively, Section 3.3 describes the workflows and interfaces used to harmonize the *scopes* and exchange data between the demand models, the biomass model, the fuel import data, and the energy system model. Chapter 3 concludes with the overarching scenario framework in Section 3.4.

3.1. Energy system modeling

A general linear cost-minimization problem can be defined as shown in Eq. 3.1 by its variables ξ, its associated specific costs c, boundary conditions b, and the coefficient matrix A.

$$\begin{gathered} min\ \Xi = c^T \xi \\ s.t.\ A \times \xi = b \\ c \in \mathbb{R}^{n\times 1}, \xi \in \mathbb{R}^{n\times 1}, A \in \mathbb{R}^{m\times n}, b \in \mathbb{R}^{m\times 1} \end{gathered} \tag{3.1}$$

As $m < n$, there are less equations than variables, thus the problem is underdetermined. For solving 3.1, a *dual problem* can be defined and solved simulta-

neously. The solutions of the *dual problem* are closely related to the problem's *primal solution*. Each variable of the *dual problem* is related to an equation of the *primal problem*. The *dual variables* of the equations in the global solution have interpretative meaning - they represent the change of the objective function when the constraint represented by the equation is relaxed by one unit. They are denoted by the *marginal value* μ. Among the most relevant *dual variables* are the ones of the power balance equation as they represent the cost increase with one additional unit of electricity demand often interpreted as an estimate for the supply cost of electricity.

The energy system model framework *REMix-OptiMo* (Scholz, 2012) has been extended for BEV, domestic *RFNBO* and imported *RFNBO* modeling in the scope of this research.

In the following, the *dimensionality*, main variables and main equations for the *objective function* (system costs) and energy balancing are given. Where relevant for the methodological extensions, specifically on BEV modeling and *model coupling*, more detailed equations are described.

Bottom-up energy system models vary the installed energy infrastructure capacity and its dispatch in high spatial and temporal resolution in order to minimize the cost of energy supply under given constraints. The temporal, spatial and scenario-related *dimensionality* of the model is shown in the upper part of Table 3.2. One scenario, i.e. one element of the scenario-set $s \in \mathbb{S}$ possibly consists of multiple models e.g. four; one for each of years 2020, 2030, 2040 and 2045 (see below).

The *objective function* of an abstract energy system model is shown below in Eq. 3.2, with the component superset $\mathbb{M}$ (Hoffmann et al., 2024) also taking into account *typical day-implementations* with p_s and optimization across various scenarios $s \in \mathbb{S}$. $C^{CAPEX}_{c,r,y}$ describes the capital expenditure of technology c in region r in year y, $c^{op}_{c,y,r,s,t}$ is the operation-specific costs of technology c in scenario s and timestep t in $\frac{\text{EUR}}{\text{MWh}}$ and x^{op} the respective operation of technology c - production, charging, discharging, transmission, etc.

$$\Xi = \sum_{c} \sum_{y} \sum_{r} \left(C^{CAPEX}_{c,r,y} + \sum_{s} \sum_{t} p_s c^{op}_{c,y,r,s,t} x^{op}_{c,y,r,s,t} \right) \tag{3.2}$$

For this thesis, Eq. 3.3 shows the simplified version of Eq. 3.2 for *target-year optimization* employed in this work. $c^{OPEX,fix}(s,r,y,c)$ are fix operational costs independent of operation. $c^{OPEX,var}$ and $\xi(s,r,y,c,t)$ relate to c^{op} and x^{op} from Eq. 3.2. The superset TEC relates to the component set $\mathbb{M}$ from above. Typical-day implementation p_s as well as inter-scenario optimization - adding costs across multiple scenarios $s \in \mathbb{S}$ - are not employed in this thesis.

For each target year y, one optimization model with one instance of the total system cost in Eq. 3.3 is compiled and solved. Consecutive years of the same scenario are related by legacy energy system infrastructure until respective life time is reached. This mechanism is implemented outside the optimization itself (Gils et al., 2021b).

Sets (*subsets*)	Model dimensionality
$a \in \mathbb{A}$	All European airports
$f \in \mathbb{F}$ ($\mathbb{F}_{in}$, $\mathbb{F}_{out}$)	Considered fuel
$y \in \mathbb{I}$	Investment period, $\mathbb{I} \in \mathbb{Y}$
$j \in \mathbb{J}$	Transport sub-sector
$k \in \mathbb{K}$	Fuel demand technologies and exogenous demand
$l \in \mathbb{L}$	Fuel supply technologies and import
$m \in \mathbb{M}$	Model
$r \in \mathbb{R}_m$	Region relating to model $m \in \mathbb{M}$
$s \in \mathbb{S}_m$	Scenario relating to model $m \in \mathbb{M}$
$t \in \mathbb{T}$	Time step with resolution Δt
$y \in \mathbb{Y}$	All years between 2020-2050
Technological *sets*	$c \in TEC$ (technology superset)
$x \in CHP$	Combined heat and power plant
CON	Conventional power plant
$e \in EVE$	Plug-in electric vehicles
$g \in EG$	AC and DC electricity transmission line
$g \in GG$	Gas transmission superset ($HG \cup MG$)
$h \in HEA$	Heat supply technology
HG	Hydrogen transmission grid
MG	Methane transmission grid
$c \in PP$	Power plant $\{CHP, CON, RES\}$
$p \in RES$	Fluctuating renewable energy
$l \in SFE$	Synthetic fuel electrolysis
$v \in SFC$	Synthetic fuel conversion
$i \in SFI$	Synthetic fuel import
Variables	
Ψ	Charging of PEV battery
Φ	Discharging BEV battery
ζ	Model endogenous demand and export of energy
ξ	Model endogenous production and import of energy
ν	Intermittent RES curtailment
Ω	Capacity of technology
σ	Controllable share of PEV fleet
Λ	PEV fleet battery level
Objective function	
Ξ	Total system cost

Table 3.2.: Dimensions, main variable categories and objective function of *REMix-OptiMo*. Electric mobility specific input parameters, variables and equations are explained in Section 3.1.2. Fuel conversion specific input parameters, variables and equations are explained in Sections 3.1.3, 3.1.4, and 3.1.5.

$$\Xi(s,y) = \sum_{c}\sum_{r}(C^{CAPEX}(s,r,y,c) + c^{OPEX,fix}(s,r,y,c) + \sum_{t} c^{OPEX,var}(s,r,y,c,t) \times \xi(s,r,y,c,t)) \quad \forall y \in \mathbb{I}, s \in \mathbb{S} \tag{3.3}$$

The middle part of Table 3.2 specifies the technological *dimensions* relevant to this work. Each of the technological sets shown in the middle part of Table 3.2 corresponds to a specific *module* with its unique data input characteristics, definition of sets, input parameters, options, variables and equations as well as output processing routines. The technology *superset* TEC corresponds to the components $\mathbb{M}$ in the notation from Hoffmann et al. (Hoffmann et al., 2024).

In the model, the most relevant equations are the balance equations for electricity, heat, and fuels in each scenario, region and year, $s \in \mathbb{S}, r \in \mathbb{R}, y \in \mathbb{I}$. The balance equations for electricity and energy carriers are shown in a simplified version in Eqs. 3.4 and 3.5. The comprehensive balance equations have additional terms for storage charging and discharging, electricity demand for gas transmission and gas storage, see Gils (Hans Christian Gils, 2015), Gils et al. (Gils et al., 2021b) and Scholz (Scholz, 2012) for a detailed formalization. Additionally, the grid import and export is simplified in Eq. 3.4, see Cao and Wetzel (Cao and Wetzel, 2020) for more details. Since all terms of Eq. 3.4 depend on r and y, these are omitted in the description below. In the optimization, Eq. 3.4 is constructed $r \times t$-times for each year y.

$$\begin{aligned} D^{elec}(t) + \sum_{e}(\Psi_{unc}(e,t) + \Psi_{CC}(e,t) + \Psi_{BDC}(e,t)) + \sum_{h}\zeta^{elec}_{heat}(h,t) \\ + \sum_{l}\zeta^{elec}_{ELY}(l,t) + \sum_{v}\zeta^{elec}_{SFC}(v,t) + \sum_{g}\zeta^{elec}_{EG,exp}(g,t) \\ = \sum_{p}\xi^{elec}_{RES}(p,t) + \sum_{x}\xi^{elec}_{CHP}(x,t) + \sum_{e}\Phi_{EVE}(e,t) + \sum_{g}\xi^{elec}_{EG,imp}(g,t) \\ \forall t \in \mathbb{T} \end{aligned} \tag{3.4}$$

In Eq. 3.4, D^{elec} represents the exogeneously given electricity demand, Ψ the demand for charging of the PEV fleet, ζ^{elec}_{heat} the electricity demand for heat applications, ζ^{elec}_{ELY} the electricity demand for electrolysis, ζ^{elec}_{SFC} additional demand for refinery pumps and equipment, $\zeta^{elec}_{EG,exp}$ electricity exports, $\xi^{elec}_{RES}, \xi^{elec}_{CHP}$ electricity production from intermittent RES and Combined Heat and Power (CHP) plants, Φ_{EVE} the electricity fed back from the BEV fleet to the grid, and $\xi^{elec}_{EG,imp}$ imported electricity.

The most relevant terms for *direct electrification* of the transport sector are Ψ_{unc}, Ψ_{CC}, Ψ_{BDC}, and Φ_{BDC} as they represent the demands for charging of the BEV fleet

and the discharging to the grid. The demand for driving itself P_{drive} is not accounted for in Eq. 3.4 as it does not directly represent a grid load (see Section 3.1.2).

As described above, the *dual variables* of Eq. 3.4, $\mu(y, r, t)$ can be interpreted as the costs of electricity supply in that region. In the following, this is used for estimating the annual costs for electricity supply in Germany as described below in Section 3.3.2. The fuel balance (Eq. 3.5) balances fuel demand and supply. In this thesis, it is instantiated for the *RFNBO* e-diesel, e-gasoline, e-kerosene, *e-H_2*, and e-methane. As all terms depend on r and y, those are omitted below.

$$D^f + \sum_v \zeta^f_{SFC}(v) + \sum_h \zeta^f_{HEA}(h) + \sum_x \zeta^f_{CHP}(x) + \sum_g \zeta^f_{GG,exp}(g) = \sum_l \xi^{H_2}_{ELY}(l) + \sum_v \xi^f_{SFC}(v) + \sum_g \xi^f_{GG,imp}(g) + \sum_i \xi^f_{SFI}(i) \quad \forall f \in \mathbb{F} \tag{3.5}$$

with D^f being the annual fuel demand (see Section 3.3.2), ζ^{elec}_{ELY} and $\xi^{H_2}_{ELY}$ being directly connected via the electrolysis efficiency. Similarly, ζ^f_{SFC} and ξ^f_{SFC} are connected via the chemical efficiency of the respective refinery technology $v \in SFC$ with ξ^f_{SFC} appearing in hydrocarbon instances of Eq. 3.5. For the hydrogen instance of Eq. 3.5, $\xi^{H_2}_{SFC}$ is omitted and $\zeta^{H_2}_{SFC}$ represents the H_2 demand for *RFNBO* conversion.

It is important to note, that Eq. 3.5 is not a closed energy balance as applied in mass and energy balances in process engineering, e.g. heat losses are not accounted for. The production terms ξ^{elec} and ξ^f on the right-hand side of Eqs. 3.4 and 3.5 are bound by respective production capacities Ω^{elec}_{PP}, Ω^f_{SF} as shown in Eqs. 3.6 and 3.7. Ω_{TEC} consists of legacy capacities from previous years and newly installed capacity through optimization variables.

$$\xi^{elec}(r, y, c, t) \leq \Omega^{elec}_{TEC}(r, y, c) \times \Delta t, \forall r \in \mathbb{R}, y \in \mathbb{I}, c \in \mathbb{PP} \tag{3.6}$$

$$\xi^f_{SFC}(r, y, v, t) \leq \Omega^f_{SFC}(r, y, v) \times \Delta t, \forall r \in \mathbb{R}, y \in \mathbb{I}, v \in \mathbb{SFC}, t \in \mathbb{T} \tag{3.7}$$

The most relevant term from the fuel balance equation for *indirect electrification* of transport demands is D^f_{fix} as it represents the fix fuel demand, exogenously assigned. It is the central parameter for *model coupling* and further described in Section 3.3. The fuel demand is calculated differently depending on the respective sector and fuel, as described in Section 3.3.

The annual electricity mix of all power plant technologies c for Germany in year y is available by $m_{PP,DE}$ as shown in Eq. 3.8.

$$m_{PP,DE}(y, c) = \sum_{r \in DE} \sum_t \xi(r, y, c, t), \forall y \in \mathbb{I}, c \in PP \tag{3.8}$$

3.1.1. Intermittent renewable energy model

The set RES comprises of onshore wind, offshore wind, solar PV, and hydro run-of-river power plants building on feed-in timeseries $P_{max,RES}$ developed in (Scholz, 2012) and consecutively updated (Gils et al., 2021a). Intermittent RES capacity expansion potential was assumed based on a previous version of the scenario frame for the Grid Development Plan (Drees et al., 2022). The model sensitivity towards techno-economic values - the development for intermittent RES Capital Expenditure (CAPEX) is tested in Paper II (Section B.2) by three different coherent sets of CAPEX developments. An overview of the timeseries duration curves is given in the Appendix of Paper II. A sensitivity of the model for the year 2030 to the weather years 2006-2012 is conducted in Subsection 3.3 of Paper II.

Relevant for *model coupling* with the Extended BioENergy OPTimization Model (*BENOPTex*) is the curtailed electricity from intermittent RES, ν shown in Eq. 3.9. Together with the grid feed-in it has to follow a pre-defined maximum feed-in timeseries π resulting from an hourly capacity factor profile P_{RES} and the total installed RES capacity Ω as described in Eq. 3.10.

$$\xi^{elec}(y,r,p,t) + \nu(y,r,p,t) = \pi(y,r,p,t),\ \forall y \in \mathbb{I}, r \in \mathbb{R}, p \in RES, t \in \mathbb{T} \tag{3.9}$$

$$\pi(y,r,p,t) = P_{RES}(y,r,p,t) \times \Omega(y,r,p),\ \forall y \in \mathbb{I}, r \in \mathbb{R}, p \in RES, t \in \mathbb{T} \tag{3.10}$$

3.1.2. Plug-in electric vehicle model

PEV technologies are defined by the technological set EVE. In the scope of this study the elements only comprise BEV in small, medium and large size. PHEV and FCEV are modeled but not analyzed in detail. The complexity of the *module* arises from the various ways of modeling BEV fleets, its annual electricity demand, its uncontrolled charging in high temporal detail, and its temporal flexibility of charging. The implementation extends previous work (Luca de Tena and Pregger, 2018; Fette et al., 2020).

The basic modeling logic is described in Paper II, the following descriptions focus on the technical description of the input and processing steps. The module comprises ten variables and 13 equations, most of them depending on $\mathbb{I}$, $\mathbb{R}$, $\mathbb{T}$ and EVE. The model requires a set of five input profiles in hourly resolution $\forall y \in \mathbb{I}, r \in \mathbb{R}, e \in EVE, t \in \mathbb{T}$:

- A profile for uncontrolled charging in GW per hour $C_{unc,in}(y,r,e,t)$,
- a profile for grid connection of the fleet in GW per hour $P_{charge,in}(y,r,e,t)$,
- a profile for energy drain for driving in TWh per hour $P_{drive,in}(y,r,e,t)$,
- a profile for the maximum fleet SOC in TWh $L_{max,in}(y,r,e,t)$, and
- a profile for the minimum fleet SOC in TWh $L_{min,in}(y,r,e,t)$.

All of the above are fleet profiles aggregated for the entire vehicle fleet. The detailed calculation backgrounds from mobility patterns to vehicle travel diaries and from those to the above mentioned profiles are subject of Paper I. The first three profiles are referenced similarly by other tools such as *emobpy* (Gaete-Morales et al., 2021). However, the battery level SOC profiles are based on Luca de Tena Costales (Diego Luca de Tena Costales, 2014) and consider the time-dependent presence and absence at charging stations throughout a week. They provide an upper boundary for the fleet flexibility, as it has been shown that the approach of an aggregated vehicle fleet battery irrespective of the vehicle owner heterogeneity overestimates the fleet's flexibility potential (Muessel et al., 2023; Ried et al., 2020; Wang et al., 2022).

A bulk charging efficiency has to be given for charging η_{charge} and discharging $\eta_{discharge}$. Both contain all losses between the grid and the battery, i.e. the losses at the interface between grid and Electric Vehicle Supply Equipment (EVSE), the losses in the EVSE, the losses between EVSE and vehicle plug, and the vehicle-internal losses. A study on the revenue potential of BDC, including multiple Original Equipment Manufacturer (OEM) companies assumed a range between 92-95% of charging and discharging efficiency (Kern et al., 2020). An upper-end value of 95% for 2030 is assumed.

The PEV related variables are shown below in Table 3.3.

Variable symbol	description	Sets	Bound by Eqs.
σ_{CC}	Fleet share CC	$\mathbb{R}$,$\mathbb{I}$,EVE	3.11, 3.14, 3.15
σ_{BDC}	Fleet share BDC	$\mathbb{R}$,$\mathbb{I}$,EVE	3.12, 3.14, 3.16
Ψ_{unc}	Charge power UC	$\mathbb{R}$,$\mathbb{I}$,$\mathbb{T}$,EVE	3.18, 3.19
Ψ_{CC}	Charge power CC	$\mathbb{R}$,$\mathbb{I}$,$\mathbb{T}$,EVE	3.11, 3.19
Ψ_{BDC}	Charge power BDC	$\mathbb{R}$,$\mathbb{I}$,$\mathbb{T}$,EVE	3.16, 3.19
Φ_{BDC}	Discharge power BDC	$\mathbb{R}$,$\mathbb{I}$,$\mathbb{T}$,EVE	3.17, 3.19
Λ	Fleet battery level	$\mathbb{R}$,$\mathbb{I}$,$\mathbb{T}$,EVE	3.19, 3.20, 3.21
ρ	Load reduction*	$\mathbb{R}$,$\mathbb{I}$,$\mathbb{T}$,EVE	3.22

Table 3.3.: Variables of the electric mobility module of the energy system model framework. Abbreviations: CC=Controlled charging, BDC=Bidirectional charging, UC=Uncontrolled charging. *Due to shifted power

There are two additional variables on investment cost in flexibility and operational costs but they are not the analytical focus and thus not discussed here. The following Eqs. 3.11-3.22 constrain the optimization variables with the respective input parameters shown in Table 3.3. As every variable relates to a year $y \in \mathbb{I}$, a region $r \in \mathbb{R}$ and an PEV technology class $e \in EVE$, those sets are omitted in Eqs. 3.11-3.22, whereas time-dependence $t \in \mathbb{T}$ is given, where it applies.

$$\sigma_{CC} + s_{CC} \leq s_{CC,max} \tag{3.11}$$

$$\sigma_{BDC} + s_{BDC} \leq s_{BDC,max} \tag{3.12}$$

$$\sigma = \sigma_{CC} + \sigma_{BDC} + s_{CC} + s_{BDC} \tag{3.13}$$

$$1 > \sigma \tag{3.14}$$

$$\frac{\Psi_{CC}(t)}{\eta_{charge}} < P_{charge,avail}(t) \times (\sigma_{cc} + s_{cc}) \tag{3.15}$$

$$\frac{\Psi_{BDC}(t)}{\eta_{charge}} < P_{charge,avail}(t) \times (\sigma_{BDC} + s_{BDC}) \tag{3.16}$$

$$\Phi_{BDC}(t) \times \eta_{charge} < P_{charge,avail}(t) \times (\sigma_{BDC} + s_{BDC}) \tag{3.17}$$

$$\Psi_{unc}(t) = C_{unc}(t) \times (1 - \sigma) \tag{3.18}$$

$$\Lambda(t) - \Lambda(t-1) = \Psi_{unc}(t) + \Psi_{CC}(t) + \Psi_{BDC}(t) - \Phi_{BDC}(t) - P_{drive}(t) \tag{3.19}$$

$$\Lambda(t) < L_{max}(t) \tag{3.20}$$

$$\Lambda(t) > L_{min}(t) \tag{3.21}$$

$$\rho(t) = \frac{\sigma \times C_{unc}(t) - (\Psi_{CC}(t) + \Psi_{BDC}(t))}{\eta_{charge}} \tag{3.22}$$

s_{CC}, s_{BDC} represent the fleet shares that can access controlled and BDC respectively, with the maximum possible shares $s_{CC,max}$ and $s_{BDC,max}$ and the optimization variables σ_{CC} and σ_{BDC} representing additional fleet shares as investment options. Eqs. 3.16 and 3.15 constrain the controlled charging by the available cumulative fleet charging power $P_{charge,avail}$ in each timestep. Vice-versa, Eq. 3.17 constrains the power fed back to the grid. Eq. 3.18 calculates the uncontrolled charging profile resulting from investments into controlled and BDC capabilities. Eq. 3.19 balances the fleet battery level with charged and discharged electricity between timesteps. The shifted load ρ determined by Eq. 3.22 is only used for determining the load difference between uncontrolled and resulting charging in each timestep.

The variables shown in Table 3.3 are variable categories. In the optimization model itself, each variable category (e.g. $\Psi_{CC}(y, r, e, t)$) comprises as many variables as there are unique set combinations living in $\mathbb{R} \times \mathbb{I} \times \mathbb{T} \times EVE$. Since a *target-year optimization* is employed in Paper II, Appendix B.2 and a *myopic optimization* in Paper III, Appendix B.3, the investment horizon $\mathbb{I}$ is a *set* with one element per optimization model. Still, the three remaining *sets* above lead to almost 114,000 variables per PEV technology e in the simple model of Paper II with Germany split in a northern and a southern region with its adjacent neighboring countries (cardinality $C(\mathbb{R}) = 13$), totaling around 342,000 individual variables just for the modeling of PEV charging in that variable category yielding a total of 2.4 Mio. operational and 117 investment variables for the module of PEVs.

Different from Thelen et al. with similar spatial scope (Thelen et al., 2024), the vehicle fleet composition itself is not a *degree-of-freedom* of the model. While it may seem interesting to assess scenarios optimal to the system, the purchasing decision of a vehicle strongly depends on other factors than costs (see Section 3.2.1). This may be an interesting analytical approach but is an assumption that abstracts the model

$l \in SFE$	$y \in \mathbb{I}$	η %	CAPEX $\frac{kEUR}{MW_{el}}$	Am.t. #	Li.t. #	int. %	FOM %	VOM $\frac{\text{EUR}}{\text{MWh}_{\text{el}}}$
AEL	2020	64.2	1869	20	25	5	1	1
	2030	69.4	1202	20	25	5	2	1
	2040	72.2	1202	20	25	5	2.1	1
	2045	75	1202	20	25	5	2.3	1
PEM	2020	61.4	3898	20	25	5	3	0
	2030	65	2163	20	25	5	4	0
	2040	68	1762	20	25	5	4	0
	2045	71	1362	20	25	5	4	0

Table 3.4.: Techno-economic assumptions of electrolysis technologies assumed in Paper III. Am.t.=Amortization time, CAPEX=Capital expenditure, FOM=Fix operational and maintenance cost in percentage of CAPEX, Li.t.=Life time, int.=interest, VOM=Variable operational and maintenance costs

from real world cause-and-effect relationships thus reducing the tractability. This thesis instead applies vehicle purchasing scenarios including multiple *dimensions* of user preferences.

3.1.3. Electrolysis model

The module for electrolysis is used largely as described in Gils et al. (Gils et al., 2021b). Electrolyzer capacity can be expanded for specified annualized investment either as Alkaline Electrolysis (*AEL*) or as Proton Exchange Membrane (*PEM*) electrolyzer or a combination of both. Capacity is linearly expanded, not in fix multiple of capacity.

Hydrogen storage can be extended either as caverns (with limited capacity) or as tanks (more expensive but unlimited capacity). Between German nodes, hydrogen grid transmission capacity can be built for specified annualized investments. This also implies that the system model may expand capacities that may not match real-world actor behavior. This "economic granularity gap" (Cao et al., 2021) is a known problem in linear energy system optimization models.

The data for *AEL* and *PEM* electrolysis is taken from the framework assumptions developed for the project Evaluatory research for the initiative Energy Transition in Transport (German: Begleitforschung Energiewende im Verkehr) (*BEniVer*) (Aigner et al., 2023) and are shown in Table 3.4.

Hydrogen can also be imported at dynamically decreasing costs with given potentials, see Section 3.1.5.

3.1.4. Synthetic fuel conversion model

The conversion model is taken from Gils et al. (Gils et al., 2021b) but is extended to cover the multi-input, multi-output *Fischer-Tropsch* process. *Methanation* is taken into account as well. Both processes require a source of CO_2. It is assumed, that

DAC is available on a commercial scale from 2030 onward and thus used. Point-sources of CO_2 from steel or cement plants are not assumed. CAPEX based on the set of framework assumptions from the project *BEniVer* are used as inputs (Aigner et al., 2023).

The costs, technical properties and the fuel shares are assumed based on two calculations: A Techno-Economic Process Evaluation Tool (Techno Economic Process Evaluation Tool (*TEPET*)) and a process simulation using the process simulation software *Aspen* (Albrecht et al., 2017). From there, costs, technical properties and fuel shares are extracted and used to parametrize a *blackbox model* for Fischer Tropsch (FT)-refineries and *methanation* plants. The general procedure of integrating techno-economic design software, process simulation, Life Cycle Assessment (LCA), and energy systems analysis is described in Heimann (Heimann et al., submitted).

Production of *RFNBO* in *REMix-OptiMo* is handled in seven modules for the import, production, conversion, transport, storage, demand, and balancing with other sectors separately. The technological sets for electrolysis SFE, conversion SFC, and import SFI are given in Table 3.2, the other modules have not been changed and are employed as described in (Gils et al., 2021b). Transmission of fuel is only modeled for $f \in H_2, CH_4$ between the Germany model *nodes* in the scope of this thesis.

The implementation for modeling the conversion of synthetic fuel is a linear blackbox model and employs three technical variables:

- fuel input $\zeta^{f_{in}}_{SFC}(y, r, v, l, t)\ \forall v \in SFC, l \in \{AEL, PEM, DAC\}$,
- fuel output $\xi^{f_{out}}_{SFC}(y, r, v, k, t)\ \forall v \in SFC,\ k \in \mathbb{K}$, and
- added capacity $\Omega^{f}_{SFC}(r, y, v)\ \forall v \in SFC$

and four cost-variables that are not the focus of this thesis but described in (Gils et al., 2021b).

Input parameters required are the product and educt shares $e^{f_{in}}_{SFC}$ and $e^{f_{out}}_{SFC}$, the overall process conversion efficiency η_{SFC}, power demand for auxiliary equipment such as pumps ζ^{elec}_{SFC} and cost parameters for investment, amortization time, interest rate, and Operation and Maintenance (OM) costs.

The production of fuels are balanced in the following Eqs. 3.23-3.25 in which the variables' dependence on $r \in \mathbb{R}_m$, $y \in \mathbb{I}$ and $t \in \mathbb{T}$ is omitted due to brevity.

$$\sum_{f_{out}} \xi^{f_{out}}_{SFC}(v) = \sum_{f_{in}} \zeta^{f_{in}}_{SFC}(v) \times \eta_{SFC}(v),\ \forall v \in SFC \tag{3.23}$$

$$\xi^{f_{out}}_{SFC}(v) = e^{f_{in}}_{SFC}(v) \times \eta(v) \times \sum_{f_{in}} \zeta^{f_{in}}_{SFC}(v),\ \forall v \in SFC, f \in \mathbb{F}_{out} \tag{3.24}$$

$$\zeta^{f_{in}}_{SFC}(v) = e^{f_{in}}_{SFC}(v) \times \eta(v) \times \sum_{f_{out}} \xi^{f_{out}}_{SFC}(v),\ \forall v \in SFC, f \in \mathbb{F}_{in} \tag{3.25}$$

$$\sum_{f_{in}} \zeta^{f_{in}}_{SFC}(v, t) \leq \Omega_{SFC}(v),\ \forall v \in SFC, f \in \mathbb{F}_{in} \tag{3.26}$$

f_{in} and f_{out} are mapped to respective conversion technologies $v \in SFC$, e.g. $f_{in} \in \{H_2, CO_2\}$ for $v = Fischer - Tropsch$. $\zeta_{SFC}^{H_2}$, $\xi_{ELY}^{H_2}$ and $\xi_{DAC}^{CO_2}$ are mapped via the H_2-instance of Eq. 3.5.

Eqs. 3.5, 3.23-3.26 hold true on high temporal resolution. They are thus instantiated for each of the 2190 timesteps in a 4h-resolution year per fuel y, conversion technology v and model node r. Input and production shares are assumed to be fix across nodes and years, thus costly slack demand and supply is introduced to balance fix output and demand. This fix output-relation of multi-output processes is a limitation of this thesis' approach to be overcome by future research.

The technical inputs and cost assumptions for FT-based refineries and *methanation* plants are further described in Section 3.3.2. Next to domestic production of methane, diesel, gasoline and kerosene, $RFNBO$ can also be imported through ξ_{SFI}, which is described next.

3.1.5. Synthetic fuel import model

The general functionalities for importing *clean fuels* has been implemented and described in Gils et al. (Gils et al., 2021b). However, additional data based on a comprehensive global data set of *clean fuel* bids is used. It is based on a GIS-analysis for intermittent RES production potential, various CO_2 sources, techno-economic optimization, different risk levels, and transport routes to importing ports (Viebahn et al., 2022).

A German population-based fair-share of global bids is used and aggregated into discrete $50\frac{\text{EUR}}{\text{MWh}}$ steps of *cost potentials*. All detailed processing steps are described in Paper III.

3.2. Transport modeling approaches

To model the transformation to a clean energy supply of the German transport sector, transport research models were integrated into energy system modeling. Before the harmonization of *scope* of the various models is described in Section 3.3, now a brief overview on two distinct features of transportation research is given: Vehicle fleet modeling and BEV charging modeling. The relevant novelty is not so much the added technical detail or simulation of non-linear behavior, but the inclusion of behavioral aspects for purchase and charging decision-making. By this, two central shortcomings of recent energy system modelers are addressed: Sectoral integration and user behavior integration (Fodstad et al., 2022).

Huckebrink & Bertsch propose a framework differentiating the behavioral aspects of acceptance, adoption, and use of energy technologies and services (Huckebrink and Bertsch, 2021). Section 3.2.1 concentrates on the adoption of vehicles while Section 3.2.2 describes the preference-driven usage patterns of BEV.

3.2.1. Vehicle fleet modeling

Vehicle fleet modeling is a cornerstone of transport emission reduction modeling as the majority of energy demand and respective emissions of the transport sector stem from road transport. Early integration of behavioral models into the energy system model TIMES was conducted and described by Ramea et al. (Ramea et al., 2018). They describe the deficiency that arises from energy system models implementing vehicle purchases within their central planner logic because of a lack of heterogeneity of consumer preferences and suggest 36 segments with varying preferences.

Similarly, the model *VECTOR21* categorizes user groups based on unique combinations of the five preference groups for purchasing price, vehicle range, acceleration, infrastructure availability and an overall attractiveness index. The model was first developed by Peter Mock (Mock, 2010) and consecutively refined adding user heterogeneity and - recently - expanded to other European national markets (Möring-Martínez et al., 2024).

Two other input categories shape the vehicle fleet scenarios calculated in *VECTOR21* - first the technical and cost characteristics of available vehicle models. Secondly, policies shaping the vehicles' properties or constraining purchase decisions such as fleet emission quotas, fuel quota, fuel blending possibilities, fuel prices or purchasing premiums for specific drivetrain technologies.

A detailed description of the model is given in Paper III.

3.2.2. User-driven charging decisions

Behavior aspects of BEV charging in high temporal resolution have rarely been integrated in energy systems analysis studies. Figure 3.1 shows the scope of Papers I and II. Paper I describes the techno-economic modeling of the profiles described in Section 3.1.2 based on the national travel survey *Mobilität in Deutschland* (Nobis and Kuhnimhof, 2019), assumptions on vehicle consumption, battery sizes, and infrastructure availability. In this section, the approach taken by the charging decision model Charging Infrastructure for Electric Vehicles Analysis Tool (*CURRENT*) as used for Paper II (Anderson et al., 2018; Felix Steck et al., 2019) is summarized. The work has been developed by the co-authors of Paper II, Felix Steck and John Anderson.

Generally the algorithm is based on activities consisting of parking and trip activities. Users are assigned a specified utility considering the users locational preference and their preference for the electricity price at each charging location. Then, a utility-based probability is assigned per location and randomly sampled via Monte Carlo Simulation.

During trips, fast-charging may occur up to 80% of the respective SOC. During a parking activity, charging may occur if there is a charging station, the parking time is longer than 30 minutes and the SOC is below a specific threshold, marking a non-choice option (see also Fattler (2021)).

If a PEV user charges, depends on the utility they gain from the specific location for a specific price. Additionally it depends on the PEV battery SOC.

Each vehicle is mapped to a specific weekday and the simulation is repeated 11

times with the daily end-SOC as the start-SOC of the consecutive day. After that, a charging profile per vehicle for one day is obtained. A weighting is conducted based on a fleet composition scenario of vehicle sizes and the daily profiles are merged to vehicle fleet profiles for charging.

This yields the vehicle fleet profile for uncontrolled charging $C_{unc,in}(e,t)$. The remaining profiles for fleet connection capacity and fleet drain are then obtained from the underlying results on connection and trip activities. For the fleet battery levels, it is assumed that charging flexibility is only available when the parking time exceeds the charging time. In that case $L_{max,in}(y,r,e,t)$ follows an as-soon-as-possible charging logic and $L_{min,in}(e,t)$ an as-late-as-possible logic.

The weekly profiles are then extended to an annual profile in a similar manner as the output from Vehicle Energy Consumption in Python (*venco.py*).

3.3. *Model coupling*, interfaces and harmonization of model scope

The novelty of this work arises from the combination of individual state-of-the art sub-models at the interface of energy system and transport modeling. For the interface between two research fields, technical interfaces are needed as well and combined with methods to assure the consistency across different models.

Model coupling for integrated long-term assessment of BEV fleets and energy systems analysis has been first introduced by Heinrichs (Heinrichs, 2013). A systematic concept for modeling largely sector-coupled energy systems was introduced by Robinius (Robinius et al., 2017). As this work is highly centered on a power-sector-coupled transport sector, approaches to harmonize various *data scopes* are described in the following. Figure 3.2 shows four methods of harmonizing *scopes* of different models (Wulff, 2019; Wulff et al., 2019).

Assume model m1 is a transport model providing data for an energy system model m2. A *selection* could be carried out, because m1 provides annual data on fuel demand for all years from 2020-2050, but m2 only models specific *base years*. An *aggregation* could be necessary, because m1 differentiates vehicle or photovoltaic size classes, whereas m2 only assesses aggregate capacity of technology categories independent of size. *Consecutive runs* are generally needed when the scope of m1 is specific and e.g. one model run per model *node* in m2 has to be carried out by m1. The fourth method, *data processing*, is usually carried out to harmonize units, data references (e.g. Lower Heating Value (LHV) vs Higher Heating Value (HHV)) or to implement bilateral *model coupling* with feedback loops.

Table 3.3.1 gives an overview on all models of this work, their scopes and harmonization techniques.

3.3.1. Electric mobility *model coupling*

The model *venco.py* is developed and applied to two German national travel surveys (Paper I) and consecutively used in conjunction with the fleet model *VECTOR21* and a more user-focused approach to assess the impacts of user-preference-induced

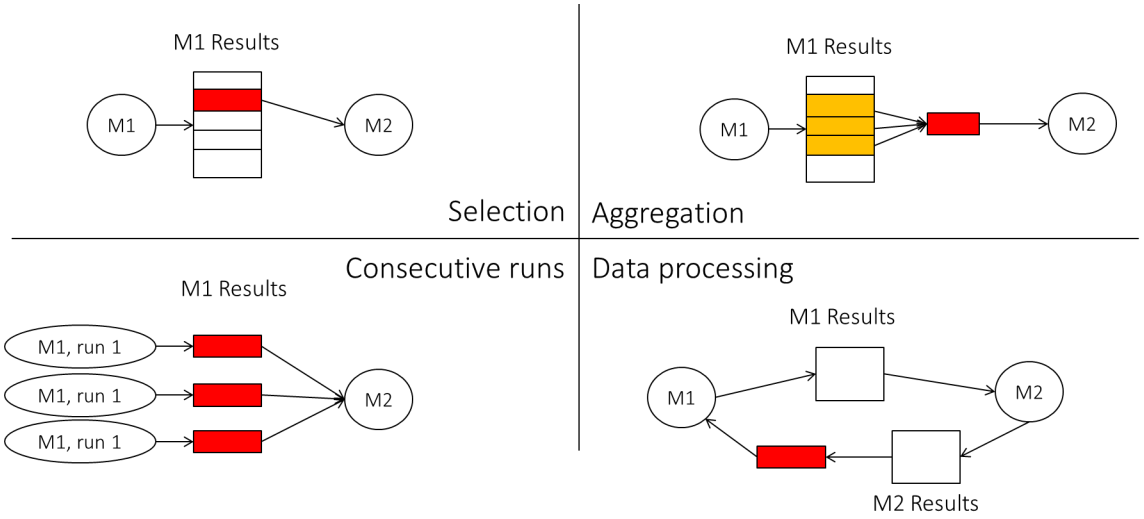


Figure 3.2.: Schematic depiction of data harmonization techniques for *model coupling*. Selection describes using a limited subset of model 1 as input to model 2, aggregation is used when the first model result resolution is higher than the expected input resolution to model 2. *Consecutive runs* are used in the opposite case - when the required input resolution to model 1 is higher than the output resolution of model 1. *Data processing* describes more complex intermediary post- and pre-processing routines possibly also involving other models or datasets.

constraints on charging flexibility and on energy system infrastructure and operation (Paper II).

As described in Section 3.1.2, the energy system model uses five profiles, one for uncontrolled charging $C_{unc,in}$ and four for controlled charging $P_{charge,in}$, $P_{drive,in}$, $L_{max,in}$, and $L_{min,in}$. While *venco.py* builds on real-world travel patterns to build park and trip diaries, it takes those patterns as a basis to develop a model for controlled charging on top. Aside from trips and parking itself, user-choices are neglected and it is assumed that users always connect their vehicles when possible. This approach is also chosen in order to be able to estimate potentials for BDC.

In order to serve as input to the energy system model *REMix-OptiMo*, two further steps are required for the profiles from *venco.py*, transferring the profiles to annual profiles and scaling them to the vehicle fleet scenario from *VECTOR21*. The first is done by a simple cloning algorithm, but taking into account the first day of the year, in order to keep weekday-weekend characteristics. Scaling is then conducted using fleet scenarios on the level of German zip-codes, aggregating the respective vehicle numbers to northern und southern Germany and three respective size classes.

On the contrary, PEV user decisions of plugging are considered in the charging simulation model *CURRENT* as described in Section 3.2.2. Scaling to a respective vehicle fleet scenario is part of the *CURRENT* algorithm. Annual cloning was performed in the same manner as for the *venco.py* profiles.

Descriptions on the profiles can be found in Paper I and on aggregating them to a scenario of a regional German BEV fleet in 2030 in Paper II.

Model	Description	Temp. res.	Spatial res.	Techn. res.	Fuels	Scenarios	*Model coupling* techniques
CURRENT	Charging decision simulation	1h	*NUTS0*	BEV-S,M,L	Elec	region, consu, bat	cons
venco.py	Technical charging flexibility quantification	15min-1h	*NUTS0*	BEV-S,M,L	Elec	infra, consu, bat	Cons
VECTOR21	Road vehicle fleet diffusion model	annual	*NUTS0*	drivetrain*	5*	4*	sel,agg
4DRACE	Aviation vehicle fleet diffusion model	annual	Airport	aircraft*	Jet-A1, H2, Elec	tec,covid	sel,agg
TEPET	Techno-economic assessment	-	-	components	various	-	datproc
SZEM/LENS	Energy balance	annual	*NUTS0*	high*	6*	4*	sel,agg, cons,datproc
BENOPTex	Fuel allocation model	annual	*NUTS0*	medium*	high*,**	4	datproc
Importbids	Global *RFNBO* bids	30, 40, 50	*NUTS0*	RES, transport	2	dem,risk	sel,datproc
REMix-OptiMo	Energy system model	20,30, 40,45	*NUTS0*-1	medium*	6	8(amb, dem, bio)	-

Table 3.5.: Overview of models used in this work and harmonization techniques. Abbreviations: Agg=Aggregation, amb=CO2 reduction ambition, bat=Battery size, BEV=Battery electric vehicle, bio=availability of biogenic energy carriers, consu=specific electric consumption, Cons=Consecutive runs, Datproc=Data processing, DE=Germany, dem=demand, Elec=Electricity, H2=Hydrogen, infra=charging infrastructure, Jet-A1=flight kerosene, L=Large, M=Medium, NUTS=Nomenclature des unités territoriales statistiques, res.=resolution, RES=Renewable Energy Source, risk=country risk variation, S=Small, Sel=Select, *see App. of Paper III, **see Section 2.3 of Paper III

3.3.2. Fuel demand *model coupling*

The models *VECTOR21*, *4DRACE*, *SZEM/LENS*, *TEPET*, and *BENOPTex* were used for providing various inputs to the energy system model *REMix-OptiMo* (Paper III). In the following, the model harmonization, *coupling*, and convergence are described.

REMix-OptiMo is an energy system model focusing on the balancing of electricity with additional modeling capabilities for heat and gas. For this thesis, the modules used for modeling hydrogen and gas demand were extended to also model multi-input, multi-output processes such as the *Fischer-Tropsch* process. Additionally, an import *module* was used to parametrize cost-potentials for the importation of *RFNBO*.

Techno-economic modeling of fuel conversion processes

The techno-economic input for *methanation* and *Fischer-Tropsch* refineries was taken from a techno-economic setup described in Albrecht et al. (Albrecht et al., 2017) as well as overarching framework assumptions from the research project *BEniVer* (Aigner et al., 2023).

For the former, a manual data-interface was established incorporating the following properties of each fuel conversion system $v \in SFC$ and for each year $y \in 2018, 2030, 2050$: product share, total fuel production, full load hours, hydrogen, power and CO_2 demand from the *Aspen* simulation results and Fix Capital Investment (FCI), costs, and revenues from the techno-economic calculations.

Costs, technical properties and product shares for 2018 are assumed for 2020. Values for 2050 are assumed to apply for 2045 as well. Values for 2040 are interpolated between 2030 and 2050 values.

From the project framework assumptions, detailed direct and indirect costs for calculating CAPEX and Operational Expenditure (OPEX) for each *synthetic fuel* conversion technology v are taken into account. For interested readers, all interface data from *TEPET* and the corresponding Python scripts are published in the data appendix to Paper III.

The interface routine calculates the following parameters for each $v \in SFC$:

- specific investment / CAPEX in $\frac{\text{kEUR}}{\text{GW}}$
- Fix OPEX in % of CAPEX
- variable OPEX in $\frac{\text{kEUR}}{\text{MWh}}$
- product composition for *Fischer-Tropsch* in % of output stream (LHV)
- chemical efficiency in % of LHV
- power demand in $\frac{\text{MWh}_{\text{el}}}{\text{MWh}_{\text{ch}}}$

The interest rate for new *Fischer-Tropsch* and *methanation* refinery projects was assumed to be at 5% in accordance with project partners. Amortization and life time were both assumed to be 20 years.

Dimension	*VECTOR21*	*REMix-OptiMo*	Harmonization
Temp. res.	$\mathbb{Y}$	$\mathbb{I}$	sel
Spat. res. (in DE)	-	*NUTS1*	disagg
Techn. res.	medium	low	sel,agg
Fuel res.	Elec., F-diesel, F-gasoline, CNG, H2, syn-diesel, syn-gasoline, syn-CNG	Elec., H2, CH4, syn-diesel, syn-gasoline, syn-kerosene	sel,map,agg
Scenarios	REF, DEL, H2, PtX	REF, DEL, HYD, SYN	map

Table 3.6.: Model dimensionality of VECTOR21 and harmonization with REMix-OptiMo scope. Abbreviations: agg=aggregation, CNG=Compressed Natural Gas, disagg=disaggregation, Elec.=Electricity, F=fossil, Fuel res.= Fuel resolution, Spat. H2=Hydrogen, map=mapping, res.=Spatial resolution, syn=synthetic, Techn. res.=Technical resolution, Temp. res.=Temporal resolution.

Vehicle fleet modeling

The demand $D(r, y, f, j)$ for various fuels $f \in \mathbb{F}$ is calculated based on the output of the model *VECTOR21* that calculates annual vehicle stock, annual demand $D^{f}_{fix}(s, y, , j, e)$ for liquid and gaseous fuels and $D^{elec}(s, y, j, e)$ $\forall s \in \mathbb{S}$, $y \in \mathbb{Y}$, $j \in road_{pass}, road_{freight}$, $e \in EVE$ for electricity. Table 3.6 shows the *dimensionality* of both models with the respective harmonization strategies in each *dimension*.

Both outputs, D_{fuel} and D_{elec} are calculated for the two sub-sectors passenger and freight in separate sub-models as different preferential patterns apply to private passenger vehicles and freight vehicles.

In the interface, only vehicles are considered that use electricity or *synthetic fuels*, as well as the relevant years $y \in \mathbb{I}$ (*selection*). Those annual demands for Germany per road sub-sector and fuel are then disaggregated to *NUTS1* (federal states) using *disaggregation* factors F. After spatial *disaggregation*, energy demands are aggregated across the two sectors j as shown in Eqs. 3.27 and 3.28.

$$D^{elec}(r, y) = \sum_{j} D^{elec}(DE, y, f, j) \times F^{elec}(r, y, f, j),\ \forall r \in \{DE\}, y \in \mathbb{I} \tag{3.27}$$

$$D^{f}(r, y) = \sum_{j} D^{f}(DE, y, f, j) \times F^{f}(r, y, f, j),$$
$$\forall r \in \{DE\}, y \in \mathbb{I}, f \in \{H_2, CH_4, diesel, gasoline\} \tag{3.28}$$

For disaggregating annual demand of fuel and electricity $D(j = road_{pass})$, federal state driving statistics from the survey MiD are used (infas, DLR, IVT und infas

Dimension	*4DRACE*	*REMix-OptiMo*	Harmonization
Temp. res.	$\mathbb{Y}$	$\mathbb{I}$	sel
Spat. res.(in DE)	$\mathbb{A}$	*NUTS1*	sel,agg
Techn. res.	-	low	-
Fuel res.	Elec., H_2, syn-kerosene	Elec., H_2, Methane (CH_4), syn-diesel, syn-gasoline, syn-kerosene	map
Scenarios	PROG-nCOV, H2	REF, DEL, HYD, SYN	map (REF, SYN: PROG-nCOV, DEL, HYD: H2)

Table 3.7.: Model dimensionality of 4DRACE and harmonization with REMix-OptiMo scope. Abbreviations: agg=aggregation, Elec.=Electricity, Fuel res.= Fuel resolution, H2=Hydrogen (scenario), map=mapping, nCOV=without COVID demand reductions, PROG=progressive, Spat. res.=Spatial resolution, syn=synthetic, Techn. res.=Technical resolution, Temp. res.=Temporal resolution.

360, 2017). For disaggregating $D(j = road_{freight})$, Eurostat data for freight travel on the level of *NUTS2* is used (Eurostat, the statistical office of the European Union, 2023). For disaggregating the stock data, statistics from the German Federal Vehicle Agency (Kraftfahrbundesamt) are used (Federal German Automotive Agency, 2020).

Energy demand from aviation

Energy demand for aviation is used from Leipold et al. (Leipold et al., 2021). Table 3.7 shows the *dimensionality* of the model output and the harmonization strategies

From the five scenarios, the two scenarios *PROG-nCOV* and H_2 were selected as they were most consistent with transport sector *defossilization*. The scenario H_2 is taken from Grimme and Braun (Grimme and Braun, 2022), assuming the introduction of short-range hydrogen and hybrid electric aviation from 2040 onward. This aviation-scenario is mapped to the two demand scenarios *REF* and *SYN*, while the aviation-scenario *H2* is used for the scenarios *DEL* and *HYD*.

Fuel demands could then easily be aggregated to any spatial level, in this case, *NUTS1* in Germany and *NUTS0* throughout the rest of Europe as shown in Eq. 3.29.

$$D_{fix}(r, y, f, j = aviation) = \sum_{a \in \mathbb{A} \in \mathbb{R}} D_{fix}(a, y, f, j = aviation) \tag{3.29}$$

$$\forall y \in \mathbb{I}, f \in \{elec, H_2, kerosene\}$$

Dimension	*SZEM*	*REMix-OptiMo*	Harmonization
Temp. res.	5a	$\mathbb{I}$	sel
Spat. res.	*NUTS0*	*NUTS1*	disagg (in DE)
Techn. res.	high	low	sel,agg
Fuel res.	medium	Elec., H_2, CH_4, syn-diesel, syn-gasoline, syn-kerosene	map,datproc
Scenarios	REF, DEL, HYD, SYN	REF, DEL, HYD, SYN	map

Table 3.8.: Model dimensionality of SZEM and harmonization with REMix-OptiMo scope. Abbreviations: agg=aggregation, datproc=data processing, Elec.=Electricity, Fuel res.= Fuel resolution, H2=Hydrogen, map=mapping, Spat. res.=Spatial resolution, syn=synthetic, Techn. res.=Technical resolution, Temp. res.=Temporal resolution.

Energy balances

General energy balances in high sectoral and technological detail for 33 countries on *NUTS0* level are taken from an accounting framework for providing consistent energy balances across a wide set of technologies and energy-related sectors. Table 3.8 shows the *dimensionality* of the model output and the harmonization approaches with *REMix-OptiMo*.

The Scenario energy accounting model (*SZEM*) provides dynamic energy balances for the four scenarios $s \in \mathbb{S}$ for each country in Europe $r \in \{NUTS0\} \in \mathbb{R}$ with a base-year resolution of five years. The accounting framework differentiates between the sectors public, transport, households and services, and industry. It also contains non-energetic uses of energy carriers and agricultural use.

The scenarios lean on the European scenarios *Clean planet for all* (COM, 2018) as they provide detailed energy balances.

For all countries, the following data is extracted from *SZEM*

- household, public and company electricity demand,
- CO_2 limitations on national level,
- heat demand, and *heat group* shares (Fette et al., 2020),
- rail and navigation energy demand, and
- Non-energetic use of H_2 and CH_4.

For non-German countries, additionally road vehicle fleet development and energy demand and are extracted from *SZEM*.

For Germany, electricity, heat, rail demands, and non-energetic use are disaggregated to German federal states using population statistics. Navigation energy

Dimension	*BENOPTex*	*REMix-OptiMo*	Harmonization
Temp. res.	$\mathbb{Y}$	$\mathbb{I}$	sel
Spat. res.(in DE)	-	*NUTS1*	agg
Techn. res.	high	low	agg
Fuel res.	very high*	Elec., H_2, CH_4, syn-diesel, syn-gasoline, syn-kerosene	agg,map
Scenarios	REF, DEL, HYD, SYN	REF, DEL, HYD, SYN	map

Table 3.9.: Model dimensionality of BENOPTex and REMix-OptiMo with respective harmonization techniques. *See Appendix of Paper III and Aliabadi et al. (Esmaeili Aliabadi et al., 2023). Abbreviations: agg=aggregation, datproc=data processing, Elec.=Electricity, Fuel res.= Fuel resolution, H2=Hydrogen, map=mapping, Spat. res.=Spatial resolution, syn=synthetic, Techn. res.=Technical resolution, Temp. res.=Temporal resolution.

demand is allocated to federal states based on freight volumes of the largest ports taken from European statistics (Eurostat, 2024). More details on the scenario design can be found in Paper III.

Incorporating *biofuels*

The basic functionality of *BENOPTex* is described in Section 2.3.4, this section focuses on describing the interfaces. The application of the bilateral coupling of *REMix-OptiMo* and *BENOPTex* is one of the key novelties of this work (Paper III). It has been methodologically described and applied in a simplified scenario context in Aliabadi et al. (Esmaeili Aliabadi et al., 2022, 2023). The *dimensionality* of *BENOPTex* and the harmonization with *REMix-OptiMo* are shown below in Table 3.9.

A schematic depiction of the data flow can be found in Figure 1 of Paper III. Cost-optimal electricity supply infrastructure, marginal electricity costs, and H_2 production are calculated with *REMix-OptiMo*. Electricity mix, costs, and curtailed renewable energy is then aggregated for Germany as shown in Eqs. 3.8, 3.30-3.34 and used in *BENOPTex* to calculate the optimal allocation of biogenic waste and crops to final transport sectors. As all variables and parameters below depend on the year $y \in \mathbb{I}$, this dependence is omitted below.

$$m_{PP,DE}(t) = \sum_{r \in DE} \sum_{c} \xi_{PP}(r, c, t), \forall t \in \mathbb{T} \tag{3.30}$$

$$m_{DE} = \sum_{t} m_{PP,DE}(t) \tag{3.31}$$

$$\mu_{DE}(t) = \max_{r} \mu(r, t), \forall t \in \mathbb{T} \tag{3.32}$$

$$c_{elec,DE} = \frac{\sum_t (\mu_{DE}(t) \times m_{PP,DE}(t))}{m_{DE}} \tag{3.33}$$

$$P_{curt,DE}(t) = \sum_{r} \sum_{p} \nu(r, p, t), \forall t \in \mathbb{T} \tag{3.34}$$

$$P_{ELY,DE}(t) = \sum_{r \in DE} \sum_{e} \zeta_{ELY}(r, l, t), \forall t \in \mathbb{T} \tag{3.35}$$

The total German electricity production $m_{PP,DE}$ in every year $t \in \mathbb{T}$ and every timestep $t \in \mathbb{T}$ is calculated from all German power plant operations ξ_{PP} across a year for all ten regions in Germany $r \in DE$. The total annual power production in Germany m_{DE} is calculated from the annual power plant specific power production given above in Eq. 3.8 as described in Eq. 3.31. An approximation for the hourly German wholesale market price is then calculated from the marginal values in each of the German regions in each timestep by choosing a "price-setting" region by the maximum *marginal value* in each timestep according to Eq. 3.32. Annual electricity prices are approximated using the electricity-volume-weighted average as shown in Eq. 3.33. The curtailed power $P_{curt,DE}$ from intermittent RES is shown in Eq. 3.34. The power needed for the production of *e-H₂* is synchronized with *BENOPTex* as well and calculated according to Eq. 3.35.

The final sectoral demands from *VECTOR21*, Aviation Energy Consumption Model (*4DRACE*), and *SZEM* are reduced by the optimally allocated volumes of biofuel. The remaining *RFNBO* demands are used as an input for *REMix-OptiMo* to calculate the cost-optimal energy infrastructure transformation pathway from the adapted demands. Only transport sector demands are affected. Non-transport electricity and heat demands vary across the scenarios but are not assumed to be supplied by *biofuels* with the exception of solid biomass for CHP plants.

With the reduced demand for *RFNBO*, the energy system optimization is run in its first iteration and the process is continued until the convergence criterion is reached. This is defined based on the biofuel production allocated to the transport sector (Esmaeili Aliabadi et al., 2022). If this BENOPTex result does not change more than 10% from one iteration to the next, convergence is accepted. For the scenario Synthetic Fuel Scenario (SYN), convergence is reached after four iterations.

The model is based on Gils et al. (Gils et al., 2021b) with a spatial extension to comprise all European countries. Due to the added detail, the heat sector is simplified in the model compared to the implementation used in Gils et al. (Gils et al., 2021b). The temporal resolution is decreased to $\Delta t = 4h$. As shown e.g. in Schyska et al. (2021), this does not lead to significant changes in the basic infrastructure composition.

3.4. Scenarios of energy system transformation pathways

As described in Section 2.1, a common approach to tackle the challenge of structural uncertainty towards future developments is scenario analysis. Known issues associated with formulating detailed storylines (Morgan and Keith, 2008) are tackled by keeping scenario *dimensions* largely to parametric variations in the system boundary. However, no probabilistic scenarios are developed. The section gives an overview over the various *dimensions* that have been varied across scenarios. A discussion of scenario modeling is presented in Section 5.4.

Two categories of scenario approaches can be distinguished: Scenarios assessing structural uncertainty such as the role of international cooperation (Wetzel et al., 2023) or general societal willingness for energy reductions (Rodrigues et al., 2022). Usually those scenarios are storyline-driven and are supposed to follow narrated developments. They do then translate model input parameters related to energy demand for various energy forms, CO_2 emission constraints, intermittent RES capacity limitations or the availability of fuels. This approach implicitly suggests consistency of the narrated storylines and has been criticized before (Morgan and Keith, 2008).

The second category represents parametric uncertainty. There, "scenario" refers to a specific value, e.g. the specific investment for a PV power plant in EUR/kW in a target year or as a pathway (Löffler et al., 2022). Commonly, input parameters directly affecting investment parameters (through costs c or constraints b) are varied. Other examples contain the variation of annual emission constraints, emission allowance prices (Löffler et al., 2022), or maximum transmission grid capacity (Wetzel et al., 2023).

Scenarios in the middle between the two categories are the variation of sets of timeseries in order to assess the model sensitivity for a specific weather or demand year. Here, the underlying base data year is taken as an indication for consistency. Cramer et al. describe those as a "set of discrete realizations known as scenario" (Cramer et al., 2022). However, as it does not follow a narrated storyline but rather a specific logic of consistency across quantitative input parameters, these are mainly parametric scenarios.

In this thesis, a background parametric set is used that defines dynamic energy system inputs. It consists of the existing power plant park, existing transmission grid capacities, storage capacity and techno-economic assumptions such as CAPEX, variable and fix OPEX and efficiencies. However, both sets vary, as the model resolution differs.

Paper II employs a target year optimization with a limited spatial scope with Germany separated in Northern and Southern Germany with Germany's electric neighbors included in the model to account for import and export of electricity. The target year is 2030. The aim of Paper II is to assess the influence of two ways of representing BEV fleet charging in energy system models - not so much on an energy system modeling level but rather on the representation of BEV user behavior in deriving BEV fleet profiles for uncontrolled and controlled charging. Because of the rather methodological scope of the Paper complemented by a case study, two

dimensions are varied: The share of controlled charging and the representation itself. While the first *dimension* is a boolean *dimension* (is controlled charging available or not?), the second *dimension* implies five scenario-specific input sets of profiles per German node. Additionally, a reference scenario is calculated without any additional BEV load for comparison.

Paper II contains a sensitivity analysis to test the robustness of the insights into charging representations towards CO_2 emission reduction ambition, weather years, PV, onshore wind and offshore wind power plant CAPEX, and exogenous assumptions for load shifting potential. In Paper II, the relationship between operational and capacity variables are important and both are analyzed.

As Paper III has a different objective - showing the impacts of fuel demand scenarios and biofuel availability on energy supply infrastructure - the scenario frame is more complex, differentiating three *dimensions*: CO_2 emission reduction ambition, *conversion depth*, and the availability of biofuel in the transportation sector.

The parametric background set is more extensive than in Paper II, as a European energy system is modeled for a *myopic pathway*, assuming full sector-coupling. Thus, the background set comprises the following input parameters:

The *REMix-OptiMo* concept of *heat groups* has been developed in order to model district heating grids and was first introduced in Hans Christian Gils (2015) and extended to gas infrastructure in Fette et al. (2020) and Gils et al. (2021b). Within the scope of this thesis, *heat groups*, i.e. the technology-share supplying heat at a specific temperature level, were taken from *SZEM* as described in Section 3.3.2. They develop over time but are an exogenous assumption. The heat sector is represented in the model for Paper III, but in a more simplified way compared to Gils et al. (2021b).

Input parameter	Paper II	Paper III	Other studies
Interest rate	bg	bg	(Krüger et al., in review)
Electricity demand ts	sens	bg	-
Annual fuel demand	-	sc	-
RES, conventional pp, CHP plants, heat technology tec-ec	sens	bg	(Neumann and Brown, 2023)
RES feed-in timeseries ("weather years")	sens	bg	(Pfenninger, 2017)
RES capacity expansion potential	bg	bg	(Thelen et al., 2024)
Conventional and CHP power plant park and legacy dynamic	bg	bg	-
Electric grid legacy capacity	bg	bg	-
Electric grid tec-ec	bg	bg	-
Gas grid tec-ec[1]	-	bg	(Wetzel et al., 2023)
Gas storage potentials (for caverns) and tec-ec	-	bg	-
Storage[2] tec-ec	bg	bg	(Cebulla et al., 2017)
Fuel prices for coal and lignite	bg	bg	-
Fuel import cost-potentials	-	bg	(Luderer et al., 2021; Sensfuß et al., 2022b; Bartos et al., 2024)
Synthetic fuel facility[4] tec-ec	-	bg	(Runge et al., 2023)
Heat technology tec-ec	-	bg	-
Technology mappings	-	bg	-
Electric vehicle (EV) profiles[5]	sc	bg	-
CO_2 emission limit	sens	isc	(Gils et al., 2021b)
CO_2 emission allowance cost development	bg	bg	-
Annual heat demand	-	isc	(Hans Christian Gils, 2015)
Heat group shares	-	isc	(Hans Christian Gils, 2015; Gils et al., 2021b)
EU fleets and road demand[6]	bg	isc	(Luderer et al., 2021)
Navigation and rail demand	bg[7]	isc	-

Table 3.10.: Most important model inputs into REMix-OptiMo and categorization to background model, sensitivity variation and scenario together with other studies assessing the resepctive input's impact on energy system results. [1]Gas grids comprise of H_2 and CH_4 grids. [2] Battery and pumped hydro storage. [3] H_2, fossil and clean CH_4, diesel, gasoline and kerosene (see Paper III) [4] Electrolysis, *methanation* and *Fischer-Tropsch* refinery (see Section 3.3.2). [5]See Section B.1, [6]For non-German countries. [7]Electricity only. Abbreviations. bg: Background, isc: Implicit scenario, sc: Scenario, sens: Sensitivity, tec-ec: Techno economics.

4. Summary of Paper and results

After the introduction of the main methods, the following section summarizes the questions, methods and results of Paper I-III. For every paper, an objective, a methodological novelty, a summary of results, and the CRediT authorship statements are given in order to show the specific contributions.

4.1. Paper I: Vehicle energy consumption in python (VencoPy): Presenting and Demonstrating an Open-Source Tool to Calculate Electric Vehicle Charging Flexibility

Objective A tool including interfaces, filtering and cleaning routines of national travel surveys together with methods for simulating BEV load shifting potential is developed. The tool Vehicle Energy Consumption in Python (VencoPy) aims at filling a gap for researchers that have access to national travel survey data, potentially in high geographical and temporal resolution.

Methodological novelty

- The full formal description of a tool to calculate BEV fleet charging profile and its flexibility
- The publication of all code including the MiD interfaces
- A comparative case study of the two national travel surveys MiD 2008 and MiD 2017 to demonstrate the capability of the tool

Summary Growing PEV fleets pose the challenge of increased electricity demand and chances of integrating intermittent RES by load shifting. The tool *venco.py* builds on recent detailed trip data from the national travel survey MiD (Nobis and Kuhnimhof, 2019) to provide possible future uncontrolled charging profiles and profiles that can serve as an upper-bound of vehicle fleet flexibility in high temporal resolution. The last two instances of MiD are then analyzed in a case study, weekly profiles of travel distance, uncontrolled charging, connection, drain, maximum, and minimum battery level are calculated, and compared to each other. While the results show large increases in *absolute* travel distance due to vastly increased sample size in 2017s MiD, normalized profiles show little differences in their weekly patterns between the two national travel surveys. Electricity consumption, grid connectivity,

and uncontrolled charging is found to be slightly higher during the day. Connection- and demand-driven aggregated fleet flexibility was slightly reduced.

CRediT authorship contribution statement and description Conceptualization: **NW**, methodology: **NW**, software: **NW**, formal analysis: **NW**, investigation: **NW**, resources: HCG, data curation: **NW**, writing - original draft: **NW**, FM, HCG & PJ, writing - review and editing: **NW**, FM, HCG & PJ, visualization: **NW**, supervisison: HCG & PJ, project administration: HCG.

4.2. Paper II: Comparing Power-System and User-Oriented Battery Electric Vehicle Charging Representation and Its Implications on Energy System Modeling

Research question How are energy system optimization modeling results affected by representing BEV charging based on a power-system oriented perspective vs. a more user-oriented perspective?

Methodological novelty

- Interfacing the BEV fleet model *VECTOR21* to the energy system optimization model *REMix-OptiMo*.
- Formal harmonization of outputs of the two BEV charging models *venco.py* and *CURRENT* and interfacing to *REMix-OptiMo*.
- Analysis of the effect of reduced electric fleet flexibility on German energy supply system for 2030 including north-south transmission and electric neighbors.
- Testing of sensitivities of the results towards 2030 CO_2 limitations, underlying weather years for PV and wind feed-in, and electric demand profiles, as well as intermittent RES CAPEX developments.

Summary Increasing shares of intermittent RES and growing BEV fleets motivate closer research on the interaction between BEV fleet charging and energy system infrastructure and operation. The impact of implementing user-oriented charging constraints are assessed together with related reductions in vehicle fleet flexibility on energy system extension and operation in the medium term. We identify three major effects of BEV modeling that reduce the load shifting potential - temporal reference for the weekly boundary condition for fleet battery level, the non-choice option to avoid charging, and including fast charging as well as three minor factors - public and workplace charging, lack of home charging availability, weekday-specific travel patterns. Especially grid connectivity and the fleet battery level constraints are strongly affected. In a second-order impact assessment of the reduced load

shifting from 24 to 8 TWh/a, reduced flexibility leads to additional gas power plant capacity in northern and southern Germany of around 1 GW each and slightly increasing intermittent RES curtailment. Lower short-term temporal load flexibility is additionally compensated by slightly higher electricity transmission from northern to southern Germany. An analysis of the *dual variables* of fleet flexibility constraints reveals that temporal detail of battery level constraints is more important than of grid connection. However, the overall effects of controlled charging as a short-term flexibility are limited in the scope of the analyzed energy system model.

CRediT authorship contribution statement and description Conceptualization: **NW**, FS & CHK, methodology: **NW** & FS, software: **NW**, FS, HCG & BvdA, data curation: **NW**, FS, & BvdA, formal analysis: **NW**, investigation: **NW**, Writing - original draft: **NW** & FS, writing - review and editing: **NW**, JEA, HCG and CHK, visualization: **NW**, project administration: CHK & JEA

4.3. Paper III: Energy system implications of demand scenarios and supply strategies for renewable transportation fuels

Research question What are energy-system trade-offs between domestically produced *RFNBO*, imported *RFNBO* and biogenic fuels for transport sector *defossilization* in Germany? The overarching research question is answered divided in three sub-questions:

- How large is the primary clean energy demand of a CO_2 neutral transport sector?
- How do the differences in *conversion depth* affect cost-optimal energy system compositions and build-up dynamics?
- To what degree alleviates biofuel availability sharp gradients in electricity and hydrogen supply infrastructure build-up?

Methodological novelty

- Four comprehensive scenarios of transport energy demand incorporate user-preferences for road vehicle categories and high technical detail in aviation.
- A novel interface integrates transport, heat, and electricity demand scenarios with an electricity supply model and a fuel allocation model.
- A novel method for incorporating endogenous choice of *RFNBO* imports for fulfilling future fuel demands is proposed.
- The impact of biofuel availability on electricity supply infrastructure and *RFNBO* imports is assessed.

Summary Transport sector CO_2 emission reduction requires a mix of different strategies. While reducing transport demand and shifting modes may have significant impact to transport sector energy requirements, developments motivate scenarios with comparable road sector energy demands as well as high clean energy supply. In this context, we suggest a framework for assessing trade-offs between *conversion depth*, domestic *RFNBO* production, *RFNBO* imports and domestic *biofuels*.

We find, that primary energy demands of clean transport energy supply varies less than back-of-the-envelope estimations through integration of user-preferences and detailed technological constraints. Highest gradients are observed between 2030 and 2040 in our scenarios, due to moderate aviation and navigation fuel increases and high road sector *RFNBO* demands in the medium term. In the long-term, e-kerosene for aviation and e-diesel for navigation make up the major share of transport sector fuel demand.

While *conversion depth* has limited influence on intermittent RES expansion, it moderately affects grid infrastructure and strongly influences domestic H_2 and fuel production capacity dynamics. Restraining from *direct electrification* to higher shares of H_2 and *RFNBO*, implies twice as high domestic H_2 demands, driven by transport sector fuel demand and demands for H_2 and CH_4 in CHP plants. Domestic *RFNBO* production itself peaks in 2040 and is slightly reduced thereafter, due to more competitive imports and low availability of electricity based on intermittent RES.

Biofuels could contribute to reducing the demands for *RFNBO* significantly from 260 TWh/a to 110 TWh/a in 2045. For diesel and kerosene demands this effect grows over time and is strongest for the years 2040 and 2045 while for gasoline, the impact peaks in 2030 due to bioethanol requiring sufficient fossil fuel for drop-in-capability under norm-conformity. *Biofuel* replaces mainly imported *RFNBO* under cost-optimality but some effects on the energy supply and transmission infrastructure can be observed. *Biofuel* availability is shown to have some medium-term alleviating effect on necessary energy supply infrastructure, when high *conversion depth* is assumed. Under a *direct electrification* scenario, higher domestic transmission capacity compensates lower H_2 infrastructure and respective flexibility. Electricity imports are largely affected by both *conversion depth* and biofuel availability. They are halved in a low-*conversion-depth*-scenario compared to higher *conversion depths* and reduced by a factor of four if biofuel is additionally available to volumes comparable to today's levels. Overall, we show the high relevance of modeling the demand for *RFNBO* demands when considering transition pathways as they may be specifically important for compensating a lack of capability or willingness to shift to BEV.

CRediT authorship contribution statement and description Conceptualization: **NW** & DEA, methodology: **NW** & DEA, software: **NW**, DEA, SH & WG, visualization: **NW** & DEA, formal analysis: **NW**, investigation: **NW**, data curation: **NW**, SH, SK, TP & WG, writing - original draft: **NW**, DEA, JH, SH, TP & WG, writing - review & editing: **NW**, DEA, HCG, PJ & TP, supervision: HCG & PJ, project administration: **NW** & CHK, resources: HCG & CHK.

5. Critical reflection and discussion

In the following, the results are discussed from a broader perspective. Then, overarching limitations are formulated, the general approach is critically reviewed and suggestions are proposed how to overcome them.

5.1. Discussion of Paper I in the light of the background of other available approaches

Paper I presented a novel approach on modeling BEV fleet load and its flexibility in high temporal resolution based on real mobility data. The publication was the first one that fully disclosed its source code, including all interfaces to the mobility pattern data set.

Since then, three other open models have been published, namely emobpy (Gaete-Morales et al., 2021), SimBEV (RLI, 2024) for Germany and RAMPmobility (Mangipinto et al., 2022) for bottom-up stochastic load simulation based on European work travel statistics. Additionally, Strobl et al. have used a similar method for assessing the difference between locally-oriented and nationally-oriented controlled charging (Strobel et al., 2022).

They argue that - opposed to the proposed approach in Paper I - extracting stochastic properties from a national travel survey connected to their respective properties, e.g. day-of-week, employment status, age, region type etc. and sampling profiles makes it possible to model arbitrarily large fleets. On the opposite, our approach could create false simultaneity (Strobel et al., 2022). This criticism is valid for the case of uncontrolled charging profiles $C_{unc,in}(y, r, e, t)$ and electric demand profiles for driving $P_{drive,in}(y, r, e, t)$ (see Section 3.1.2). Mobility patterns from around 100,000 users are interpreted as representative for the entire fleet of more than 10 million vehicle users. However, the weight of the argument strongly depends on the research context. As Fischer et al. describe, charging depends on social, technical, spatial, and interrelated factors. Especially in cases where spatial and social factors are the focus of analysis, the argument holds true, e.g. if charging patterns of employed males in Stuttgart are the subject in question. For energy system modeling on the level of *NUTS1* regions (federal states) or coarser - as implemented in this thesis - this effect is of lower importance.

The national travel survey MiD is representative only for Germany as a whole and the number of survey respondents greatly varies across states with eastern German states being less represented. Thus, charging patterns calculated with venco.py

are not based on state-specific mobility patterns or their respective socio-economic properties. Rather, a downgrading-approach from the national data entirety to federal states is used based on fleet sizes and electric demands.

The overarching question that this discussion leads to is, what the main determinants of trip distance and trip purpose are. Interesting pursues for future research comprise calculating profiles depending on region categorization as basis for region-specific *aggregation* (Strobel et al., 2022) or other socio-economic factors (Fischer et al., 2019).

A factor that was not accounted for in Papers I and II was seasonal temperature dependency and its impact on consumption. This does not influence the connection capacity but it does influence the time-specific drain as auxiliary vehicle consumers such as heating and air-condition depend on the outside temperature. Simplified relationships of temperature and consumption have been described (Fischer et al., 2019; Gaete-Morales et al., 2021; Strobel et al., 2022) with the approach of *emobpy* assuming simplified vehicle-model-specific aerodynamics and other consumption factors.

Another relevant approach is the comparison of resulting charging profiles with measured charging data as proposed by Pareschi et al. (2020). Ideally, SOC, charge-rate and locational data is available annotated with timestamps in high temporal resolution. However, this data is difficult to obtain, especially for Germany, as charging data is protected either due to personal data rights or to commercial interests of OEM companies. A recent example of an evaluation of such data is given by Märtz et al. (2022). Charging or at least connection data is more available since occupational live-data is often publicly available through application programming interfaces. A few recent studies have conducted assessments of occupational data (Hecht et al., 2022), real charging data for the Netherlands (Flammini et al., 2019) and Germany (Weiß et al., 2022) or real vehicle fleet charging data of employees from health care and energy supply companies (Figgener et al., 2022).

The question, how many representative vehicles should be explicitly modeled in a large-scale energy system model is still open for future research with first important steps taken by Strobel et al. (Strobel et al., 2022). The *aggregation* introduced in Paper I and used in Papers II and III is known to overestimate the BEV fleet flexibility. For aggregating individual profiles to fleet level, multiple ways have been described since then by Wang et al. (2022) and Muessel et al. (2023). Another approach of flexibility aggregation, without compromising on individual model detail using *Minkowski sums*, has been demonstrated, but only for a low number of vehicles and timesteps (Ried et al., 2020) which is identified as one of the most interesting approaches for more mathematical BEV fleet modeling approaches.

5.2. Discussion of Paper II on the background of other available studies focusing on BEV integration in energy system modeling

In Paper II, a method is proposed to compare a purely technical potential with a user-oriented potential of controlled charging and to show respective differences for cost-optimal energy supply in 2030.

The technical potential is found to be significantly influenced by two modeling assumptions: Boundary conditions for the vehicle battery SOC and the availability of the option, not to connect the vehicle if sufficient energy is still available. The availability of fast-charging significantly shifts uncontrolled charging from limited morning and extensive evening charging towards midday. Despite a flexibility reduction by factors of more than 10, system-optimal load shifting is reduced by a factor of 3 with limited impact on optimal energy system infrastructure. Related peak load increases lead to a 5% increase of gas power plant capacity and slightly higher intermittent RES curtailments in the energy system.

Other studies have similarly assessed the role of controlled charging for energy system infrastructure and operation. Taljegaard et al. show that demand increases do not have to be compensated by the same capacity of fossil power plants (Taljegard et al., 2019a). They also evaluate the role of BDC on the optimal power system and find a reduction of 20-40% in required solar PV capacity through BDC.

Especially for energy scenarios with the focus on medium-term and little load increases through flexible H_2 electrolysis, BEV fleet representations should take into account plugging behavior. With only controlled charging, optimal energy system infrastructure may overestimate BEV fleet flexibility in the order of around 5% of backup power plant capacity if user-oriented plugging behavior is ignored. As described above, fleet flexibility is likely to be overestimated by the approach presented in Paper I. However, it is unclear, if overcoming this overestimation of the overall approach would lead to a stronger or lesser effect of user-preference-oriented modeling on energy system results, which is left for future research.

Most energy system outcomes are found to be more sensitive to the variation of CO_2 emission limitations, underlying weather and demand data years and intermittent RES CAPEX assumptions for 2030 than to differences in charging modeling.

First steps are developed to use the linear optimization problem's *dual values* as indications for the importance of a specific constraint. It is demonstrated, how the value of the battery level balance constraint revealed a higher value of BEV flexibility to the energy system in northern Germany. Using *dual variable* values to show the global importance of constraints for specific model setups could be an interesting pursue for future research.

In the analysis of Paper II, the six identified differences in the modeling approach were not isolated which makes it hard to identify individual contributions. Thus, it was not possible to isolate the influence, e.g. of fast-charging, or of the preference of users towards a full battery. By co-developing and integrating tools such as *venco.py* and *CURRENT* with a broad variety of features, the isolation of these factors could more easily be achieved.

5.3. Discussion of Paper III on the background of other studies

In Paper III, the influence of *conversion depth* on various cost-optimal transport sector energy supply options and their trade-offs is assessed. A *myopic* optimization approach allows for identifying various key aspects of transformation dynamics towards CO_2 neutrality.

Advancing recent studies, *clean fuel* imports of five gaseous and liquid fuels are analyzed as endogenous variables based on a data base of global import bids.

Conversion depth is found to drive H_2 and fuel production capacity as well as imports. A *direct electrification* scenario shows the lowest dependence on imports and the smallest H_2 production capacity extension gradients.

The limited availability of biofuel for transport applications could significantly reduce *RFNBO* demands to less than half of the original *clean fuel* demand. This has a similar influence on both import dependence and H_2 production infrastructure. Both effects are strongest in the medium term towards 2040 when significant H_2 production capacity would otherwise be required.

Optimal biomass allocation may be affected by integrating heat sector demands in the biomass allocation model which was not done in the scope of this thesis but is shown by Jordan et al. in a recent study (Jordan et al., 2023). The authors show lower biomass usage in transportation when transport, heat, and industry compete for the fairly low remaining volumes. However, they only apply their broad sectoral scope to an optimistic transport scenario with little *clean fuel* demands. A combined approach of their broad sectoral scope with the high degree of detail in transport demand modeling from this thesis could yield further insights.

The analysis presented here refrains from formulating storylines for realistic developments of different energy demands and the availability of biofuel. Instead, scenarios understood as *relevant possibilities* are proposed, despite the controversial role of biomass for energy purposes in general. High *conversion depth* is systemically more costly, requires increased infrastructure, and results in higher import dependence. *Biofuels* could potentially act as a bridge towards a system of *direct* and *indirect electrification* somewhat relieving domestic and foreign infrastructure expansion in the medium term and thus opening up new transformation options.

A methodological limitation of the approach is the *myopic* optimization neglecting individual companies' profitability requirements and expected returns-of-investment. Intermittent RES, H_2 and fuel production facilities' profitability is generally not evaluated in the scope of this thesis. It is up to future research to prove profitability - or to political decision-makers to provide boundary conditions in which it can be brought to coherence with energy system needs.

Another limitation is the fix output ratio of *synthetic fuel* production facilities assumed as constant. Other processes of synthesizing fuels exist that are more optimizied to one product. Including a broader range of production processes would yield insights on production technology heterogeneity. This is specifically important, because in the analysis, end-use specific demand developments e.g. for kerosene instead of for syncrude are modeled, taking into account local fuel demand, e.g. for

kerosene in Hesse because of the airport in Frankfurt am Main. Also, carbon sources were not modeled in detail but rather *DAC* assumed as the only option. Including also fossil point sources could have implications for medium term defossilization strategies.

The analysis confirms findings by Victoria et al. (2020), that intermediary system designs show broader varieties than long-term target designs.

For the case of H_2 production facilities, a challenge is to find companies that invest early, initiating projected economies-of-scale (Odenweller et al., 2022). If those early investments are not made because of the expected decrease in investment costs, they may never be realized.

Other studies showed that *e-H₂* imports would only be competitive at prices as low as 30-50 EUR/kWh (Gils et al., 2021b; Göke et al., 2023). Since the lowest cost-step analyzed here is at 50 EUR/kWh, assessing lower cost-steps could yield interesting insights. The analysis shows comparatively late and low *e-H₂* imports. Methods of including progressively increasing costs for intermittent RES capacity expansion (Lohr et al., 2022; Hoffmann et al., 2024) may alleviate this without exogenously defining import shares. However, it is likely that introducing the suggested method - a quadratic formulation of costs - forces analysts to compromise on other aspects of fully sector-coupled energy system models, such as time resolution, spatial horizon, technology or sectoral scope.

Strategies of demand *avoidance* and modal *shift* were not assessed but have been shown to have potentially great impact on resulting transport final energy demands. Similar to *biofuel*, it may thus be an option to reduce strong increases in electric demand driven, first by *decarbonization*, and later by *defossilization*.

Motivated by combating climate-change, energy systems analysis needs to translate its results more to climate science, e.g. the compatibility of scenarios with specific representative carbon pathways. This brings about the challenge of i) defining the global remaining budget and ii) allocating it to regions or countries among other challenges such as the role of non-CO_2 emissions. Both challenges have been heavily discussed elsewhere (IPCC, 2023a; van den Berg et al., 2020; Williges et al., 2022). For the German case specifically, the German Advisory Council for the Environment has recently published a statement that Germany is likely to have overshot the German 1.5 °C budget within 2024 (Hornberg et al., 2024). Assessments of cumulative CO_2 emissions along transformation pathways from literature and from Paper III (Figure 5.1) show the consistency or inconsistency of energy scenarios with German remaining carbon budgets (Wulff et al., 2024). This metric, that can be calculated ex-post from transformation pathways should be calculated more often to assess the suggested energy system transformation pathway's coherence or incoherence with necessary climate protection.

5.4. Critical reflection on the general approach

After discussing the individual parts of the thesis, this section discusses the general approach of linear optimization modeling and scenario analysis. After discussing limitations of linear energy system optimization models, first ideas are developed on

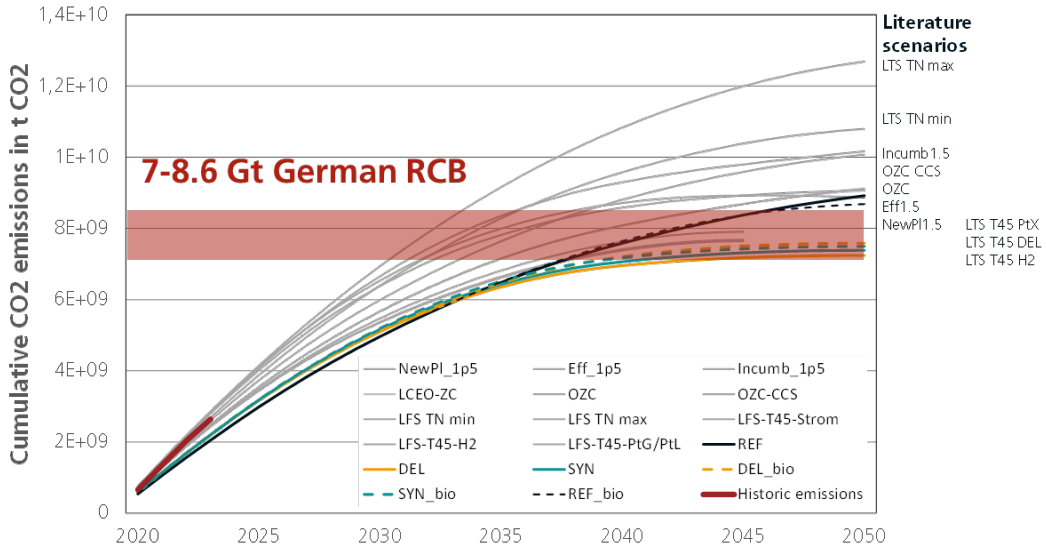


Figure 5.1.: German cumulative CO_2 emissions up to 2050 for various literature studies adapted from (Wulff et al., 2024). Abbreviations: RCB - Remaining Carbon Budget. For a reference of the individual scenario studies, see the original source.

coping with an inherent problem to researching the future - contingency. Based on studies from theory of science, this concept is described in more detail and applied to the subject.

On the modeling side itself, *REMix-OptiMo* contains simplifications, some of which have been discussed in Papers I-III or in the preceding Sections. More general limitations also apply, such as the granularity gap between BEV owners and the energy infrastructure planning (Cao et al., 2021). This is important for BEV users as the assumption of cost-optimal purchasing and charging choices often taken in other studies simplify human behavior. Paper II takes first steps in overcoming those for the case of charging decisions, and Paper III for the case of purchasing decisions in a temporal dynamic.

REMix-OptiMo is a linear optimization model, thus all relationships between the modeling variables are approximated to be linear with mostly one coefficient, i.e. one slope of the linear relationship, which is a simplification. Investments are modeled using annuities for specific target-years, thus the profitability of an invested technology in the consecutive years is not assessed. Fossil fuel prices are exogenously given based on IEA forecasts which have a high uncertainty. However, their role progressively decreases as they are phased out of the energy system. Acceptance aspects, e.g. of wind power or transmission grid extension are not assessed. Integrating those together with above-mentioned progressively increasing costs for intermittent RES is left for future research.

Another challenge is a fundamental conflict between expected increases in complexity of energy systems through sector-coupling and recommended parsimonious use of modeling, especially on long-term horizons (Morgan and Keith, 2008). In this work, this challenge is addressed by refraining from analyzing the detailed intra-

annual energy system operation in the long-term analysis of Paper III, drafting infrastructures and their respective expansion gradients.

The general contingency of an energy scenario - the same possibility for it to occur as not to occur (Esposito, 2023) - poses a challenge in energy systems analysis. It leads to the question "what is a useful scenario?" that so far is rarely discussed let alone answered properly. As most energy system modelers avoid making statements on the probability of their scenarios - mostly for good reasons - still the research field could benefit from more theoretical underpinnings on the employed methods, especially on quality criteria of scenarios.

The engineering-based mindset of problem-solving poses a serious challenge to the deepening of theoretical and epistemic foundations of energy systems analysis as the question "what is a good scenario?" cannot solely be answered by consistency criteria, step-by-step checklists or ever-increasing complexity, scope, and resolution of the applied models. A deeper understanding of scientific quality under contingency is needed. It also touches on epistemic foundations of the research field.

Cacean suggests to separate model-based research into three steps (Cacean, 2016): Deduction, the simplification of a real-world system to a model, Demonstration, the model experiment itself, and Interpretation, the step of extracting meaning from model results and reapplying it on a real-world system or decision situation. He uses this approach to theoretically proof the general capability of model-based research to derive recommendations under specific conditions. However, this approach is also useful for coping with contingency on the more practical questions raised above. Approaches for model validation would e.g. corroborate the step of Demonstration. The above-mentioned decision to refrain from assessing dispatch variables in Paper III of this study is taken on the level of Interpretation.

The author also mentions a two-step justification challenge: Research designs have to be able to provide sufficient detail to evaluate actions against each other. For this, models have to be specific enough to show that an action is better than another one. However, requiring too high details of models may make their application infeasible. An example of a very strong requirement is given in the debate between Heard et al. (2017) and Brown et al. (2018a). Despite the technological bias of the former list of authors, debates like this should be reflected upon, since they provide valuable input on an epistemic level.

A central question of understanding ones scientific role is where a researcher or research group position themselves between the poles of being engineers - designing feasible energy systems, a consultant - suggesting specific actions, or a scientist - understanding and describing the patterns of energy systems as social, technical, economic and political system-of-systems.

What constitutes good scenario design always has to be related to a concrete research question, thus it is rather a question about the *adequacy* of a scenario. This leads to a systematization or categorization of research questions in energy systems analysis on various scopes. The adequacy of model *dimensionality*, resolution and scenario detail could then potentially be mapped. In which context is it better to develop one scenario with smaller parametric sensitivity studies? For what purpose is a broad parametric sensitivity analysis required as suggested by Moret et al. (2017) that can be costly? As Cacean shows, the *relevant possibility* of *empirical*

adequacy formally suffices as a statement to justify possibility statements for the future (Cacean, 2016). Then, how can *empirical inadequacy* be proven, i.e. how can a specific model or a scenario be *"falsified"*? A variety of criteria could be proposed

- Lack of model availability, i.e. openness of framework code, openness and availability of model data including all timeseries, demand assumptions and input parameters. At best availability of raw data and processing pipelines.
- Comparison of model with a historic energy system of the same scope. Here, different levels of adequacy can be derived also possibly yielding insights into ranges of uncertainty, e.g. adequacy with annual power mix, annual imports and exports or annual energy volumes charged or discharged, adequacy of residual load duration curve (Mangipinto et al., 2022), technical adequacy with monthly power mix, technical adequacy with hourly dispatch.

This, of course can hold true on multiple resolutions in different *dimensions*. It is not necessarily given, that a higher resolution model scores higher on validity. As the research in Papers II and III show together with findings from previous studies, ignoring user-behavior or fast-charging in a charging model can have large implications on the resulting flexibility. This, however, does not necessarily imply a strong impact on energy system results. Also, as shown in Göke et al. (2023), for largely *defossilized* highly sector-coupled energy systems, the flexibility by the necessary hydrogen infrastructure is much greater, also motivating a lesser detail on PEV fleet charging profiles. Of course, in medium-term-scenarios and especially in local contexts this may not be the case.

A great problem is the *lack of falsifiability* of a scenario as a relevant possibility, because "it works", it may even be convincing. This is to some degree also true for the scenarios presented in this thesis. While the scenarios in Paper II fulfilled the purpose of providing boundary conditions for testing the influence of vehicle fleet modeling under a broad set of input parameter variations, the three transport demand scenarios in Paper III are clearly falsifiable by either proving infeasibility or lack of socio-economic viability (Brown et al., 2018a).

They demonstrate feasible pathways towards transport sector *defossilization* with varying degrees of *conversion depth*. This could be proven infeasible if respective road vehicle assumptions do not develop, e.g. fleet emission restrictions requiring car manufacturers to reduce CO_2 emissions by 55% in 2030 against 1990 emission levels are not introduced. The SYN scenario specifically would be falsified by a denial of OEM companies to count drop-in synthetic fuels into fleet emission reductions. Both aforementioned falsifications hold true as long as there are no major other drivers of *direct* or *indirect electrification* than governmental policies. Another proof of infeasibility of the biofuel availability scenarios would be a top-down-exclusion of biomass for use in the transport sector.

The assumption of optimistic development of societal and political will, driven by rational choices that is implicitly assumed in the scenarios (Paper III) is also explicitly described by Bogdanov et al. (2019). However, as governments' rationale for energy policy changes, this is a strong assumption. Ignoring available background knowledge such as the consistency of energy scenarios with climate change, i.e.

ambitious mitigation, would lead to scenarios more in line with current behavior but at the same time to questionable lower ambition of CO_2 mitigation. These examples show a certain bias in energy system model research towards environmentally and socially desirable, yet not observable, trends. From a scientific perspective, this notion is questionable.

In this work, especially in Paper III, a complex energy system model is set up based on the framework *REMix-OptiMo*. Despite out of the scope of the research questions, non-German European countries and the heat sector were modeled in order to grasp important interrelationships between the "background energy system" and the parts of interest. To this end - and rather for a consulting context - it may not prove necessary to develop models as detailed as the one proposed in this thesis if energy and transport policy deliberately values short-term German economic interest higher than long-term global environmental stability. Energy systems analysis could also have a hinge function between climate science and energy policy making.

One way forward for research is to focus more on empirical, measurable data - e.g. on recent energy system investments and operations -, as well as short-term scenarios that unfold within the next months to years in order to study the real world behavior of energy systems. This way, at least researchers have the possibility to falsify hypotheses.

Latest work on combining Modeling to Generate Alternatives (*MGA*) and global sensitivity analysis by Neumann & Brown analyzes the source of output variance across more than 50,000 techno-economic cost assumptions for PV, wind power, hydrogen, and battery storage (Neumann and Brown, 2023). Their analysis is valuable despite its limited *scope* ignoring energy system flexibility by heat and transport sector-coupling. The global sensitivity analysis shows how much technology expansion relies on their own cost variations or that of other technologies. Some technologies vary because of direct competition with another technology (such as onshore wind), others because they rely on complementing technologies (such as solar PV).

They also find robust transmission capacity expansion on a European scope comparable to the ones shown in Paper III and show that hydrogen storage as a temporal flexibility may substitute transmission capacity - a spatial flexibility. Combining their methodological approach with the here-introduced detail of transport sector demand modeling would be an interesting pursue, as it could explicitly quantify multi-dimensional trade-offs between individual components of energy systems. The results show that there are many degrees of freedom, from end-use technology to supply system and all balancing and transmission infrastructure in between.

An analysis of the cumulative emissions of the quite ambitious scenarios of Paper III, it is shown that the scenarios may keep cumulative energy system emissions until CO_2 neutrality below a level of 8 Gt CO_2 - the estimated remaining German 2020 budget (Wulff et al., 2024). Energy system researchers must be aware of the climate-change implications of their scenarios, be transparent about the significant costs outside their analytical scopes and . Scenarios overshooting 2°C (budgets) significantly threaten the environmental, social and economic fundaments of peaceful anthropogenic life on earth (IPCC, 2023a).

6. Conclusion and outlook

This thesis describes novel methods of modeling the increasing interdependence between the transforming energy and transport sectors. BEV modeling had been subject of energy systems analysis research for over a decade on various scopes. However, open and transparent tools, flexible enough to provide BEV fleet charging profiles, and respective flexibility was lacking. At the same time, the specific influence of different approaches of BEV charging modeling on load flexibility and the respective potential to integrate intermittent RES was still unclear, especially regionally within Germany. As the German government was forced to increase CO_2 reduction ambitions and specify sectoral targets more clearly, attention shifted towards full transport *defossilization* including end-use technologies where fuels could not easily be replaced. The overarching objective was to provide methods that can translate various transport sector energy demand scenarios into energy system models, in order to assess their respective impact on energy supply and transmission infrastructure.

BEV fleet charging can be approximated by the approach introduced in the first part of the thesis. It describes BEV fleet load and its flexibility based on real-world driving patterns. The case study with two recent national travel surveys from 2008 and 2017 shows that decreased average number of trips per day leads to slightly higher connection during daytime while increased average distance per trip leads to higher uncontrolled charging and drain peaks and slightly reduced fleet flexibility of the representative vehicle especially on Sundays. To the knowledge of the author, the published tool, venco.py, was one of the first tools made available under an open source license by the time of publication. It is until today the only tool present comprising all interface routines to national travel surveys and provides a straight forward way of estimating uncontrolled, controlled and BDC of future BEV fleets for various energy system models.

On the medium-term, controlled charging may play a decisive role in keeping peak demand increases low and integrating intermittent RES, thus, the adequate modeling of controlled charging is the pursue of Paper II. The analysis shows that, taking a more user-focused approach may reduce charging flexibility by a factor of 10 leading to a decrease of a factor of 3 of shifted load throughout the year. Shifted load is found to be more robust against variations of CO_2 emission limitations, weather years and intermittent RES CAPEX assumptions than most other energy model results such as intermittent RES curtailment or transmission of energy from northern to southern Germany. Even though a strong impact of flexibility on charging patterns under cost-optimality is shown, the impact of the difference on energy system infrastructure is relatively small with an observed 5% increase in gas turbine capacity and slight increases in intermittent RES curtailment.

Modeling full transport sector *defossilization* should incorporate user-constrained

vehicle purchasing decisions and fuel demands, as fuels are likely to be provided based on hydrogen from electrolysis powered by RES in the long-term. The energy system implications of varying *conversion depth* demand scenarios as well as respective trade-offs between *clean fuel* supply options are assessed in Paper III. Strict energy system and vehicle fleet CO_2 emission limits are assumed in all target scenarios. Transport sector clean energy demand is found to follow a fairly robust path with steepest increases between 2030 and 2040. Researchers at the interface of transport and energy sector have to be aware of technological details such as blending-limits for bioethanol, but also passenger and goods aviation vehicle specifics implied by designs not yet on the market.

A general trade-off between *direct electrification* and challenges in energy system transformation is observed. If vehicle end-users are unwilling or incapable of purchasing BEV, this is likely to increase the need for infrastructure expansion, especially of medium term *e-H_2* production capacity and additional imports for *synthetic fuels* and electricity. Intermittent RES power plants are needed to their full potential independent of *conversion depth*, although other analyses showed vast degrees of freedom in similarly cost-intensive energy system designs. Assuming availability of biowaste streams and crops comparable to today's levels for transport demands has specifically strong substituting impacts on hydrocarbon imports. It may alleviate needed medium-term intermittent RES and H_2 infrastructure expansion and keep electricity imports to today's levels in the case of *direct electrification*.

Challenges remain for the future at the interface between transport and energy system research. The development of more accurate approaches for BEV fleet flexibility *aggregation* and the systematic comparison of various BEV user and charging infrastructure combinations with empirical data are identified as most important questions. Integrating profitability criteria for H_2 and fuel production sites, more granular import cost-potentials as well as inner-European fuel trade are most pressing for beyond-2040-modeling of coupled energy and transport systems.

For the development of the research field, a critical reflection of scenario techniques common to energy systems analysis was conducted answering to criticism from the climate research community. Energy systems analysis still lacks a systematization of adequacy criteria for scenarios as well as a scientific culture of reproducing each others scientific results - something that must be overcome in order for the young field to establish itself as a serious field of scientific research beyond tools for designing energy systems and policy consulting. First steps were drafted into that direction based on an epistemic approach for justifying relevant possibilities through idealized models. Also, there is a structural paradox between anticipated increase in energy system complexity through sector-coupling and recommendations to use simpler models, the further away the systems lie.

A few insights with direct relevance to decision-making can be highlighted. Energy planners need to be aware of the potential *self-unfulfilling prophecy* of electrolysis investments due to anticipated cost decreases. The analysis shows the high relevance of imported clean fuels to Germany, especially for long-term transport defossilization. Decision-makers need to be aware of historic power dynamics and (sometimes exaggerated) risk perceptions, and develop cooperation agreements at eye-level without exploiting the best foreign renewable energy sites for exportation.

First assessments on *modal shift* and useful energy demand reduction measures exist and show that combined approaches of *improvements*, *shifting* to other modes and *avoiding* transport demand may lead to lower necessary installed capacities of solar and wind power. Previous studies also showed that these strategies are also beneficial for fulfilling biofuel quotas. Scenarios describing demand *avoidance* and *modal shift* combined with detailed *improve* scenarios described in this thesis could form a powerful analytical basis. If those were to be subjected to methodological approaches of *MGA* and global sensitivity analysis, this would provide relevant insights to decision-makers for integrated transport and energy sectors beyond 2030.

The scenarios analyzed here and in other studies are present futures (Esposito, 2023). The future present will unfold not as a scenario or a combination of them, but exactly as it will be. Highly coupled transport-energy-systems will be shaped by a variety of innovations in the decades to come that have yet been modeled only to a very limited degree.

Bibliography

Lennart Adenaw and Sebastian Krapf. Placing bev charging infrastructure: Influencing factors, metrics, and their influence on observed charger utilization. *World Electric Vehicle Journal*, 13(4):56, 2022. doi: 10.3390/wevj13040056.

AGEB. Auswertungstabellen zur energiebilanz 1990-2023, 2024. URL `https://ag-energiebilanzen.de/daten-und-fakten/auswertungstabellen/`.

Manfred Aigner, Danial Esmaeili Aliabadi, Andrea Amri-Henkel, John Anderson, Lisa Becker, Moritz Bergfeld, Urte Brand-Daniels, Marina Braun-Unkhoff, Sabine Brinkop, André Brosowski, Özcan Deniz, Ralph-Uwe Dietrich, Christine Eisenmann, David Ennen, Jonas Eschmann, Benjamin Frieske, Wolfgang Grimme, Sofia Haas, Samuel Hasselwander, Eva Hauser, Sascha Heib, Nathanael Heimann, Johannes Hendricks, Jan Hildebrand, Carsten Hoyer-Klick, Matthias Jordan, Stefan Kronshage, Christian Lutz, Henrik Mantke, Patrick Matschoss, Mariano Mertens, Anika Neitz-Regett, Ines Österle, Matthias Oswald, Simon Pichlmaier, Juliane Prause, Thomas Pregger, Moritz Raab, Sandra Richter, Eugenio Salvador Arellano Ruiz, Niklas Wulff, and Benjamin Zeck. Roadmap für strombasierte kraftstoffe: Gesamtbericht zur begleitforschung energiewende im verkehr (beniver), 2023.

Friedemann G. Albrecht, Daniel H. König, Nadine Baucks, and Ralph-Uwe Dietrich. A standardized methodology for the techno-economic evaluation of alternative fuels – a case study. *Fuel*, 194:511–526, 2017. ISSN 00162361. doi: 10.1016/j.fuel.2016.12.003.

John E. Anderson, Felix Steck, and Tobias Kuhnimhof. Can renewable energy sources meet electric vehicle charging demand today and in the future? a microscopic time-specific travel demand analysis for germany. In Transportation Research Board, editor, *TRB 97th annual meeting*, 2018. URL `https://trid.trb.org/View/1495437`.

Eugenio Salvador Arellano Ruiz. *Dynamic modeling of cost potential curves of captured CO2*. Master thesis, University of Stuttgart, Stuttgart, 2021.

Eugenio Salvador Arellano Ruiz, Niklas Wulff, Benjamin Fuchs, and Wenxuan Hu. autumn: A python library for dynamic modelling of captured co˜2˜ cost potential curves. *Journal of Open Source Software*, 6(64):3203, 2021. doi: 10.21105/joss.03203.

Marlin Arnz. The demand-side mitigation gap in german passenger transport. *European Transport Research Review*, 14(1), 2022. ISSN 1867-0717. doi: 10.1186/s12544-022-00568-9.

Marlin Arnz, Leonard Göke, Johannes Thema, Frauke Wiese, Niklas Wulff, Mario Kendziorski, Karlo Hainsch, Philipp Blechinger, and Christian von Hirschhausen. Avoid, shift or improve passenger transport? impacts on the energy system. *Energy Strategy Reviews*, 52:101302, 2024. doi: https://doi.org/10.1016/j.esr.2024.101302.

Hans-Karl Bartholdsen, Anna Eidens, Konstantin Löffler, Frederik Seehaus, Felix Wejda, Thorsten Burandt, Pao-Yu Oei, Claudia Kemfert, and Christian Hirschhausen. Pathways for germany's low-carbon energy transformation towards 2050. *Energies*, 12(15):2988, 2019. doi: 10.3390/en12152988.

Kerstin Eva Bartos, Christine Dede, Christian Brehm, and Patrizia Kaiser. Szenariorahmen zum netzentwicklungsplan strom 2037/2045: Version 2025: Entwurf der übertragungsnetzbetreiber, 2024. URL `https://www.netzentwicklungsplan.de/sites/default/files/2024-07/Szenariorahmenentwurf_NEP2037_2025.pdf`.

Dmitrii Bogdanov, Javier Farfan, Kristina Sadovskaia, Arman Aghahosseini, Michael Child, Ashish Gulagi, Ayobami Solomon Oyewo, Larissa de Souza Noel Simas Barbosa, and Christian Breyer. Radical transformation pathway towards sustainable electricity via evolutionary steps. *Nature communications*, 10(1):1077, 2019. doi: 10.1038/s41467-019-08855-1.

Julian Brandes, Markus Haun, Charlotte Senkpiel, Christoph Kost, Andreas Bett, and Hans-Martin Henning. Wege zu einem klimaneutralen energiesystem: Die deutsche energiewende im kontext gesellschaftlicher verhaltensweisen, 2020. URL `https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/Fraunhofer-ISE-Studie-Wege-zu-einem-klimaneutralen-Energiesystem.pdf`.

Julian Brandes, Markus Haun, Daniel Wrede, Patrick Jürgens, Christoph Kost, and Hans-Martin Henning. Studie: Wege zu einem klimaneutralen energiesystem: Update klimaneutralität 2045, 2021.

Christian Breyer, Gabriel Lopez, Dmitrii Bogdanov, and Petteri Laaksonen. The role of electricity-based hydrogen in the emerging power-to-x economy. *International Journal of Hydrogen Energy*, 49:351–359, 2024. ISSN 03603199. doi: 10.1016/j.ijhydene.2023.08.170.

André Brosowski, Ralf Bill, and Daniela Thrän. Temporal and spatial availability of cereal straw in germany—case study: Biomethane for the transport sector. *Energy, Sustainability and Society*, 10(1), 2020. doi: 10.1186/s13705-020-00274-1.

Tom Brown, Tobias Bischof-Niemz, Kornelis Blok, Christian Breyer, Henrik Lund, and Brian V. Mathiesen. Response to 'burden of proof: A comprehensive review of the feasibility of 100% renewable-electricity systems'. *Renewable and Sustainable Energy Reviews*, 92:834–847, 2018a. ISSN 13640321. doi: 10.1016/j.rser.2018.04.113.

Tom Brown, David Schlachtberger, Alex Kies, Sebastian Schramm, and Martin Greiner. Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable european energy system. *Energy*, 160:720–739, 2018b. ISSN 03605442. doi: 10.1016/j.energy.2018.06.222.

Jens Burchardt, Katharina Franke, Patrick Herhold, Maria Hohaus, Henri Humpert, Joonas Päivärinta, Elisabeth Richenhagen, Daniel Ritter, Stefan Schönberger, Jonas Schröder, Sophie Strobl, Christoph Tries, and Alexander Türpitz. Klimapfade 2.0: Ein wirtschaftsprogramm für klima und zukunft, 2021.

BVerfG. Das ksg vom 12. dezember 2019 ist verfassungswidrig, weil die emissionsreduktionen ab 2030 zu wenig geregelt werden., 2021. URL `https://www.bundesverfassungsgericht.de/SharedDocs/Downloads/DE/2021/03/rs20210324_1bvr265618.pdf?__blob=publicationFile&v=1`.

Sebastian Cacean. Die begründung relevanter möglichkeiten durch idealisierte modelle. In Christian Dieckhoff and Anna Leuschner, editors, *Die Energiewende und ihre Modelle*, Science studies, pages 45–74. transcript Verlag, s.l., 2016. ISBN 9783839431719. doi: 10.14361/9783839431719-003.

Karl-Kien Cao and Manuel Wetzel. High performance computing vs. heuristic: A performance benchmark for optimization problems with linear power flows. In *Smart grids: key enablers of a green power system*, pages 1104–1108, Piscataway, NJ, 2020. IEEE. ISBN 978-1-7281-7100-5. doi: 10.1109/ISGT-Europe47291.2020.9248780.

Karl-Kiên Cao, Jannik Haas, Evelyn Sperber, Shima Sasanpour, Seyedfarzad Sarfarazi, Thomas Pregger, Oussama Alaya, Hendrik Lens, Simon R. Drauz, and Tanja M. Kneiske. Bridging granularity gaps to decarbonize large–scale energy systems—the case of power system planning. *Energy Science & Engineering*, 9 (8):1052–1060, 2021. ISSN 2050-0505. doi: 10.1002/ese3.891.

Felix Cebulla, Tobias Naegler, and Markus Pohl. Electrical energy storage in highly renewable european energy systems: Capacity requirements, spatial distribution, and storage dispatch. *Journal of Energy Storage*, 14:211–223, 2017. ISSN 2352152X. doi: 10.1016/j.est.2017.10.004.

EU COM. A clean planet for all: A european long-term strategic vision for a prosperous, modern, competitive and climate neutral economy: In-depth analysis in support of the commission communication com(2018) 773, 2018. URL `https://climate.ec.europa.eu/document/download/dc751b7f-6bff-47eb-9535-32181f35607a_en?filename=com_2018_733_analysis_in_support_en.pdf`.

Eike Cramer, Leonardo Rydin Gorjao, Alexander Mitsos, Benjamin Schafer, Dirk Witthaut, and Manuel Dahmen. Validation methods for energy time series scenarios from deep generative models. *IEEE Access*, 10:8194–8207, 2022. doi: 10.1109/ACCESS.2022.3141875.

Felix Creutzig, Patrick Jochem, Oreane Y Edelenbosch, Linus Mattauch, Detlef P van Vuuren, David McCollum, and Jan Minx. Transport: A roadblock to climate change mitigation? *Science*, 350(6263):911–912, 2015.

Jorge Cristóbal, Md Jubayed, Niklas Wulff, and Liselotte Schebek. Life cycle losses of critical raw materials from solar and wind energy technologies and their role in the future material availability. *Resources, Conservation and Recycling*, 161: 104916, 2020. ISSN 09213449. doi: 10.1016/j.resconrec.2020.104916.

Luiz Enrique Vieira de Souza, Estevão Mota Gomes Ribas Lima Bosco, Alina Gilmanova Cavalcante, and Leila da Costa Ferreira. Postcolonial theories meet energy studies:"institutional orientalism" as a barrier for renewable electricity trade in the Mediterranean region. *Energy research & social science*, 40:91–100, 2018. doi: 10.1016/j.erss.2017.12.001.

Mark M. Dekker, Vassilis Daioglou, Robert Pietzcker, Renato Rodrigues, Harmen-Sytze de Boer, Francesco Dalla Longa, Laurent Drouet, Johannes Emmerling, Amir Fattahi, Theofano Fotiou, Panagiotis Fragkos, Oliver Fricko, Ema Gusheva, Mathijs Harmsen, Daniel Huppmann, Maria Kannavou, Volker Krey, Francesco Lombardi, Gunnar Luderer, Stefan Pfenninger, Ioannis Tsiropoulos, Behnam Zakeri, Bob van der Zwaan, Will Usher, and Detlef van Vuuren. Identifying energy model fingerprints in mitigation scenarios. *Nature Energy*, 8(12):1395–1404, 2023. doi: 10.1038/s41560-023-01399-1.

Deutsches Biomasseforschungszentrum. Dbfz biomassemonitor für deutschland, 2024. URL `https://datalab.dbfz.de/resdb/potentials?lang=de`.

Chris Develder, Nasrin Sadeghianpourhamami, Matthias Strobbe, and Nazir Refa. Quantifying flexibility in ev charging as dr potential: Analysis of two real-world data sets. In *2016 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 600–605, Piscataway, NJ, 2016. IEEE. ISBN 978-1-5090-4075-9. doi: 10.1109/SmartGridComm.2016.7778827.

Diego Luca de Tena Costales. *Large Scale Renewable Power Integration wit Electric Vehicles: Long term analysis for Germany with a renewable based power supply*. Dissertation, University Stuttgart, Stuttgart, 2014. URL `https://elib.dlr.de/92151/1/Dissertation_Diego_Luca_de_Tena.pdf`.

Tim Drees, Thomas Dederichs, Mario Meinecke, and Astrid Dolak. Szenariorahmen zum netzentwicklungsplan strom 2037 mit ausblick 2045, version 2023: Entwurf der übertragungsnetzbetreiber, 2022. URL `https://www.netzentwicklungsplan.de/sites/default/files/2023-01/Szenariorahmenentwurf_NEP2037_2023.pdf`.

Lisa Ecke, Jan Vallee, Bastian Chlond, and Peter Vortisch. Mobilitätspanel // deutsches mobilitätspanel (mop) – wissenschaftliche begleitung und auswertungen bericht 2022/2023: Alltagsmobilität und fahrleistung: Eine längsschnittstudie zum mobilitätsverhalten der bevölkerung, 2023. URL `https://mobilitaetspanel.ifv.kit.edu/downloads/Bericht_MOP_22_23.pdf`.

Danial Esmaeili Aliabadi, Niklas Wulff, Matthias Jordan, Karl-Friedrich Cyffka, and Markus Millinger. Soft-coupling energy and power system models to analyze pathways toward a de-fossilized German transport sector. In *Operations Research Proceedings 2022*, pages 313–320. Springer, 2022. ISBN 978-3-031-24907-5. doi: 10.1007/978-3-031-24907-5_38.

Danial Esmaeili Aliabadi, Katrina Chan, Niklas Wulff, Kathleen Meisel, Matthias Jordan, Ines Österle, Thomas Pregger, and Daniela Thrän. Future renewable energy targets in the EU: Impacts on the German transport. *Transportation Research Part D: Transport and Environment*, 124:103963, 2023. doi: 10.1016/j.trd.2023.103963.

Danial Esmaeili Aliabadi, Matthias Jordan, Andreas Meurer, and Niklas Wulff. Power-to-x and bioenergy: Competition and synergy in germany. In Amjad Anvari-Moghaddam, editor, *Power-to-X in Regional Energy Systems*. CRC, Florida, USA, 2025.

Elena Esposito. *Die Fiktion der wahrscheinlichen Realität*, volume 2485 of *Edition Suhrkamp*. Suhrkamp, Frankfurt am Main, 5. auflage, originalausgabe edition, 2023. ISBN 9783518124857.

European Commission. Commission delegated regulation (eu) 2023/1184 of 10 february 2023 supplementing directive (eu) 2018/2001 of the european parliament and of the council by establishing a union methodology setting out detailed rules for the production of renewable liquid and gaseous transport fuels of non-biological origin, 2024. URL https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv%3AOJ.L_.2023.157.01.0011.01.ENG&toc=OJ%3AL%3A2023%3A157%3ATOC.

Eurostat. Transport maritime de fret par région nuts 2, 2024.

Eurostat, the statistical office of the European Union. National annual road freight transport by regions of loading (nuts 3) and by group of goods (1 000 t), from 2008 onwards, 2023. URL https://ec.europa.eu/eurostat/de/web/products-datasets/product?code=road_go_na_rl3g.

Steffen Fattler. *Economic and Environmental Assessment of Electric Vehicle Charging Strategies*. Dissertation, Technical University of Munich, Munich, Germany, 2021. URL https://mediatum.ub.tum.de/download/1601943/1601943.pdf.

Federal German Automotive Agency. Güterbeförderung: Jahr 2020 (vd 4), 2020. URL https://www.kba.de/SharedDocs/Downloads/DE/Statistik/Kraftverkehr/VD4/vd4_2020.xlsx;jsessionid=0ADBA6B66F65CC32BD9FE54EFB0B1A0B.live21323?__blob=publicationFile&v=3.

Federal German Governement. Action program climate protection 2020. cabinet decision from december, 3rd 2014., 2014. URL https://www.bmuv.de/fileadmin/

Daten_BMU/Download_PDF/Aktionsprogramm_Klimaschutz/aktionsprogramm_klimaschutz_2020_broschuere_bf.pdf.

Felix Steck, John E. Anderson, Tobias Kuhnimhof, and Carsten Hoyer-Klick. Comprehensive transportation and energy analysis: A price sensitive, time-specific. *Transportation Research Board 98th Annual Meeting*, 2019. URL https://elib.dlr.de/127475/1/TRB-2019_EVer_Paper.pdf.

Max Fette, Christine Brandstätt, Hans Christian Gils, Hedda Gardian, Thomas Pregger, Johannes Schaffert, Eren Tali, and Nils Brücken. Multi-sektor-kopplung: Modellbasierte analyse der integration erneuerbarer stromerzeugung durch die kopplung der stromversorgung mit dem wärme, gas- und verkehrssektor: Endbericht, 2020.

Jan Figgener, Benedikt Tepe, Fabian Rücker, Ilka Schoeneberger, Christopher Hecht, Andreas Jossen, and Dirk Uwe Sauer. The influence of frequency containment reserve flexibilization on the economics of electric vehicle fleet operation. *Journal of Energy Storage*, 53:105138, 2022. ISSN 2352152X. doi: 10.1016/j.est.2022.105138.

David Fischer, Alexander Harbrecht, Arne Surmann, and Russell McKenna. Electric vehicles' impacts on residential electric local profiles – a stochastic modelling approach considering socio-economic, behavioural and spatial factors. *Applied Energy*, 233-234:644–658, 2019. ISSN 03062619. doi: 10.1016/j.apenergy.2018.10.010.

Markus Fischer, Cornelius Hardt, Jörg Elias, and Klaus Bogenberger. Simulation-based evaluation of charging infrastructure concepts: The park and ride case. *World Electric Vehicle Journal*, 13(8):151, 2022. doi: 10.3390/wevj13080151.

Marco Giacomo Flammini, Giuseppe Prettico, Andreea Julea, Gianluca Fulli, Andrea Mazza, and Gianfranco Chicco. Statistical characterisation of the real transaction data gathered from electric vehicle charging stations. *Electric Power Systems Research*, 166:136–150, 2019. ISSN 03787796. doi: 10.1016/j.epsr.2018.09.022.

Marte Fodstad, Pedro Del Crespo Granado, Lars Hellemo, Brage Rugstad Knudsen, Paolo Pisciella, Antti Silvast, Chiara Bordin, Sarah Schmidt, and Julian Straus. Next frontiers in energy system modelling: A review on challenges and the state of the art. *Renewable and Sustainable Energy Reviews*, 160:112246, 2022. ISSN 13640321. doi: 10.1016/j.rser.2022.112246.

Thomas Franke and Josef F. Krems. Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour*, 21:75–89, 2013. ISSN 13698478. doi: 10.1016/j.trf.2013.09.002.

Martha Maria Frysztacki, Jonas Hörsch, Veit Hagenmeyer, and Tom Brown. The strong effect of network resolution on electricity system models with high shares

of wind and solar. *Applied Energy*, 291:116726, 2021. ISSN 03062619. doi: 10.1016/j.apenergy.2021.116726.

Carlos Gaete-Morales, Hendrik Kramer, Wolf-Peter Schill, and Alexander Zerrahn. An open tool for creating battery-electric vehicle time series from empirical data, emobpy. *Scientific data*, 8(1):152, 2021. doi: 10.1038/s41597-021-00932-9.

Max Gierkink, Johannes Wagner, Berit H. Czock, Arne Lilienkamp, Michael Moritz, Lena Pickert, Tobias Sprenger, Jonas Zinke, Jonas von Haebler, Maik Tretschock, Christian Wagner, Marco Greve, Stephanie Fiedler, and Linh Ho. dena-leitstudie aufbruch klimaneutralität: Klimaneutralität 2045 - transformation der verbrauchssektoren und des energiesystems: Gutachterbericht im auftrag der deutschen energie-agentur (dena), 2021. URL `https://www.ewi.uni-koeln.de/cms/wp-content/uploads/2022/03/211005_EWI-Gutachterbericht_dena-Leitstudie-Aufbruch-Klimaneutralitaet.pdf`.

Hans Christian Gils, Hedda Gardian, Thomas Pregger, Johannes Schaffert, Eren Tali, Max Fette, and Christine Brandstätt. Remix model input data for the thg95/ghg95 scenario analysed within the museko project: This dataset was created within the project 'museko' supported by the german federal ministry of economic affairs and energy under grant number 03et4038., 2021a. URL `https://doi.org/10.5281/zenodo.5705414`.

Hans Christian Gils, Hedda Gardian, and Jens Schmugge. Interaction of hydrogen infrastructures with other sector coupling options towards a zero-emission energy system in Germany. *Renewable Energy*, 180:140–156, 2021b. ISSN 09601481. doi: 10.1016/j.renene.2021.08.016.

Leonard Göke, Jens Weibezahn, and Christian von Hirschhausen. A collective blueprint, not a crystal ball: How expectations and participation shape long-term energy scenarios. *Energy Research & Social Science*, 97:102957, 2023. ISSN 22146296. doi: 10.1016/j.erss.2023.102957.

Wolfgang Grimme and Matthias Braun. Estimation of potential hydrogen demand and co2 mitigation in global passenger air transport by the year 2050. In *11th International Conference on Air Transport – INAIR 2022, Returning to the Skies*, volume 65, pages 24–33. Elsevier, 2022. doi: 10.1016/j.trpro.2022.11.004. URL `https://elib.dlr.de/190337/1/1-s2.0-S2352146522006718-main.pdf`.

Julia B. Gutiérrez-Lopez and Dominik Möst. Characterising the flexibility of electric vehicle charging strategies: a systematic review and assessment. *Transport Reviews*, 43(6):1237–1262, 2023. ISSN 0144-1647. doi: 10.1080/01441647.2023.2217519.

Johannes Hampp, Michael Düren, and Tom Brown. Import options for chemical energy carriers from renewable sources to germany. *PLOS ONE*, 18(2):e0262340, 2023. ISSN 1932-6203. doi: 10.1371/journal.pone.0281380. URL `http://arxiv.org/pdf/2107.01092v3`.

Hans Christian Gils. *Balancing of Intermittent Renewable Power Generation by Demand Response and Thermal Energy Storage*. Dissertation, University Stuttgart, 2015. URL `https://elib.uni-stuttgart.de/bitstream/11682/6905/1/Gils_Dissertation_online.pdf`.

Ingo A. Hansen. Review of planning and capacity analysis for stations with multiple platforms – case stuttgart 21. *Journal of Rail Transport Planning & Management*, 6(4):313–330, 2017. ISSN 22109706. doi: 10.1016/j.jrtpm.2016.12.002.

Kenneth Hansen, Brian Vad Mathiesen, and Iva Ridjan Skov. Full energy system transition towards 100% renewable energy in Germany in 2050. *Renewable and Sustainable Energy Reviews*, 102:1–13, 2019.

B. P. Heard, B. W. Brook, T.M.L. Wigley, and C.J.A. Bradshaw. Burden of proof: A comprehensive review of the feasibility of 100% renewable-electricity systems. *Renewable and Sustainable Energy Reviews*, 76:1122–1133, 2017. ISSN 13640321. doi: 10.1016/j.rser.2017.03.114.

Christopher Hecht, Jan Figgener, and Dirk Uwe Sauer. Simultaneity factors of public electric vehicle charging stations based on real-world occupation data. *World Electric Vehicle Journal*, 13(7):129, 2022. doi: 10.3390/wevj13070129.

Nathanael Heimann, Moritz Raab, Ralph-Uwe Dietrich, Sofia Haas, Simon Pichlmaier, and Niklas Wulff. Beitrag zur einheitlichen ökonomischen und ökologischen analyse von strombasierten prozessen zur kraftstoffherstellung in deutschland. *Chemie Ingenieur Technik*, submitted.

Heidi Ursula Heinrichs. *Analyse der langfristigen Auswirkungen von Elektromobilität auf das deutsche Energiesystem im europäischen Energieverbund*. Ph.d. thesis, Karlsruhe University, Erscheinungsort nicht ermittelbar, 2013. URL `https://directory.doabooks.org/handle/20.500.12854/40802`.

Hans-Martin Henning and Andreas Palzer. Was kostet die energiewende? wege zur transformation des deutschen energiesystems bis 2050, 2015. URL `https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/Fraunhofer-ISE-Studie-Was-kostet-die-Energiewende.pdf`.

Maximilian Hoffmann, Bruno U. Schyska, Julian Bartels, Tristan Pelser, Johannes Behrens, Manuel Wetzel, Hans Christian Gils, Chuen-Fung Tang, Marius Tillmanns, Jan Stock, André Xhonneux, Leander Kotzur, Aaron Praktiknjo, Thomas Vogt, Patrick Jochem, Jochen Linßen, Jann M. Weinand, and Detlef Stolten. A review of mixed-integer linear formulations for framework-based energy system models. *Advances in Applied Energy*, 16:100190, 2024. ISSN 26667924. doi: 10.1016/j.adapen.2024.100190.

Claudia Hornberg, Claudia Kemfert, Christina Dornack, Wolfgang Köck, Wolfgang Lucht, Josef Settele, and Annette Elisabeth Töller. Wo stehen wir beim co2-budget? eine aktualisierung. stellungnahme märz 2024, 2024. URL

https://www.umweltrat.de/SharedDocs/Downloads/DE/04_Stellungnahmen/2020_2024/2024_03_CO2_Budget.pdf?__blob=publicationFile&v=17.

Jonas Hörsch, Fabian Hofmann, David Schlachtberger, and Tom Brown. Pypsa-eur: An open optimisation model of the european transmission system. *Energy Strategy Reviews*, 22:207–215, 2018. ISSN 2211467X. doi: 10.1016/j.esr.2018.08.012.

Mark Howells, Holger Rogner, Neil Strachan, Charles Heaps, Hillard Huntington, Socrates Kypreos, Alison Hughes, Semida Silveira, Joe DeCarolis, Morgan Bazillian, and Alexander Roehrl. Osemosys: The open source energy modeling system. *Energy Policy*, 39(10):5850–5870, 2011. ISSN 03014215. doi: 10.1016/j.enpol.2011.06.033.

David Huckebrink and Valentin Bertsch. Integrating behavioural aspects in energy system modelling—a review. *Energies*, 14(15):4579, 2021. doi: 10.3390/en14154579.

Svetlana A. Ikonnikova, Bridget R. Scanlon, and Sofia A. Berdysheva. A global energy system perspective on hydrogen trade: A framework for the market color and the size analysis. *Applied Energy*, 330:120267, 2023. doi: 10.1016/j.apenergy.2022.120267.

Jimena Incer-Valverde, Amira Korayem, George Tsatsaronis, and Tatiana Morosuk. "colors" of hydrogen: Definitions and carbon intensity. *Energy Conversion and Management*, 291:117294, 2023. ISSN 01968904. doi: 10.1016/j.enconman.2023.117294.

infas, DLR, IVT und infas 360. Mobilität in tabellen., 2017. URL https://mobilitaet-in-tabellen.dlr.de/.

IPCC. Climate change 2023: Synthesis report: Contribution of working groups i, ii and iii to the sixth assessment report of the intergovernmental panel on climate change, 2023a. URL https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_LongerReport.pdf.

IPCC. Climate change 2022: Mitigation of climate change: Working group iii contribution to the sixth assessment report of the intergovernmental panel on climate change, 2023b. URL https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_FullReport.pdf.

Patrick Jochem, Sonja Babrowski, and Wolf Fichtner. Assessing co 2 emissions of electric vehicles in germany in 2030. *Transportation Research Part A: Policy and Practice*, 78:68–83, 2015. ISSN 09658564. doi: 10.1016/j.tra.2015.05.007.

Matthias Jordan, Kathleen Meisel, Martin Dotzauer, Jörg Schröder, Karl-Friedrich Cyffka, Niels Dögnitz, Christopher Schmid, Volker Lenz, Karin Naumann, Jaqueline Daniel-Gromke, Gabriel Costa de Paiva, Harry Schindler, Danial Esmaeili Aliabadi, Nora Szarka, and Daniela Thrän. The controversial role of energy crops in the future German energy system: The trade offs of a phase-out and allocation

priorities of the remaining biomass residues. *Energy Reports*, 10:3848–3858, 2023. doi: 10.1016/j.egyr.2023.10.055.

Matthias Jordan, Kathleen Meisel, Martin Dotzauer, Harry Schindler, Jörg Schröder, Karl-Friedrich Cyffka, Niels Dögnitz, Karin Naumann, Christopher Schmid, Volker Lenz, Jaqueline Daniel-Gromke, Gabriel Costa de Paiva, Danial Esmaeili Aliabadi, Nora Szarka, and Daniela Thrän. Do current energy policies in germany promote the use of biomass in areas where it is particularly beneficial to the system? analysing short- and long-term energy scenarios. *Energy, Sustainability and Society*, 14(1), 2024. doi: 10.1186/s13705-024-00464-1.

C. Jugel, M. Albicker, C. Bamberg, M. Battaglia, E. Brunken, T. Bründlinger, P. Dorfinger, A. Döring, J. Friese, D. Gründig, P. Hader, D. Horneber, K. Jankowska, A. Kuhlmann, H. May, E. Meidel, T. Mennel, M. Nieswand, P. Richard, M. Robers, A.-K. Schenk, S. Schmelcher, H. Seidl, S. Siegemund, C. Stolte, L. Strippchen, G. Weber, A. Willers, and J. Willke. dena-leitstudie aufbruch klimaneutralität. eine gesamtgesellschaftliche aufgabe. abschlussbericht, 2021. URL `https://www.dena.de/infocenter/dena-leitstudie-aufbruch-klimaneutralitaet-1/`.

Tobias Junne, Niklas Wulff, Christian Breyer, and Tobias Naegler. Critical materials in global low-carbon energy scenarios: The case for neodymium, dysprosium, lithium, and cobalt. *Energy*, 211:118532, 2020. ISSN 03605442. doi: 10.1016/j.energy.2020.118532.

KBA. Bestand nach umwelt-merkmalen: Bestand an personenkraftwagen in den jahren 2015 bis 2024 nach ausgewählten kraftstoffarten, 2024. URL `https://www.kba.de/DE/Statistik/Fahrzeuge/Bestand/Umwelt/2024/2024_b_umwelt_zeitreihen.html?nn=3525028&fromStatistic=3525028&yearFilter=2024&fromStatistic=3525028&yearFilter=2024`.

Timo Kern, Patrick Dossow, and Serafin von Roon. Integrating bidirectionally chargeable electric vehicles into the electricity markets. *Energies*, 13(21):5812, 2020. doi: 10.3390/en13215812.

Tim Krause, Udo Mantau, Bernd Mahro, Anja Noke, Felix Richter, Thomas Raussen, Roland Bischof, Thomas Hering, Daniela Thrän, and André Brosowski. Nationales monitoring biogener reststoffe, nebenprodukte und abfälle in deutschland teil 1 : Basisdaten zu biomassepotenzialen, 2020.

C. Krüger, L. Doré, M. Saurat, T. Janßen, A. Nebel, and P. Viebahn. Providing the transport sector in europe with carbon free energy - a model-based analysis under consideration of the mena region. *Frontiers in Energy Research*, in review.

Laura Cozzi, Tim Gould, and Team of WEO at IEA. World energy outlook: 2024, 2024. URL `https://iea.blob.core.windows.net/assets/02b65de2-1939-47ee-8e8a-4f62c38c44b0/WorldEnergyOutlook2024.pdf`.

Alexandra Leipold, Gubaz Aptsiauri, Amir Ayazkhani, Uwe Bauder, Richard-Gregor Becker, Ralf Berghof, Axel Claßen, Alireza Dadashi, Katrin Dahlmann, Niclas Dzikus, Nico Flüthmann, Volker Grewe, Lukas Göhlich, Wolfgang Grimme, Yves Günther, Roman Jaksche, Martin Jung, Franz Knabe, Peter Kutne, Patrick Le Clercq, Holger Pabst, Steffen Poggel, Martin Staggat, Kai Wicke, Florian Wolters, Jan Zanger, and Thomas Zill. Development pathways for aviation up to 2050 – study report, 2021. URL `https://elib.dlr.de/142185/1/DEPA2050_StudyReport.pdf`.

Konstantin Löffler, Thorsten Burandt, Karlo Hainsch, Pao-Yu Oei, Frederik Seehaus, and Felix Wejda. Chances and barriers for germany's low carbon transition - quantifying uncertainties in key influential factors. *Energy*, 239:121901, 2022. ISSN 03605442. doi: 10.1016/j.energy.2021.121901.

C. Lohr, M. Schlemminger, F. Peterssen, A. Bensmann, R. Niepelt, R. Brendel, and R. Hanke-Rauschenbach. Spatial concentration of renewables in energy system optimization models. *Renewable Energy*, 198:144–154, 2022. ISSN 09601481. doi: 10.1016/j.renene.2022.07.144.

Gabriel Lopez, Arman Aghahosseini, Michael Child, Siavash Khalili, Mahdi Fasihi, Dmitrii Bogdanov, and Christian Breyer. Impacts of model structure, framework, and flexibility on perspectives of 100% renewable energy transition decision-making. *Renewable and Sustainable Energy Reviews*, 164:112452, 2022. ISSN 13640321. doi: 10.1016/j.rser.2022.112452.

Diego Luca de Tena and Thomas Pregger. Impact of electric vehicles on a future renewable energy-based power system in europe with a focus on germany. *International Journal of Energy Research*, 42(8):2670–2685, 2018. ISSN 0363907X. doi: 10.1002/er.4056.

G. Luderer, C. Kost, and D. Sörgel. Deutschland auf dem weg zur klimaneutralität 2045 - szenarien und pfade im modellvergleich: Szenarien und pfade im modellvergleich, 2021. URL `https://doi.org/10.48485/pik.2021.006`.

Gunnar Luderer, Silvia Madeddu, Leon Merfort, Falko Ueckerdt, Michaja Pehl, Robert Pietzcker, Marianna Rottoli, Felix Schreyer, Nico Bauer, Lavinia Baumstark, Christoph Bertram, Alois Dirnaichner, Florian Humpenöder, Antoine Levesque, Alexander Popp, Renato Rodrigues, Jessica Strefler, and Elmar Kriegler. Impact of declining renewable energy costs on electrification in low-emission scenarios. *Nature Energy*, 7(1):32–42, 2022. doi: 10.1038/s41560-021-00937-z.

Benjamin Lux, Johanna Gegenheimer, Katja Franke, Frank Sensfuß, and Benjamin Pfluger. Supply curves of electricity-based gaseous fuels in the mena region. *Computers & Industrial Engineering*, 162:107647, 2021. ISSN 03608352. doi: 10.1016/j.cie.2021.107647.

Andrea Mangipinto, Francesco Lombardi, Francesco Davide Sanvito, Matija Pavičević, Sylvain Quoilin, and Emanuela Colombo. Impact of mass-scale deployment

of electric vehicles and benefits of smart charging across all european countries. *Applied Energy*, 312:118676, 2022. ISSN 03062619. doi: 10.1016/j.apenergy.2022.118676.

Alexandra Märtz, Uwe Langenmayr, Sabrina Ried, Katrin Seddig, and Patrick Jochem. Charging behavior of electric vehicles: Temporal clustering based on real-world data. *Energies*, 15(18):6575, 2022. doi: 10.3390/en15186575.

Kathleen Meisel, Matthias Jordan, Martin Dotzauer, Jörg Schröder, Volker Lenz, Karin Naumann, Karl-Friedrich Cyffka, Niels Dögnitz, Harry Schindler, Jaqueline Daniel-Gromke, Gabriel Costa de Paiva, Christopher Schmid, Nora Szarka, Stefan Majer, Franziska Müller-Langer, and Daniela Thrän. Quo vadis, biomass? long–term scenarios of an optimal energetic use of biomass for the german energy transition. *International Journal of Energy Research*, 2024(1), 2024. ISSN 0363907X. doi: 10.1155/2024/6687376.

Andreas Meurer, Patrick Jochem, and Jürgen Kern. Decentralised production of e-fuels for aviation: implications and trade-offs of a targeted small-scale production of sustainable aviation fuel based on fischer–tropsch synthesis. *Sustainable Energy & Fuels*, 8(4):752–765, 2024. doi: 10.1039/D3SE01156A.

Markus Millinger, Philip Tafarte, Matthias Jordan, Alena Hahn, Kathleen Meisel, and Daniela Thrän. Electrofuels from excess renewable electricity at high variable renewable shares: cost, greenhouse gas abatement, carbon use and competition. *Sustainable Energy & Fuels*, 5(3):828–843, 2021. doi: 10.1039/D0SE01067G.

Markus Millinger, Philip Tafarte, Matthias Jordan, Frazer Musonda, Katrina Chan, Kathleen Meisel, and Danial Aliabadi Esmaeili. A model for cost- and greenhouse gas optimal material and energy allocation of biomass and hydrogen. *SoftwareX*, 20:101264, 2022. ISSN 2352-7110. doi: 10.1016/j.softx.2022.101264.

Atom Mirakyan and Roland de Guio. Modelling and uncertainties in integrated energy planning. *Renewable and Sustainable Energy Reviews*, 46:62–69, 2015. ISSN 13640321. doi: 10.1016/j.rser.2015.02.028.

Peter Mock. *Entwicklung eines Szenariomodells zur Simulation der zukünftigen Marktanteile und CO2-Emissionen von Kraftfahrzeugen (VECTOR21).* Dissertation, University Stuttgart, Stuttgart, 2010.

Stefano Moret, Víctor Codina Gironès, Michel Bierlaire, and François Maréchal. Characterization of input uncertainties in strategic energy planning models. *Applied Energy*, 202:597–617, 2017. ISSN 03062619. doi: 10.1016/j.apenergy.2017.05.106.

M. Granger Morgan and David W. Keith. Improving the way we think about projecting future energy use and emissions of carbon dioxide. *Climatic Change*, 90 (3):189–215, 2008. ISSN 0165-0009. doi: 10.1007/s10584-008-9458-1.

Gabriel Möring-Martínez, Murat Senzeybek, and Patrick Jochem. Clustering the european union electric vehicle markets: A scenario analysis until 2035. *Transportation Research Part D: Transport and Environment*, 135:104372, 2024. ISSN 13619209. doi: 10.1016/j.trd.2024.104372.

Jarusch Muessel, Oliver Ruhnau, and Reinhard Madlener. Accurate and scalable representation of electric vehicles in energy system models: A virtual storage-based aggregation approach. *iScience*, 26(10):107816, 2023. doi: 10.1016/j.isci.2023.107816.

Lukas Nacken, Friedrich Krebs, Timo Fischer, and Clemens Hoffmann. Integrated renewable energy systems for germany: A model-based exploration of the decision space. In *16th International Conference, 18-20 September 2019, Ljubljana, Slovenia*. EEM, 2019. doi: 10.1109/EEM45825.2019. URL `https://ieeexplore.ieee.org/servlet/opac?punumber=8907675`.

L. Nesselhauf, C. Fischer, S. Müller, P. Godron, F. Huneke, M. Koch, N. Wauer, U. Weiß, J. Metz, P. Münnich, A. Brizay, C. Chemnitz, W. Klümper, C.-F. Elmer, M. Vieweg, J. Wietschel, E. Althoff, H. Dambeck, A. Kemmler, P. Kularni, S. Kreidelmeyer, S. Lengning, M. Lohmann, S. Lübbers, F. Muralter, A. Piégsa, N. Thamling, M. P. Vu, A. Wünsch, M. Wünsch, I. Ziegenhagen, W. K. Görz, K. Kreye, K. Hennenberg, P. Kasten, M. Scheffler, D. Seibert, K. Wiegmann, G. Holtz, S. Samadi, Y. Kloo, S. Bilici, Saurat M., A. Tönjes, C. Schneider, and S. Lechtenböhmer. Klimaneutrales deutschland: Von der zielsetzung zur umsetzung, 2024. URL `https://www.agora-energiewende.de/publikationen/klimaneutrales-deutschland-studie`.

Fabian Neumann and Tom Brown. Broad ranges of investment configurations for renewable power systems, robust to cost uncertainty and near-optimality. *iScience*, 26(5):106702, 2023. doi: 10.1016/j.isci.2023.106702.

Claudia Nobis and Tobias Kuhnimhof. Mobilität in deutschland mid: Ergebnisbericht, 2019. URL `https://www.mobilitaet-in-deutschland.de/archive/pdf/MiD2017_Ergebnisbericht.pdf`.

Claudia Nobis, Tobias Kuhnimhof, Robert Follmer, and Marcus Bäumer. Mobilität in deutschland - zeitreihenbericht 2002 - 2008 - 2017, 2019. URL `https://www.mobilitaet-in-deutschland.de/archive/pdf/MiD2017_Zeitreihenbericht_2002_2008_2017.pdf`.

Adrian Odenweller, Falko Ueckerdt, Gregory F. Nemet, Miha Jensterle, and Gunnar Luderer. Probabilistic feasibility space of scaling up green hydrogen supply. *Nature Energy*, 7(9):854–865, 2022. ISSN 2058-7546. doi: 10.1038/s41560-022-01097-4.

Giacomo Pareschi, Lukas Küng, Gil Georges, and Konstantinos Boulouchos. Are travel surveys a good basis for ev models? validation of simulated charging profiles against empirical data. *Applied Energy*, 275:115318, 2020. ISSN 03062619. doi: 10.1016/j.apenergy.2020.115318.

Martin Pehnt, Hinrich Helms, Udo Lambrecht, David Dallinger, Martin Wietschel, Heidi Heinrichs, Robert Kohrs, Jochen Link, Stefan Trommer, Thomas Pollok, and Petra Behrens. Elektroautos in einer von erneuerbaren energien geprägten energiewirtschaft. *Zeitschrift für Energiewirtschaft*, 35(3):221–234, 2011. ISSN 0343-5377. doi: 10.1007/s12398-011-0056-y.

Maximilian Pfennig, Diana Böttger, Benedikt Häckner, David Geiger, Christoph Zink, André Bisevic, and Lukas Jansen. Global GIS-based potential analysis and cost assessment of Power-to-X fuels in 2050. *Applied Energy*, 347:121289, 2023. doi: 10.1016/j.apenergy.2023.121289.

Stefan Pfenninger. Dealing with multiple decades of hourly wind and pv time series in energy models: A comparison of methods to reduce time resolution and the planning implications of inter-annual variability. *Applied Energy*, 197:1–13, 2017. ISSN 03062619. doi: 10.1016/j.apenergy.2017.03.051.

Stefan Pfenninger, Lion Hirth, Ingmar Schlecht, Eva Schmid, Frauke Wiese, Tom Brown, Chris Davis, Matthew Gidden, Heidi Heinrichs, Clara Heuberger, Simon Hilpert, Uwe Krien, Carsten Matke, Arjuna Nebel, Robbie Morrison, Berit Müller, Guido Pleßmann, Matthias Reeg, Jörn C. Richstein, Abhishek Shivakumar, Iain Staffell, Tim Tröndle, and Clemens Wingenbach. Opening the black box of energy modelling: Strategies and lessons learned. *Energy Strategy Reviews*, 19:63–71, 2018. ISSN 2211467X. doi: 10.1016/j.esr.2017.12.002.

Siobhan Powell, Gustavo Vianna Cezar, Elpiniki Apostolaki-Iosifidou, and Ram Rajagopal. Large-scale scenarios of electric vehicle charging with a data-driven model of control. *Energy*, 248:123592, 2022. ISSN 03605442. doi: 10.1016/j.energy.2022.123592.

Marco Pruckner and David Eckhoff. Shared autonomous electric vehicles and the power grid: Applications and research challenges. *2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, pages 1151–1155, 2020. doi: 10.1109/ISGT-Europe47291.2020.9248844.

PtX Lab Lausitz. Synthetic fuels from germany: currently 19 power-to-liquid plants in planning and operation, 2023. URL `https://ptxlablausitz.de/en/news/synthetische-kraftstoffe-aus-deutschland-derzeit-19-power-to-liquid-anlagen-in-planung-und-betrieb/`.

Katja Purr, Jens Günther, Harry Lehmann, and Philipp Nuss. Wege in eine ressourcenschonende treibhausgasneutralität: Rescue studie, 2019. URL `https://www.umweltbundesamt.de/sites/default/files/medien/1410/publikationen/rescue_studie_cc_36-2019_wege_in_eine_ressourcenschonende_treibhausgasneutralitaet_auflage2_juni-2021.pdf`.

Judith Puttkammer and Harald Grethe. The public debate on biofuels in germany: Who drives the discourse? *German Journal of Agricultural Economics*, 64(4), 2015. doi: 10.52825/gjae.v64i4.2001.

Kalai Ramea, David S. Bunch, Christopher Yang, Sonia Yeh, and Joan M. Ogden. Integration of behavioral effects from vehicle choice models into long-term energy systems optimization models. *Energy Economics*, 74:663–676, 2018. ISSN 01409883. doi: 10.1016/j.eneco.2018.06.028.

Babak Ravanbach, Elif Turhan, Niklas Wulff, Stavros Orfanoudakis, Pedro Vergara, Vahid Vahidinasab, Luiz Dias, and Goncalo Mendes. A dynamic prediction tool for vehicle-to-grid operation and planning. In IEEE, editor, *The 22nd IEEE Mediterranean Electrotechnical Conference*, 2024. doi: 10.1109/MELECON53508.2024.

Sabrina Ried, Thomas Dengiz, Sebastian Soldner, and Patrick Jochem. Aggregating load shifting potentials of electric vehicles for energy system models: 16-18 september 2020. In *16th International Conference on the European Energy Market (EEM)*, pages 1–6. IEEE, 2020. doi: 10.1109/EEM49802.2020.9221974. URL `https://ieeexplore.ieee.org/servlet/opac?punumber=8907675`.

S. Risch, R. Maier, J. Du, N. Pflugradt, P. Stenzel, L. Kotzur, and Detlef Stolten. Potentials of renewable energy sources in germany and the influence of land use datasets. *Energies*, 15(15):5536, 2022. doi: 10.3390/en15155536.

RLI. Simulation of electric vehicle charging demand (simbev), 2024. URL `https://github.com/rl-institut/simbev?tab=readme-ov-file`.

Martin Robinius, Alexander Otto, Konstantinos Syranidis, David S. Ryberg, Philipp Heuser, Lara Welder, Thomas Grube, Peter Markewitz, Vanessa Tietze, and Detlef Stolten. Linking the power and transport sectors—part 2: Modelling a sector coupling scenario for germany. *Energies*, 10(7):957, 2017. doi: 10.3390/en10070957.

Renato Rodrigues, Robert Pietzcker, Panagiotis Fragkos, James Price, Will McDowall, Pelopidas Siskos, Theofano Fotiou, Gunnar Luderer, and Pantelis Capros. Narrative-driven alternative roads to achieve mid-century co2 net neutrality in europe. *Energy*, 239:121908, 2022. ISSN 03605442. doi: 10.1016/j.energy.2021.121908.

Oliver Ruhnau, Sergej Bannik, Sydney Otten, Aaron Praktiknjo, and Martin Robinius. Direct or indirect electrification? a review of heat generation and road transport decarbonisation scenarios for germany 2050. *Energy*, 166:989–999, 2019. ISSN 03605442. doi: 10.1016/j.energy.2018.10.114.

Philipp Runge, Christian Sölch, Jakob Albert, Peter Wasserscheid, Gregor Zöttl, and Veronika Grimm. Economic comparison of electric fuels for heavy duty mobility produced at excellent global sites - a 2035 scenario. *Applied Energy*, 347:121379, 2023. doi: 10.1016/j.apenergy.2023.121379.

Johannes Schäuble, Thomas Kaschub, Axel Ensslen, Patrick Jochem, and Wolf Fichtner. Generating electric vehicle load profiles from empirical data of three ev

fleets in southwest germany. *Journal of Cleaner Production*, 150:253–266, 2017. ISSN 09596526. doi: 10.1016/j.jclepro.2017.02.150.

Yvonne Scholz. *Renewable energy based electricity supply at low costs: Development of the REMix model and application for Europe*. Dissertation, University Stuttgart, 2012. URL `https://elib.uni-stuttgart.de/bitstream/11682/2032/1/thesis_ysdruck.pdf`.

Bruno U. Schyska, Alexander Kies, Markus Schlott, Lueder von Bremen, and Wided Medjroubi. The sensitivity of power system expansion models. *Joule*, 5(10):2606–2624, 2021. ISSN 25424351. doi: 10.1016/j.joule.2021.07.017.

F. Sensfuß, C. Maurer, Krail, M., Speht, D., T. Gnann, M. Wietschel, P. Mellwig, and J. Müller-Kirchenbauer. Langfristszenarien für die transformation des energiesystems in deutschland: Treibhausgasneutrale hauptszenarien - modul verkehr, 2022a. URL `https://www.langfristszenarien.de/enertile-explorer-wAssets/docs/LFS3_Langbericht_Verkehr_final.pdf`.

F. Sensfuß, C. Maurer, Krail, M., Speht, D., T. Gnann, M. Wietschel, P. Mellwig, and J. Müller-Kirchenbauer. Long-term scenarios 3. scientific analyses on the decarbonization of germany. tn scenarios on behalf of the german federal ministry for economic affairs and climate action, 2022b. URL `https://langfristszenarien.de/enertile-explorer-de/`.

Leo Strobel, Jonas Schlund, and Marco Pruckner. Joint analysis of regional and national power system impacts of electric vehicles—a case study for germany on the county level in 2030. *Applied Energy*, 315:118945, 2022. ISSN 03062619. doi: 10.1016/j.apenergy.2022.118945.

M. Taljegard, L. Göransson, M. Odenberger, and F. Johnsson. Impacts of electric vehicles on the electricity generation portfolio – a scandinavian-german case study. *Applied Energy*, 2019(235), 2019a. ISSN 03062619. doi: 10.1016/j.apenergy.2018.10.133.

M. Taljegard, V. Walter, L. Göransson, M. Odenberger, and F. Johnsson. Electric vehicles as flexibility management strategy for the electricity system—a comparison between different regions of europe. *Energies*, (12):2597, 2019b. doi: 10.3390/en12132597.

Connor Thelen, Hannah Nolte, Markus Kaiser, Patrick Jürgens, Paul Müller, Charlotte Senkpiel, and Christoph Kost. Wege zu einem klimaneutralen energiesystem. bundesländer im transformationsprozess, 2024. URL `https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/ISE_WegeKlimaneutralEnergiesystem_final.pdf`.

Stefan Trommer, Julia Jarass, and Viktoriya Kolarova. Early adopters of electric vehicles in germany unveiled. *World Electric Vehicle Journal*, 7(4):722–732, 2015. doi: 10.3390/wevj7040722.

Tim Tröndle, Johan Lilliestam, Stefano Marelli, and Stefan Pfenninger. Trade-offs between geographic scale, cost, and infrastructure requirements for fully renewable electricity in europe. *Joule*, 4(9):1929–1948, 2020. ISSN 25424351. doi: 10.1016/j.joule.2020.07.018.

UBA. Detaillierte treibhausgas-emissionsbilanz 2022: Emissionen sanken um 40 prozent gegenüber 1990 – eu-klimaschutzvorgaben werden eingehalten: Erste offizielle emissionsdaten für das jahr 2023 gemäß klimaschutzgesetz folgen mitte märz 2024, 2024. URL `https://www.umweltbundesamt.de/presse/pressemitteilungen/detaillierte-treibhausgas-emissionsbilanz-2022`.

Philip Ulrich, Tobias Naegler, Lisa Becker, Ulrike Lehr, Sonja Simon, Claudia Sutardhio, and Anke Weidlich. Comparison of macroeconomic developments in ten scenarios of energy system transformation in germany: National and regional results. *Energy, Sustainability and Society*, 12(1), 2022. doi: 10.1186/s13705-022-00361-5.

UNFCCC. Adoption of the paris agreement, 2015. URL `https://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf`.

Nicole J. van den Berg, Heleen L. van Soest, Andries F. Hof, Michel G. J. den Elzen, Detlef P. van Vuuren, Wenying Chen, Laurent Drouet, Johannes Emmerling, Shinichiro Fujimori, Niklas Höhne, Alexandre C. Kõberle, David McCollum, Roberto Schaeffer, Swapnil Shekhar, Saritha Sudharmma Vishwanathan, Zoi Vrontisi, and Kornelis Blok. Implications of various effort-sharing approaches for national carbon budgets and emission pathways. *Climatic Change*, 162(4):1805–1822, 2020. ISSN 0165-0009. doi: 10.1007/s10584-019-02368-y.

Jonas van Ouwerkerk, Karlo Hainsch, Soner Candas, Christoph Muschner, Stefanie Buchholz, Stephan Günther, Hendrik Huyskens, Sarah Berendes, Konstantin Löffler, Christian Bußar, Fateme Tardasti, Luja von Köckritz, and Rasmus Bramstoft. Comparing open source power system models - a case study focusing on fundamental modeling parameters for the german energy transition. *Renewable and Sustainable Energy Reviews*, 161:112331, 2022. ISSN 13640321. doi: 10.1016/j.rser.2022.112331.

Marta Victoria, Kun Zhu, Tom Brown, Gorm B. Andresen, and Martin Greiner. Early decarbonisation of the european energy system pays off. *Nature communications*, 11(1):6223, 2020. doi: 10.1038/s41467-020-20015-4.

P. Viebahn, J. Kern, J. Horst, A. Rosenstiel, J. Terrapon-Pfaff, L. Dore, C. Krüger, O. Zelt, T. Pregger, J. Braun, and U. Klann. Synthese und handlungsoptionen – ergebnisbericht des projekts mena-fuels. teilbericht 14 des wuppertal instituts, des deutschen zentrums für luft- und raumfahrt (dlr) und des instituts für zukunftsenergie- und stoffstromsysteme (izes) an das bundesministerium für wirtschaft und klimaschutz (bmwk)., 2022. URL `https://wupperinst.org/fileadmin/redaktion/downloads/projects/MENA-Fuels_Teilbericht_14_Synthesebericht_de_v3.pdf`.

Zongfei Wang, Patrick Jochem, Hasan Ümitcan Yilmaz, and Lei Xu. Integrating vehicle–to–grid technology into energy system models: Novel methods and their impact on greenhouse gas emissions. *Journal of Industrial Ecology*, 26(2):392–405, 2022. ISSN 1088-1980. doi: 10.1111/jiec.13200.

Andreas Weiß, Florian Biedenbach, and Mathias Müller. Probabilistic load profile model for public charging infrastructure to evaluate the grid load. *Energies*, 15 (13):4748, 2022. doi: 10.3390/en15134748.

Manuel Wetzel, Hans Christian Gils, and Valentin Bertsch. Green energy carriers and energy sovereignty in a climate neutral european energy system. *Renewable Energy*, 210:591–603, 2023. ISSN 09601481. doi: 10.1016/j.renene.2023.04.015.

Manuel Wetzel, Eugenio Salvador Arellano Ruiz, Francesco Witte, Jens Schmugge, Shima Sasanpour, Madhura Yeligeti, Fabia Miorelli, Jan Buschmann, Karl-Kiên Cao, Niklas Wulff, Hedda Gardian, Alexander Rubbert, Benjamin Fuchs, Yvonne Scholz, and Hans Christian Gils. Remix: A gams-based framework for optimizing energy system models. *Journal of Open Source Software*, 9(99):6330, 2024. doi: 10.21105/joss.06330.

Frauke Wiese, Johannes Thema, and Luisa Cordroch. Strategies for climate neutrality. lessons from a meta-analysis of german energy scenarios. *Renewable and Sustainable Energy Transition*, 2:100015, 2022. ISSN 2667-095X. doi: 10.1016/j.rset.2021.100015.

Keith Williges, Lukas H. Meyer, Karl W. Steininger, and Gottfried Kirchengast. Fairness critically conditions the carbon budget allocation across countries. *Global Environmental Change*, 74:102481, 2022. ISSN 09593780. doi: 10.1016/j.gloenvcha.2022.102481.

Niklas Wulff. Behaviour-driven electric vehicle charging decisions and its implications on demand response flexibility for the integration of renewable energies in germany, 2019. URL `https://elib.dlr.de/129228/1/Wulff_Behaviour-driven%20charging%20decisions_elib.pdf`.

Niklas Wulff, Felix Steck, Bent van den Adel, Carsten Hoyer-Klick, Hans Christian Gils, and John Anderson. Behaviour-driven electric vehicle charging decisions and its implications on demand response flexibility for the integration of renewable energies in germany, 2019. URL `https://elib.dlr.de/129229/`.

Niklas Wulff, Felix Steck, Hans Christian Gils, Carsten Hoyer-Klick, Bent van den Adel, and John E. Anderson. Comparing power-system and user-oriented battery electric vehicle charging representation and its implications on energy system modeling. *Energies*, 13(5):1093, 2020. doi: 10.3390/en13051093.

Niklas Wulff, Fabia Miorelli, Hans Christian Gils, and Patrick Jochem. Vehicle energy consumption in python (vencopy): Presenting and demonstrating an open-source tool to calculate electric vehicle charging flexibility. *Energies*, 14(14):4349, 2021. doi: 10.3390/en14144349.

Niklas Wulff, Andreas Meurer, Hans Christian Gils, and Patrick Jochem. Carbon dioxide emissions of transport sector transformation pathways considering co2 emission budget allocation approaches. In *International Conference on the European Energy Market, 10-12 June 2024, Istanbul, Türkiye*, pages 1–7, Piscataway, NJ, 2024. IEEE. ISBN 979-8-3503-8174-0. doi: 10.1109/EEM60825.2024.10608929.

Niklas Wulff, Danial Esmaeili Aliabadi, Samuel Hasselwander, Thomas Pregger, Hans Christian Gils, Stefan Kronshage, Wolfgang Grimme, Juri Horst, Carsten Hoyer-Klick, and Patrick Jochem. Energy system implications of demand scenarios and supply strategies for renewable transportation fuels. *Energy Strategy Reviews*, 58:101606, 2025. ISSN 2211467X. doi: 10.1016/j.esr.2024.101606.

Lei Xu, Hasan Ümitcan Yilmaz, Zongfei Wang, Witold-Roger Poganietz, and Patrick Jochem. Greenhouse gas emissions of electric vehicles in europe considering different charging strategies. *Transportation Research Part D: Transport and Environment*, 87:102534, 2020. ISSN 13619209. doi: 10.1016/j.trd.2020.102534.

Sonia Yeh, Gouri Shankar Mishra, Lew Fulton, Page Kyle, David L. McCollum, Joshua Miller, Pierpaolo Cazzola, and Jacob Teter. Detailed assessment of global transport-energy models' structures and projections. *Transportation Research Part D: Transport and Environment*, 55:294–309, 2017. ISSN 13619209. doi: 10.1016/j.trd.2016.11.001.

A. List of author's publications

A.1. Peer-reviewed journal articles

- **Wulff, N.**, Steck, F. and Gils, H.C., Hoyer-Klick, C., van den Adel, B. and Anderson, J.E. (2020). Comparing Power-System and User-Oriented Battery Electric Vehicle Charging Representation and Its Implications on Energy System Modeling. In: Energies. 13(5), pp.1093ff. DOI: 10.3390/en13051093 (Wulff et al., 2020).

- Junne, T., **Wulff, N.**, Breyer, C. and Naegler, T. (2020). Critical materials in global low-carbon energy scenarios: The case for neodymium, dysprosium, lithium, and cobalt. In: Energy. DOI: 10.1016/j.energy.2020.118532 (Junne et al., 2020).

- Cristobal, J., Jubayed, M., **Wulff, N.** and Schebek, L. (2020). Life cycle losses of critical raw materials from solar and wind energy technologies and their role in the future material availability. In: Resources, Conservation and Recycling. DOI: 10.1016/j.resconrec.2020.104916 (Cristóbal et al., 2020).

- **Wulff, N.**, Miorelli, F., Gils, H.C., Jochem, P. (2021). Vehicle Energy Consumption in Python (VencoPy): Presenting and Demonstrating an Open-Source Tool to Calculate Electric Vehicle Charging Flexibility. In: Energies. 14(14), pp. 4349ff. DOI: 10.3390/en14144349 (Wulff et al., 2021).

- Arellano, E., **Wulff, N.**, Fuchs, B. and Hu, W. (2021). autumn: A Python library for dynamic modelling of captured CO_2 cost potential curves. In: Journal of Open Source Software. DOI:10.21105/joss.03203 (Arellano Ruiz et al., 2021).

- Esmaeili Aliabadi, D., Chan, K., **Wulff, N.**, Meisel, K., Jordan, M., Österle, I., Pregger, T. and Thrän, D. (2023). Future renewable energy targets in the EU: Impacts on the German transport. In: Transportation Research Part D. DOI: 10.1016/j.trd.2023.103963 (Esmaeili Aliabadi et al., 2023).

- Arnz, M., Göke, L., Thema, J., Wiese, F., **Wulff, N.**, Kendziorski, M., Hainsch, K., Blechinger, P. and von Hirschhausen, C. (2024). Avoid, Shift or Improve passenger transport? Impacts on the energy system. In: Energy Strategy Reviews. DOI: 10.1016/j.esr.2024.101302 (Arnz et al., 2024).

- Wetzel, M., Arellano Ruiz, E.S., Witte, F., Schmugge, J., Sasanpour, S., Yeligeti, M., Miorelli, F., Buschmann, J., Cao, K.-K., **Wulff, N.**, Gardian, H., Rubbert, A., Fuchs, B., Scholz, Y. and Gils, H.C. (2024). REMix: A

GAMS-based framework for optimizing energy system models. In: Journal of Open Source Software. DOI: 10.21105/joss.06330 (Wetzel et al., 2024).

- **Wulff, N.**, Esmaeili Aliabadi, D., Hasselwander, S., Pregger, T., Gils, H.C., Kronshage, S., Grimme, W., Horst, J., Hoyer-Klick, C. and Jochem, P. (2025). Energy system implications of demand scenarios and supply strategies for renewable transportation fuels. In: Energy Strategy Reviews. DOI: 10.1016/j.esr.2024.101606 (Wulff et al., 2025).

A.2. Conference Papers and technical articles

- **Wulff, N.**, Meurer, A., Gils, H.C. and Jochem, P. (2024). Carbon dioxide emissions of transport sector transformation pathways considering CO2 emission budget allocation approaches. International Conference on the European Energy Market, 10-12 June 2024, Istanbul, Türkiye. DOI: 10.1109/EEM60825.2024.10608929 (Wulff et al., 2024)

- Esmaeili Aliabadi, D., **Wulff, N.**, Jordan, M., Cyffka, K.-F. and Millinger, M. (2022). Soft-coupling energy and power system models to analyze pathways toward a de-fossilized German transport sector. In Operations Research Proceedings 2022. Springer, 2022. DOI: 10.1007/978-3-031-24907-5 _38 (Esmaeili Aliabadi et al., 2022).

- Heimann, N., Raab, M., Dietrich, R.-U., Haas, S., Pichlmaier, S. and **Wulff, N.** (under review). Beitrag zur einheitlichen ökonomischen und ökologischen Analyse von strombasierten Prozessen zur Kraftstoffherstellung in Deutschland. Submitted to Wiley-VCH. Chemie-Ingenieur-Technik. (Heimann et al., submitted)

- Ravanbach, B., Turhan, E., **Wulff, N.**, Orfanoudakis, S., Vergara, P., Vahidinasab, V., Dias, L. and Mendes, G. (2024). A Dynamic Prediction Tool for Vehicle-to-Grid Operation and Planning. IEEE Mediterranean Electrotechnical Conference. DOI: 10.1109/MELECON53508.2024 (Ravanbach et al., 2024).

A.3. Book chapters

- Esmaeili Aliabadi, D., Jordan, M., Meurer, A. and **Wulff, N.** (forthcoming). Defossilization Dynamics: Exploring the Interplay of Power-to-X and Bioenergy. In: Anvari-Moghaddam, A., Ghaemi, S., You, S. and Blaabjerg, F. (eds.). Power-to-X in Regional Energy Systems Planning, Operation, Control, and Market Perspectives. Submitted to Routledge. ISBN: 9781032719412 (Esmaeili Aliabadi et al., 2025).

B. Papers of the thesis

In the following, the Papers of the thesis are given in the respective publishers' versions. All Papers are published under an Open Access license. Supplementary material and data appendix to Paper III can be accessed via the publisher.

B.1. Paper I - Vehicle Energy Consumption in Python (VencoPy): Presenting and Demonstrating an Open-Source Tool to Calculate Electric Vehicle Charging Flexibility

energies

MDPI

Article

Vehicle Energy Consumption in Python (VencoPy): Presenting and Demonstrating an Open-Source Tool to Calculate Electric Vehicle Charging Flexibility †

Niklas Wulff [1,*], Fabia Miorelli [1], Hans Christian Gils [1] and Patrick Jochem [1,2]

[1] Department of Energy Systems Analysis, Institute of Networked Energy Systems, German Aerospace Center (DLR), Curiestr. 4, 70563 Stuttgart, Germany; fabia.miorelli@dlr.de (F.M.); hans.gils@dlr.de (H.C.G.); patrick.jochem@dlr.de (P.J.)

[2] Institute for Industrial Production, Karlsruhe Institute of Technology, Hertzstr. 16, 76187 Karlsruhe, Germany

* Correspondence: niklas.wulff@dlr.de

† This paper is an extended version of our paper published in 6th International Conference on Smart Energy Systems 2020, Aalborg, Denmark, 6–7 October 2020.

Abstract: As electric vehicle fleets grow, rising electric loads necessitate energy systems models to incorporate their respective demand and potential flexibility. Recently, a small number of tools for electric vehicle demand and flexibility modeling have been released under open source licenses. These usually sample discrete trips based on aggregate mobility statistics. However, the full range of variables of travel surveys cannot be accessed in this way and sub-national mobility patterns cannot be modeled. Therefore, a tool is proposed to estimate future electric vehicle fleet charging flexibility while being able to directly access detailed survey results. The framework is applied in a case study involving two recent German national travel surveys (from the years 2008 and 2017) to exemplify the implications of different mobility patterns of motorized individual vehicles on load shifting potential of electric vehicle fleets. The results show that different mobility patterns, have a significant impact on the resulting load flexibilites. Most obviously, an increased daily mileage results in higher electricty demand. A reduced number of trips per day, on the other hand, leads to correspondingly higher grid connectivity of the vehicle fleet. VencoPy is an open source, well-documented and maintained tool, capable of assessing electric vehicle fleet scenarios based on national travel surveys. To scrutinize the tool, a validation of the simulated charging by empirically observed electric vehicle fleet charging is advised.

Keywords: electric vehicles; load shifting potential; demand side management; load flexibility; open source; sector coupling

check for updates

Citation: Wulff, N.; Miorelli, F.; Gils, H.-C.; Jochem, P. Vehicle Energy Consumption in Python (VencoPy): Presenting and Demonstrating an Open-Source Tool to Calculate Electric Vehicle Charging Flexibility. *Energies* **2021**, *14*, 4349. https://doi.org/10.3390/en14144349

Academic Editor: Iva Ridjan Skov

Received: 14 June 2021
Accepted: 7 July 2021
Published: 19 July 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Electric vehicles (EVs) have a widely accepted, published and well-understood technical potential of shifting their respective electric load for battery charging [1]. In energy systems analysis, different methods to estimate this potential have existed for many years [2].

As energy systems analysis models are oriented based on broader geographical and temporal scopes, they usually do not explicitly describe individual vehicles, power lines or transformers but focus on the integrative quality of EV fleets for photovoltaic and wind power feed-in in the context of long-term energy scenarios [3]. In such analyses, the focus is mainly on the power system impact of EVs, especially regarding peak loads and charging flexibility [4]. While open source tools to simulate EV charging have already been published, they mostly rely exclusively on sampling trips from mobility statistics.

1.1. State of Research

Transport and energy systems analysis approaches have been combined and compared in [5] to analyze the effects of different model details and the respective implications on energy systems optimization model results.

Although extensive research has been carried out on the effect of EVs for renewable energy (RE) integration, only a few tools have been publicly released that provide the flexibility needed to serve as data input generators for macro-scale energy systems modeling. However, in the last few years two tools have been released, which are briefly described in the following, as well as tools that are described below but are not available to reproduce scientific results.

RAMP-mobility is a stochastic generator for electric loads of single EVs [6]. Building on the broader RAMP-framework for stochastic multi-energy load profiles, it incorporates national specifics such as EV user types (students, workers or retired people), differences between vehicle sizes, and thus battery sizes, and specific consumption as well as stochastic effects of non-deterministic mobility behavior. RAMP-mobility calculates annual profiles in a minute-resolution taking also into account seasonal effects such as holiday travel and temperature-dependency of EV consumption. Three charging strategies can be simulated: uncontrolled charging, nighttime charging and RE sources integration charging. The tool has been validated against data gathered from ElaadNL with a resulting root mean square error of around 15% [7].

Emobpy is also a stochastic EV load generator taking into account user-specific probabilities of undertaking trips for shopping, work or other purposes, as well as location-specific probabilities for the charging infrastructure availability [8]. It follows a similar pattern, consisting of sampling trips throughout the time horizon to specific times of the day and incorporating consistency checks to ensure the vehicles can reach the household within the trip while being able to drive the specified daily trips with the available battery capacity. It has been applied in conjunction with the Dispatch and Investment Evaluation Tool with Endogenous Renewables (DIETER) specifying around 200 profiles, which serve as representative data basis for energy systems modeling [9].

Other methods have been described in the literature but are so far not available to researchers in open source licensed repositories and can thus neither be scrutinized by other researchers nor can their respective results be reproduced. The commercial tool synPro developed by the Fraunhofer Institute for Solar Energy Systems (ISE) and commercially applied by elink solutions focuses specifically on household electricity, heat and mobility demand [10]. The load flexibility tool eLoad of the Fraunhofer Institute for Systems and Innovation Research (ISI) has been formally well described [11]. It explicitly models arrivals and departures of vehicles of the grid-connected EV fleet increasing and decreasing the aggregate fleet battery and charging capacity. MobiFlex, the Matlab-based tool by KIT builds on the mobility patterns of the German mobility panel survey and has been demonstrated in the assessment of the RE curtailment reduction potential of electric fleets in the German federal state of Schleswig–Holstein [12].

The tool by the Fraunhofer Institute for Energy Economics and Energy System Technology (IEE) takes a decisive role in the range of EV fleet flexibility tools. Mobility groups form the core categories of the tool are modelled, being defined by population density categories, household size and household income. It differs from the above-mentioned tools in that it provides results for two analytical levels of abstraction [13]. On the one hand, it provides high-level EV fleet flexibility, on the other hand, characteristic user group-specific mobility patterns can be mapped to real-world household characteristic distributions in the context of distribution grid planning.

Energy systems analysis studies have been using national travel surveys for quite some time. Babrowski et al. analyze different EV load shifting scenarios based on national travel surveys of Denmark, Germany, Finland, The Netherlands, Switzerland and the United Kingdom [1]. For Germany, this method is applied in grid analysis in [14].

The predecessor of the tool described here, the tool VENCO (Vehicle Energy Consumption) was originally developed and applied in [3]. De Tena and Pregger use VENCO to derive consumption patterns for battery EVs, hybrid EVs and fuel cell EVs in a European scenario study [15].

As already mentioned, methods simulating EV charging flexibility have been developed, formally described and in some cases made available under an Open Source license. However, most tools go unnoticed and the ones that are formally described are mostly undisclosed while the two rare cases of published code repositories follow sampling approaches from national travel surveys rather than discrete trip diary compositions. The last point is specifically important to researchers who are interested in only a subset of survey respondents e.g., a specific federal state, socioeconomic status or vehicle size.

1.2. Contribution

A tool including interfaces, filtering and cleaning routines of national travel surveys together with methods for simulating EV load shifting potential is developed. The tool Vehicle Energy Consumption in Python (VencoPy) aims at filling a gap for researchers that have access to national travel survey data, potentially in high geographical and temporal resolution. In the following chapters, both a formal description of all algorithms of the tool as well as a reference to the codebase on gitlab [16] are provided. To demonstrate the capabilities of the tool, a case study is presented, which analyzes two German national travel survey data sets: The Mobility in Germany 2008 (in German: Mobilität in Deutschland, MiD08) and its recent update from 2017, the MiD 2017 (MiD17). The case study shows how differences in mobility patterns transfer to differences in EV charging, connection and consumption patterns in a scenario setup with vehicle battery sizes assumed to be 50 kWh and an average electric consumption of 20 kWh/100 km. Effects of differences in travel behavior on EV charging patterns have been assessed before between different European countries [1], but no analyses have presented changes within a country between different years yet.

VencoPy is compared to the body of existing literature in the field by comparing its simulation results to previously documented values for EV fleet power, respective patterns and charged energy.

The insights provided by VencoPy are valuable mainly to energy systems analysts in need of EV data adjusted to model-specific scopes as well as transport researchers interested in the effects of mobility patterns on potential charging flexibility of EV fleets. Additionally, the term EV in this context only refers to individual battery EVs.

The paper is structured as follows. Section 2 introduces the proposed and published fleet estimation calculations. Section 3 compares the main mobility patterns of the two analysed samples—MiD08 and MiD17. Most of the findings until this section reproduce or further detail findings already described in [17,18]. Subsequently, the results of an electric fleet what-if-analysis based on 2008 and 2017 data sets are presented to demonstrate VencoPy's simulation capabilities. Finally, conclusion and critical reflections on the used approach are drawn in Section 4.

2. Materials and Methods

Since VencoPy's predecessor VENCO applied in [3] and in [15] as early as 2010 has neither been formally described nor published, a comprehensive formal representation of the EV fleet charging flexibility estimation procedure is presented here.

2.1. VencoPy Structure

Figure 1 shows the detailed VencoPy components in a developer diagram. The four components—implemented as Python classes—*DataParser*, *TripDiaryBuilder*, *GridModeler* and *FlexEstimator* can be clearly distinguished. A fifth component, *Evaluator*, used to create the plots for this work is not shown in Figure 1 as it is not needed to calculate results from VencoPy.

Following [19], VencoPy is described on four Levels of abstraction:

1. Linguistic description in plain English;
2. An algebraic formulation;
3. The model implementation in code;
4. A model application to a specific context.

Descriptions in this Section follow Levels 1 and 2. The code implementation can be retrieved from the open repository [16]. The application level is finally presented in Section 3. The difference between the first two levels and the third level consists mainly of the human–machine interfaces such as configuration files, technical interfaces between the input formats, internal variable declaration, formatting and translating the algebraic formulations in machine-readable Python statements. For more details, the technically interested reader is referred to the VencoPy documentation pages available via the readme-file of the repository [16].

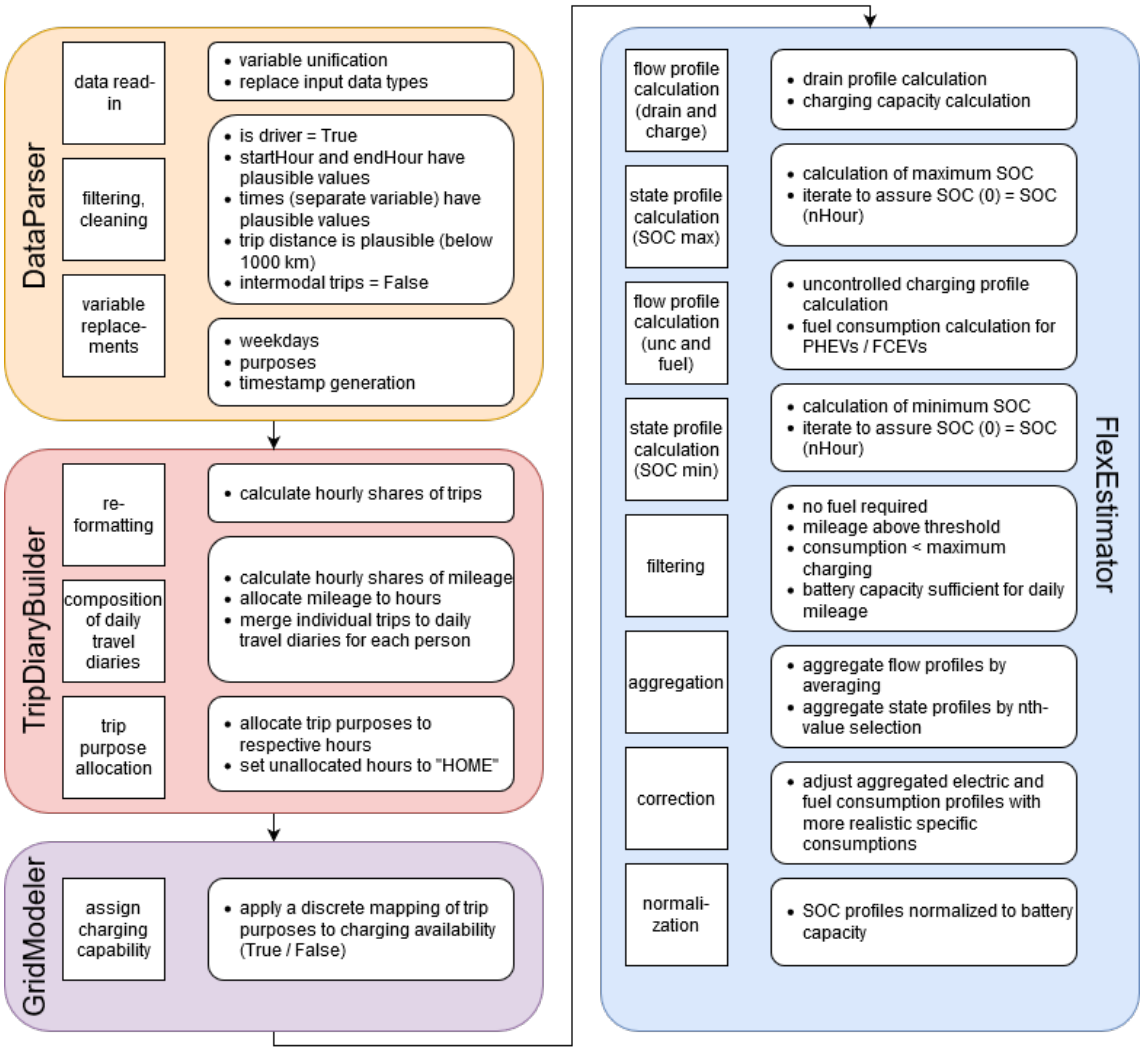


Figure 1. Schematic overview of VencoPy workflow components.

Elements of independent variables for the following derivations are shown in Table 1. In its current version, VencoPy only differentiates the vehicle sizes via the battery and consumption assumptions but not in the mobility patterns. The same is true for propulsion technologies. For the application of VencoPy results in energy systems models, the boundary conditions on the individual profile levels assure that the beginning $t = 0$ and end $t = T$ values match.

Table 1. Independent variables and respective algebraic descriptors.

Name	Element Symbol	Set Symbol	Description
Time	t	T	Time step (t) and temporal scope (T)
Vehicle	v	V	Vehicle identifier (v) and set of all vehicles (V)

2.1.1. Interface to the Dataset: *DataParser* Class

The first step in the VencoPy framework to be able to estimate EV energy consumption implies accessing a travel survey data set, such as the MiD [17]. This is carried out through a parsing interface to the original database. In the parsing interface to the data set, three main operations are carried out: the read-in of the travel survey trip data, stored in .dta or .csv files, filtering and cleaning of the original raw data set and a set of variable replacement operations to allow the composition of travel diaries in a second step.

In order to have consistent entry data for all variables and for different data sets, all database entries are harmonised, which includes generating unified data types and consistent variable naming. The naming convention for the variables and their respective input type can be specified in the VencoPy-config files. A full list of the required variables is provided in Table A1. Of the 22 variables, four variables are used for indexing, 11 variables characterise the trip time within the year, two variables are used for filtering and five variables characterize the trip itself. The representation of time may vary between travel surveys.

Starting from the initial raw trip record base set $\mathbb{D}_{\text{tot}}$, a subset data set $\mathbb{D}_{\text{sel}}$ is created after filtering irrelevant entries or those that lack necessary information.

$$\mathbb{D}_{\text{tot}} = \{1, ..., r\} \subseteq \mathbb{N}; \qquad \mathbb{D}_{\text{sel}} \subseteq \mathbb{D}_{\text{tot}} \tag{1}$$

For every trip data record in $\mathbb{D}_{\text{sel}}$, four filters are applied for cleaning purposes. The first two filters employ inclusion and exclusion conditions for specified discrete variables. Exclusion filters are mainly used to clean out incomplete variable values. For every trip data record, r, in $\mathbb{D}_{\text{sel}}$, the inclusion and exclusion filters can be written as

$$\text{filter}_{1\,(\text{include})} : variableName_{\text{r}} = validRecordValue \subseteq \mathbb{D}_{\text{sel}} \quad \forall r \in \mathbb{D}_{\text{tot}} \tag{2}$$

$$\text{filter}_{2\,(\text{exclude})} : variableName_{\text{r}} = invalidRecordValue \nsubseteq \mathbb{D}_{\text{sel}} \quad \forall r \in \mathbb{D}_{\text{tot}} \tag{3}$$

Additional two filters set upper and lower boundaries for continuous variables, such as mileage, as follows:

$$\text{filter}_{3\,(\text{upper bound})} : variableName_{\text{r}} < upperBoundaryValue \subseteq \mathbb{D}_{\text{sel}} \quad \forall r \in \mathbb{D}_{\text{tot}} \tag{4}$$

$$\text{filter}_{4\,(\text{lower bound})} : variableName_{\text{r}} > lowerBoundaryValue \subseteq \mathbb{D}_{\text{sel}} \quad \forall r \in \mathbb{D}_{\text{tot}} \tag{5}$$

Most travel surveys include motorized, non motorized as well as multi-modal trips. For the scope of VencoPy, only trips that were carried out with a motorized individual vehicle are selected. To exemplify the application of the filters described above, this implies that Equation (2) for the variable named 'driver' equals 1 ($driver_{\text{r}} = 1 \quad \forall r \in \mathbb{D}_{\text{sel}}$), which means that the person who carried out the r-th trip was the driver of the vehicle, i.e., it is a motorized trip. Similarly, trips with missing (e.g., missing tripID, missing start or end time etc.) or invalid information (e.g., implausible trip distance) are filtered out. Filters can be easily adapted to other travel survey numeric codes via the config-file.

By applying the set of filters described in Equations (2)–(5), the initial database is subset to only contain valid entries representing motorised trips. The last operation in the parsing of raw travel survey data sets is a harmonization step.

2.1.2. Daily Travel Diary Composition: *TravelDiaryBuilder* Class

In the second VencoPy component, the *travelDiaryBuilder*, individual trips at the survey day are consolidated into person-specific travel diaries comprising multiple trips.

The daily travel diary composition consists of three main steps: reformatting the database, allocating trip purposes and merging the obtained dataframe with other relevant variables from the original database.

In the first step, reformatting, the time dimension is transferred from the raw data (usually in minutes) to the necessary output format (e.g., hours). Each trip is split into shares, which are then assigned to the respective hour in which they took place, generating an hourly dataframe with a timestamp instead of a dataframe containing single trip entries.

Similarly, miles driven and the trip purpose are allocated to their respective hour and merged into daily travel diaries. Trips are assumed to determine the respective person's stay in the consecutive hours up to the next trip and therefore are related to the charging availability between two trips. Trip purposes included in surveys may comprise trips carried out for work or education reasons, trips returning to home, trips to shopping facilities and other leisure activities. Currently, trips whose purpose is not specified are allocated to trips returning to their own household.

A detailed visualized description of the steps on the first abstraction level is given in Appendix B.

At the end of the second VencoPy component *TripDiaryBuilder*, two intermediary data sets are available either directly from the class within Python or from the hard-drive as .csv files. The first one comprises mileage travel diaries $d(v,t)$ and the second one comprises parking place types derived from trip purposes $parkingType(v,t)$.

2.1.3. Charging Infrastructure Allocation: *GridModeler* Class

The charging infrastructure allocation makes use of a basic charging infrastructure model, which assumes the availability of charging stations when vehicles are parked. Since the analytical focus of the framework lies on a regional level (NUTS1-NUTS0), the infrastructure model is kept simple in the current version.

Charging availability is allocated based on a binary True–False mapping to a respective trip purpose in the VencoPy-config. Thus, different scenarios describing different charging availability scenarios, e.g., at home or at home and at work etc. can be distinguished, but neither a regional differentiation nor a charging availability probability or distribution are assumed.

At the end of the execution of the *GridModeler* class, a given parking purpose diary $parkingType(v,t)$ is transferred into a binary grid connection diary $connect_{\text{grid}}(v,t)$ with the same format but consisting only of True–False values.

2.1.4. Flexibility Estimation: *FlexEstimator* Class

There are three integral inputs to the flexibililty estimation:

1. A profile describing hourly distances for each vehicle $d(v,t)$;
2. a boolean set of profiles describing if a vehicle is connected to the grid at a given hour $connect_{\text{grid}}(v,t)$;
3. Techno–economic input assumptions described above and further specified in Table 2.

This yields the minimum and maximum battery constraints, which are calculated as:

$$C_{\text{bat, min}} = C_{\text{bat}} \times marg_{\text{min}} \tag{6}$$

$$C_{\text{bat, max}} = C_{\text{bat}} \times marg_{\text{max}} \tag{7}$$

The electricity flow from the battery to the electric motor for each EV in each hour is calculated by multiplying the driven distance by an assumed average specific electric consumption $cons_{\text{elec}}$ in $\frac{\text{kWh}}{100\,\text{km}}$:

$$drain_{\text{elec}}(v,t) = d(v,t) \times cons_{\text{elec}}/100 \tag{8}$$

$$p_{\text{charge, max}}(v,t) = connect_{\text{grid}}(v,t) \times p_{\text{charge}} \tag{9}$$

Table 2. Technical assumptions for a VencoPy run.

Name	Symbol	Unit	Description
Battery capacity	C_{bat}	kWh	The battery capacity of a single vehicle in the respective size and propulsion technology class
Battery security margin minimum	$marg_{\text{min}}$	%	Technical exclusion of battery capacity at its minimum for driving
Battery security margin maximum	$marg_{\text{max}}$	%	Technical exclusion of battery capacity at its maximum for driving
Specific electricity consumption	$cons_{\text{elec}}$	$\frac{\text{kWh}}{100\,\text{km}}$	Electric consumption of vehicle class
Specific fuel consumption	$cons_{\text{fuel}}$	$\frac{\text{l}}{100\,\text{km}}$	Fuel consumption of vehicle class
Rated power of charging column	p_{charge}	kW	Assumed rated power of each individual vehicle's grid connection for charging

For $t = 0$, the following case differentiation assures that the battery SoC of each mobility profile stays below SoC_{max} and that the following boundary condition is enforced for each individual profile:

$$SoC_{\text{max}}(v, t = 0) = SoC_{\text{max}}(v, t = n_{\text{hour}} - 1) \tag{10}$$

$$SoC_{\text{max}}(v,t) = \begin{cases} SoC_{\text{max}}(v, t = n_{\text{hour}} - 1) & \text{if } SoC_{\text{max}} \leq C_{\text{bat, max}} \quad (11) \\ C_{\text{bat}} \times marg_{\text{max}} & \text{else} \quad (12) \end{cases}$$

For $t > 0$, the following new SoC is calculated. Additionally, it is assured that SoC_{new} stays within the battery limits through:

$$SoC_{\text{max, new}}(v, t \neq 0) = SoC_{\text{max}}(v, t-1) + p_{\text{charge, max}}(v,t) - drain_{\text{elec}}(v,t) \tag{13}$$

$$SoC_{\text{max}}(v, t \neq 0) = \begin{cases} C_{\text{bat, min}} & \text{if } SoC_{\text{new}}(v,t) < C_{\text{bat, min}} \quad (14) \\ SoC_{\text{max, new}}(v,t) & \text{if } C_{\text{bat, min}} \leq SoC_{\text{max, new}}(v,t) \leq C_{\text{bat, max}} \quad (15) \\ C_{\text{bat, max}} & \text{if } SoC_{\text{new}}(v,t) > C_{\text{bat, max}} \quad (16) \end{cases}$$

Since differences at the profile boundaries should be minimized, Equations (10)–(16) are iteratively executed until a predefined number of iterations is reached. The user is displayed the sum of differences of the SoC values for $t = 0$ and $t = n_{\text{hour}} - 1$ over all profiles:

$$iterationChecksum_{\text{max}} = \sum_{v=0}^{V-1} SoC_{\text{max}}(v, t = n_{\text{hour}} - 1) - SoC_{\text{max}}(v, t = 0) \tag{17}$$

Then, uncontrolled charging is calculated as the profile that occurs when vehicles connect as soon as possible and charge with the maximum capacity available at that point in time. For brevity, the dependence on v is left out in the following case differentiation.

$$c_{\text{unc}}(t \neq 0) = \begin{cases} SoC_{\text{max}}(t) - SoC_{\text{max}}(t-1) & \text{if } SoC_{\text{max}}(t) \geq SoC_{\text{max}}(t-1) \quad (18) \\ 0 & \text{else} \quad (19) \end{cases}$$

For $t = 0$, a proxy approach is chosen:

$$c_{\text{unc}}(v, t = 0) = \frac{c_{\text{unc}}(v, t = 1) + c_{\text{unc}}(v, t = n_{\text{hour}})}{2} \tag{20}$$

The fuel demand for trips with a mileage beyond electric mileage is calculated via Equations (21) and (22) as:

$$\begin{aligned} drain_{\text{fuel}}(v, t \neq 0) = \frac{cons_{\text{fuel}}}{cons_{\text{elec}}} * drain_{\text{elec}}(v, t) - c_{\text{unc}}(v, t) \\ - \left(SoC_{\text{max}}(t-1) - SoC_{\text{max}}(t)\right) \end{aligned} \tag{21}$$

$$drain_{\text{fuel}}(v, t = 0) = \frac{drain_{\text{fuel}}(v, t = 1) + drain_{\text{fuel}}(v, t = T)}{2} \tag{22}$$

The demand-sensitive minimum SoC of each vehicle is calculated taking into account the profiles from Equations (18)–(22). Analogous to Equation (10), the following is enforced:

$$SoC_{\text{min}}(v, t = 0) = SoC_{\text{min}}(v, t = n_{\text{hour}} - 1) \tag{23}$$

$$SoC_{\text{min}}(t = n_{\text{hour}} - 1) = \begin{cases} SoC_{\text{min}}(t = 0) & \text{if } SoC_{\text{min}}(t = n_{\text{hour}} - 1) \geq C_{\text{bat, min}} \quad (24) \\ C_{\text{bat, min}} & \text{else} \quad (25) \end{cases}$$

For $t > 0$, the following new SoC is calculated. Additionally (27) assures that SoC_{new} stays within the battery limits. For brevity, the dependence on the specific vehicle is not written.

$$\begin{aligned} SoC_{\text{min, new}}(t \neq n_{\text{hour}} - 1) = SoC_{\text{min}}(t+1) + drain_{\text{elec}}(t+1) - \\ p_{\text{charge, max}}(t+1) - drain_{\text{fuel}}(t+1) \ \times \ \frac{c_{\text{elec}}}{c_{\text{fuel}}} \end{aligned} \tag{26}$$

$$SoC_{\text{min}}(t \neq n_{\text{hour}} - 1) = \begin{cases} C_{\text{bat, min}} & \text{if } SoC_{\text{min, new}}(t) < C_{\text{bat, min}} \quad (27) \\ SoC_{\text{min, new}}(t) & \text{if } C_{\text{bat, min}} \leq SoC_{\text{min, new}}(t) \leq C_{\text{bat, max}} \quad (28) \\ C_{\text{bat, max}} & \text{if } SoC_{\text{min, new}}(t) > C_{\text{bat, max}} \quad (29) \end{cases}$$

Since differences at the profile boundaries should be minimized, Equations (23)–(29) are iteratively executed until a predefined number of iterations is reached. The user is displayed the sum of differences of all profiles.

$$iterationChecksum_{\text{min}} = \sum_{v=0}^{V-1} SoC_{\text{min}}(v, t = n_{\text{hour}} - 1) - SoC_{\text{min}}(v, t = 0) \tag{30}$$

After these steps, the six profiles shown in Table 3 are provided to the user.

Table 3. Intermediary profiles of VencoPy.

Name	Symbol	Unit	Description
Battery drain	$drain_{\text{elec}}(v, t)$	kWh	The electricity that flows out of the vehicle battery each hour for driving
Charging capacity	$p_{\text{charge, max}}(v, t)$	kWh	Maximum electricity available for charging in each hour
Minimum SoC	$SoC_{\text{min}}(v, t)$	kWh	Lower limit for the battery SoC
Maximum SoC	$SoC_{\text{max}}(v, t)$	kWh	Upper limit for the battery SoC
Uncontrolled charging	$charge_{\text{unc}}(v, t)$	kWh	Electricity flow from grid to vehicle when no control is exerted
Fuel consumption	$drain_{\text{fuel}}(v, t)$	kWh	Fuel consumption of vehicle

The first four profiles can be used as constraints for other models to determine optimal charging strategies; the fifth profile simulates a case where charging is not controlled an EVs charge as soon as a charging possibility becomes available. Lastly, the sixth profile quantifies the demand for additional fuel for trips that cannot be fully carried out with an EV.

2.1.5. Filtering

Four filters are applied in the following to these profiles. The first filter excludes profiles that need fuel. The user can give a tolerance level to keep profiles in the data basis for consecutive steps. This filter is applied when only EV profiles should be calculated.

$$\text{filter}_1(v) : \sum_{t=0}^{T-1} drain_{\text{fuel}}(v,t) < tolerance_{\text{fuel}} \quad \forall v \in V \tag{31}$$

The second filter requires a random number $r(v)$ between 0 and 1 for each profile and is calculated as follows:

$$\text{filter}_2(v) : \sum_{t=0}^{T-1} d(v,t) > 2 \times r(v) \times d_{\min} + (1 - r(v)) \times d_{\min} \quad \forall v \in V \tag{32}$$

$d_{\min}$ is a global parameter of VencoPy that the user can freely adjust to manipulate the profiles for selecting either rather EV-prone profiles or rather longer-range profiles.

The third and fourth filter are additional filters to limit the amount of profiles that are taken into account as described in Equations (33) and(34).

$$\text{filter}_3(v) : \sum_{t=0}^{T-1} drain_{\text{elec}}(v,t) < \sum_{t=0}^{T-1} p_{\text{charge, max}}(v,t) \quad \forall v \in V \tag{33}$$

$$\text{filter}_4(v) : \sum_{t=0}^{T-1} drain_{\text{elec}}(v,t) < SoC_{\text{bat, max}} - SoC_{\text{bat, min}} \quad \forall v \in V \tag{34}$$

The user is displayed information on how many profiles were filtered out and how many are still part of the data.

The electric demand for driving is reduced by the share of fuel combustion to power the battery in order to gain the net electric battery outflow per hour:

$$drain_{\text{elec, net}}(v,t) = drain_{\text{elec}}(v,t) - drain_{\text{fuel}} \times \frac{c_{\text{fuel}}}{c_{\text{elec}}} \tag{35}$$

2.1.6. Normalization

The SoC profiles are normalized to the respective battery capacities in order to produce comparable profiles.

$$SoC_{\text{min, norm}}(v,t) = \frac{SoC_{\text{min}}(v,t)}{C_{\text{bat}}} \tag{36}$$

2.1.7. Aggregation

In order to draw conclusions on EV fleets, aggregation of the individual profiles to EV fleet level is performed. In its current version, this is done for the whole set of data and different vehicle sizes are not differentiated due to the missing allocation of trip data (which is only referenced by household and person but not by vehicle) to vehicles and thus vehicle sizes.

For all four flow profiles $f(v,t)$ aggregation is carried out via:

$$f(t) = \frac{\sum_{v=0}^{V-1} f(v,t)}{V} \tag{37}$$

For the two state profiles $SoC(v,t)$ aggregation is carried out by selecting the n_{th} largest or smallest value of the profile in each hour for $SoC_{\max}(v,t)$ and $SoC_{\min}(v,t)$, respectively. With α being between 0 and 1, the "n" of n^{th} element [15] and V being the total number of profiles, the limiting value is calculated as:

$$v_{\text{limit}} = \alpha \times V \tag{38}$$

De Tena describes $1 - v_{\text{limit}}$ as the confidence interval. Thus when $\alpha = 5$, this results in a confidence interval of 95% where the SoC limitations fulfil the needs of 95% of the assessed trips [3]. After this, $SoC_{\text{min, limit}}(t)$ and $SoC_{\text{max, limit}}(t)$, the threshold SoC values are calculated for each hour. To satisfy the demand of the entirety of vehicles in the confidence interval, the fleet SoC must not surpass this threshold SoC.

$$SoC_{\text{min, limit}}(t) = \min_{n=v_{\text{limit}}} \left(n_{\text{largest}}(SoC_{\text{min, limit}}(t,v))\right) \tag{39}$$

$$SoC_{\text{max, limit}}(t) = \max_{n=v_{\text{limit}}} \left(n_{\text{smallest}}(SoC_{\text{max, limit}}(t,v))\right) \tag{40}$$

where $n_{\text{largest}}()$ and $n_{\text{smallest}}()$ are the operations to select for example the 95% largest or smallest values of a set of values.

3. Results

After describing the more recent of the two data sets in greater detail, the resulting mobility profiles with and without weekday differentiation are analysed. On this analytical level the effect of applying the trip weights to account for trips being more or less representative for overall travel behavior within the sample population are visualised. These analyses mainly reproduce findings from [17] for MiD17 and from [18] for a comparison of MiD08 and MiD17. However, since the interest here mainly lies in temporal differentiations, only the effects of the already described changing patterns on the traffic volume in high temporal detail are described.

Secondly, the flexibility estimation of VencoPy is demonstrated by showing how differences between two travel surveys propagate to simulation results. The case study is limited to battery EVs, so Equations (21) and (22) and the resulting profile $drain_{\text{fuel}}(v,t)$ are disregarded.

3.1. Case Study Data

The latest German national travel survey "Mobilität in Deutschland" (MiD17) was carried out in the years 2016 and 2017. Mobility patterns for one randomly chosen day per survey participant were collected across Germany. The survey was carried out as a multiple frame survey, taking into account three samples gathered across Germany and 55 regional samples of participating federal states and counties. For comparison, trip data from the predecessor survey-"Mobilität in Deutschland 2008" (MiD08)-are taken into account [20].

The MiD17 data set can be accessed in four different degrees of detail with A being the overall national aggregates disclosed to everyone and from B1 to B3 being the datasets with an increasing spatial detail. The dataset used in this analysis is the MiD B2 dataset, which contains information on county level. The B2 dataset consists of the three tables *households*, *person* and *trips*, connected via unique household-ID, person-ID and trip-ID. Only 22 of the 157 variables given for each trip are used since the interest only lies in vehicle mobility and their most relevant variables, thus making the application of VencoPy easier for other national travel surveys. Examples of provided variables that are not relevant for the technical analytical steps described here but may be accessed for consecutive analyses (before aggregation) are federal state, region type, economic household status, age groups or boolean variables referring to the transport mode. Still, users can access the full range of information not only of the trips but also of households and persons through merging the IDs within the initial original data set.

The data set is described in multiple documents of which only the study summary and short report are available in English. More detailed descriptions are available in German in the final report [17], the travel survey user handbook [21], the method report [22] and the time series report [18].

Starting from the initial raw trip record base set $\mathbb{D}_{\text{tot}}$, containing around 961,000 entries, a subset data set $\mathbb{D}_{\text{sel}}$ is created after filtering invalid entries, resulting in slightly more than 400,000 database entries for individual trips. This reduction to less than 50% of the data set is mainly due to selecting only trips carried out by motorized individual vehicles and minor consistency cleaning steps.

For the trip data of the MiD17, the average travel time lies at one hour and 20 min as the total average over the entire dataset and one hour and 34 min for single persons, i.e., persons that carry out at least one trip on the survey day. It significantly depends on age, employment, and population density and is only slightly affected by gender (males survey respondents travel five minutes more on average than female ones).

The number of trips lies at 3.1 trips/day on average for the whole dataset and 3.7 trips/day for single persons. The number of trips, as well as the trip purposes, are not affected by population density or differences across Germany. However, the length, times or other specifics of these trips differ [17]. Seasonal differences are marginal with regard to the number of trips per person and day. However, weekdays strongly influence this metric. Trips occur more often on workdays than on weekend days with their minimum on Sundays with an average of 2.1 and 2.8 trips per person/day for the whole dataframe and single persons respectively.

Daily travel distance is the most variable metric on average. It differs by 10 km between densely populated regions vs. metropolitan regions. Seasonal effects for this metric are much more pronounced than for the number of trips. The daily travel distance ranges between 42 km in winter and 48 km in summer on average for single persons in the overall sample. The influence of weekdays on average daily travel distance differs from the influence on other metrics. Daily travel distances are lowest on Tuesdays and Wednesdays and rise towards the weekends (Mondays and Thursdays) to 44–45 km/day, respectively. Regarding this metric, Friday with its 50 km/day has a similar characteristic as Saturday (48 km/day) and the weekday maximum Sunday (52 km/day). Sunday's specific travel characteristic is also mirrored in the average trip length of 18 km/trip, which differs significantly from the 11–13 km/trip throughout the other days.

Table 4 shows the analyzed metrics for the overall MiD08 and MiD17 populations and for the filtered sample containing trips carried out by vehicles ($\mathbb{D}_{\text{sel}}$ subset).

Table 4. Aggregate mobility metrics of the original datasets (only motorized trips) and the filtered samples.

Mobility Metric	Unit	MiD08	MiD17	Filtered Sample MiD08	Filtered Sample MiD17
Mobility quota	%	90	85	-	-
Sample size (trip)	1	193,290	960,619	152,621	414,683
Number of trips	$\frac{\text{trips}}{\text{mobileperson} \times \text{day}}$	3.8	3.7	3.4	2.9
Daily travel distance	$\frac{\text{km}}{\text{mobileperson} \times \text{day}}$	44	46	32	48.5
Daily travel time	$\frac{\text{hh:mm}}{\text{mobileperson} \times \text{day}}$	1:28	1:34	1:22	1:10
Average trip distance	$\frac{\text{km}}{\text{trip}}$	11.5	12	9.4	17
Total number of trips	$\frac{\text{Mio.trips}}{\text{day}}$	281	257	120 *	111 *
Total distance travelled	$\frac{\text{bn.person}-\text{km}}{\text{day}}$	3.080	3.214	1761 *	1754 *

* Values taken from [17,18].

Other influences that were part of the survey such as the influence of gender, economical status and employment type are excluded from the detailed analysis but are a fruitful starting point for further analysis, especially on geographically smaller areas. Since VencoPy has the foremost application context of providing information for European-wide

energy systems models on a scale of federal states (3–7 Mio. inhabitants) to national regions, these influences are assumed to be negligible for the research questions at this scale. However, especially for transferring insights to other European countries, some of these measures (especially distribution of economical status, employment type and age) are promising for hypothesis building or preliminary assumptions in the case of lack of detailed national travel survey data.

Weights in the German National Travel Survey Data Set

One of the goals of the MiD is to provide aggregate statistics of German mobility. In order to do so, households, persons and trips are associated with weights describing the representativeness of a respective observation. Here, only the trip weights are considered since they comprise all necessary information to calculate trip aggregates from trip samples. Since the survey has a variety of heterogeneous selection frames, an estimator such as the Horvitz–Thompson estimator has to be applied in order to scale variables from the sample to the entirety of the German society [21]. In this regard, the steps described in [22] are followed for the scaling from the sample population to the entirety of the German population.

3.2. Case Study Results: Mobility Patterns

As described above, several steps are taken in order to calculate average profiles for entire fleets. In this paper, no results for a scenario study of 2030 or similar, as done with VencoPy in [5], are shown but the interest is rather focused on all resulting profiles on the level of the average vehicle, thus providing a basis for scaling to any fleet size.

Figure 2 shows the mobility patterns for an average vehicle in Germany differentiated by the weekday. The top plot shows the larger sample size of the MiD2017 due to its additional regional in-depth samples that were realized for the first time [22]. The bottom plot shows the effect of the increased average trip distance already shown in Table 4. Weighting has a marginal influence for average daily mobility based on the MiD08, but reduces the daytime distance travelled based on MiD17 accounting for over-represented high-distance travellers on Saturday–Monday in the sample.

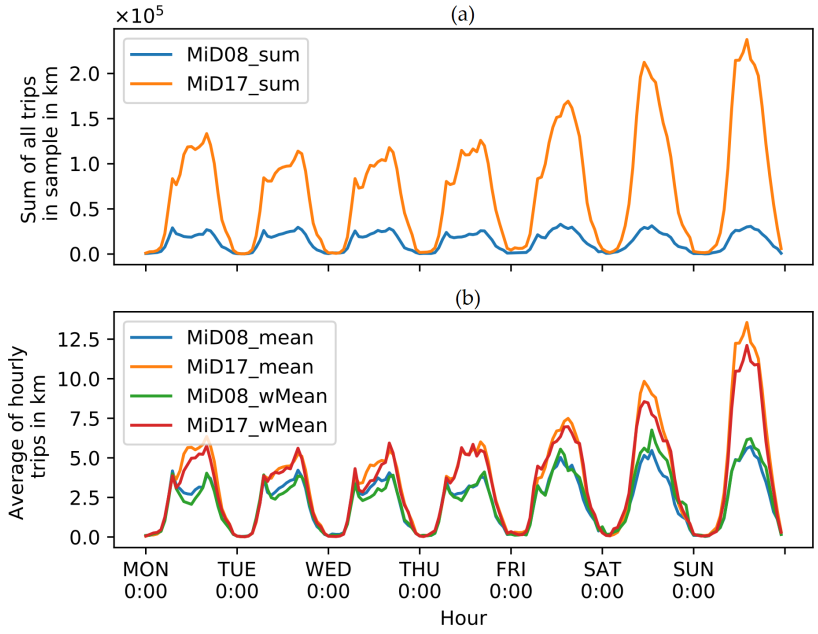


Figure 2. Results of the mobility pattern analysis for a representative week based on the sample populations of MiD08 and MiD2017. Figure (**a**) shows the absolute sample population while the bottom shows the average hourly trip distance. The mean for Figure (**b**) is calculated by the simple arithmetic mean ('_mean') and taking into account MiD trip weights ('_wMean').

Traffic volume is higher in the MiD17 specifically on weekend days, most pronounced on Sundays and moderately higher on Fridays and Mondays. While average hourly distances are comparable based on MiD08, mobility patterns show a clear increasing trend from Fridays through Saturdays and peaking on Sundays at approximately 12.5 km/h around 12:00 on average. This dynamic although already present in the MiD08 sample is more evident from the MiD17 sample.

3.3. Case Study Results: Flexibility Estimation

In the following, results of the flexibility estimation are shown which consider weights in the aggregation process from individual profiles, e.g., for uncontrolled charging, to the estimated average EV profiles. As shown in Table 3, this flexibility is described by the four profiles' battery drain $drain_{\mathrm{elec}}(t)$, maximum charging capacity $p_{\mathrm{charge,\,max}}(t)$ as well as minimum ($SoC_{\mathrm{min}}(t)$) and maximum SoC ($SoC_{\mathrm{max}}(t)$). A fifth profile, uncontrolled charging $charge_{\mathrm{unc}}(t)$, is calculated as well, assuming vehicles are charged as soon as a grid connection is available.

Figure 3 shows the counteracting effects of increased travel distances in a lower number of trips [18]. Charging is available when vehicle owners are at home which is mainly during the morning, evening and night. While daytime grid connection shares are higher based on the MiD17 data set during workdays, the opposite is the case in a milder intensity for the weekend. This can be explained by almost doubling average trip distance travelled on Sunday, compensating for less trips being carried out. However, as described above, this effect is small compared to the overall change in fleet grid connection share.

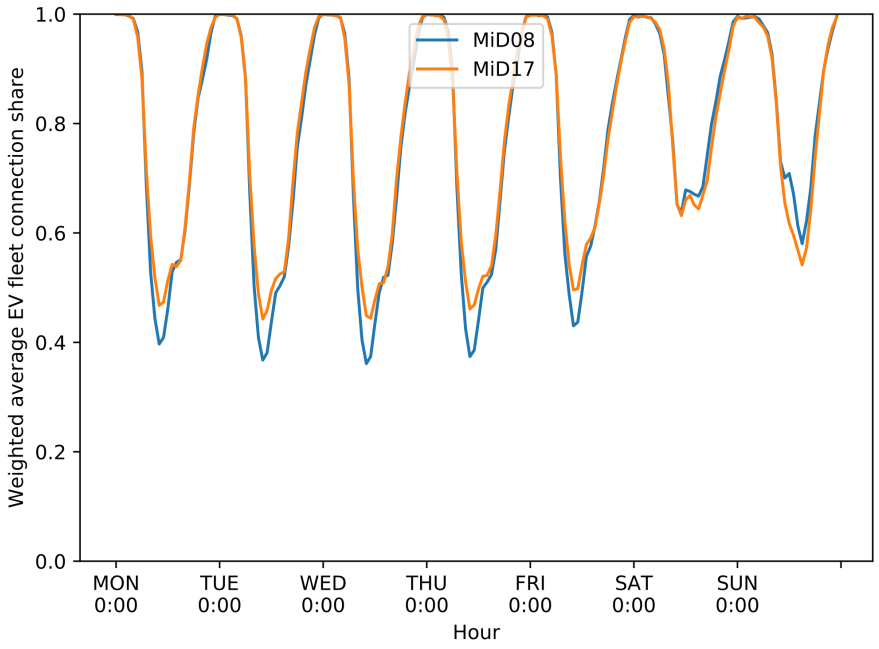


Figure 3. Weighted average grid connection for electric vehicle fleet differentiated by weekdays.

Compared to the differences in fleet grid connection shares, changes in mobility patterns imply stronger changes in electricity outflow from the battery for driving as depicted in Figure 4 since mobility changes directly translate into drain changes. Increased average trip distance travelled between 9:00 and 17:00 leads to increased electricity consumption for driving mainly from 8:00 to 17:00. In its peak at 16:00, the average electricity consumption is 0.3 kWh/h based on MiD08, whereas it is 0.55 kWh/h based on MiD17.

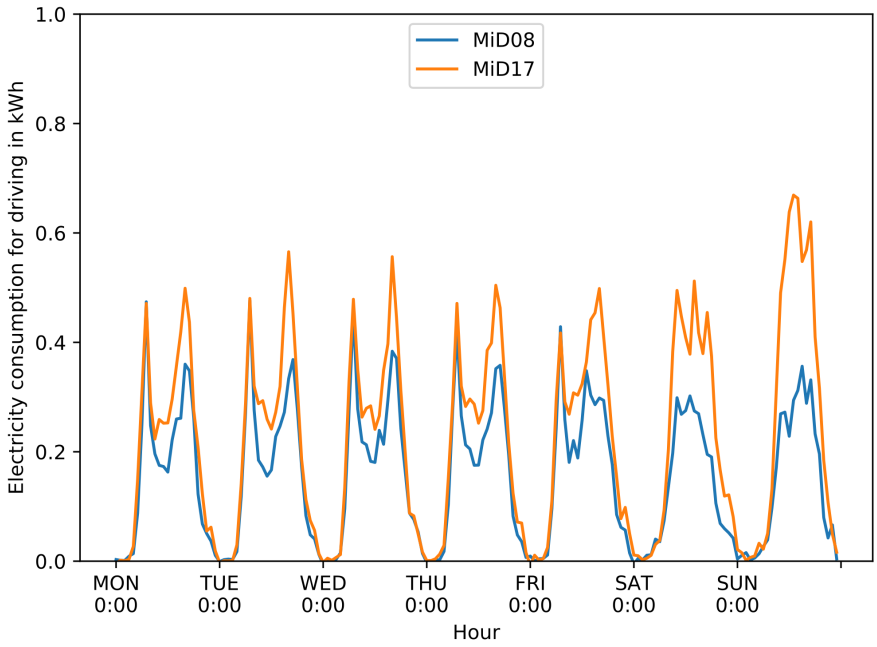


Figure 4. Weighted average electricity consumption for driving differentiated by weekday.

The average electricity consumption for driving shows characteristic morning and evening peaks throughout the week. The maximum in fleet consumption for driving $drain_{\text{elec}}(t)$ can be observed for evenings with approximately 0.6 kWh/h per vehicle on average. Increased average trip distance in MiD17 compared to MiD08 leads to higher electricity consumption at almost every hour. Sunday differences in consumption are higher by almost a factor of 2, from 0.35 kWh/h to 0.7 kWh/h on average. Saturdays show a broader travel characteristic during daytime the but peaking below Tuesday evening travels.

Uncontrolled charging shown in Figure 5 differs between the two samples in the time interval between 16:00 and 21:00 with its peak at 18:00. In this peak, $charge_{\text{unc}}(t)$ results in 0.5 and 0.8 kW for MiD08 and MiD17, respectively. The patterns in the uncontrolled charging scenario are thus quite similar.

The trends described for an average day are mirrored by weekly EV fleet uncontrolled charging. The peak broadened a bit and increased in size from under 0.6 to 0.8 kW. On Fridays and Saturdays uncontrolled charging is more distributed throughout the day with increasing peaks in the evenings. Sundays show the all-week high slightly below 1 kW on average, this having increased more than two-fold showing the stark travel increase on Sundays between the MiD08 and MiD17.

SoC profiles shown in Figure 6 depict a temporally dependent average battery range for load shifting. This battery range is reduced by a reduced maximum SoC and an increased minimum SoC at daytimes when vehicles on the road cannot charge but need a minimum of SoC for the planned trip on that respective day.

The average vehicle SoC is smaller for the estimation based on the MiD17 dataset, which is due to increased travel distances in the sample. This reduction is most pronounced on Sundays when the two profiles almost touch, implying no charging flexibility for the average vehicle at all. Still, during nights, an average vehicle provides a large source of flexibility with the full accumulator capacity of 50 kWh available for flexible charging.

Simple methods for aggregating individual SoC profiles to fleet level as used here have been shown to overestimate the fleet load shifting potential. Mathematically correct methods exist but have been shown to currently be impractical on time horizons employed in the context of energy systems analysis (T $>>$ 10 time steps) [2]. The given profiles can

be a first indication for a vehicle fleet flexibility, however greater care in applying them in the context of evidence-based decision making should be taken.

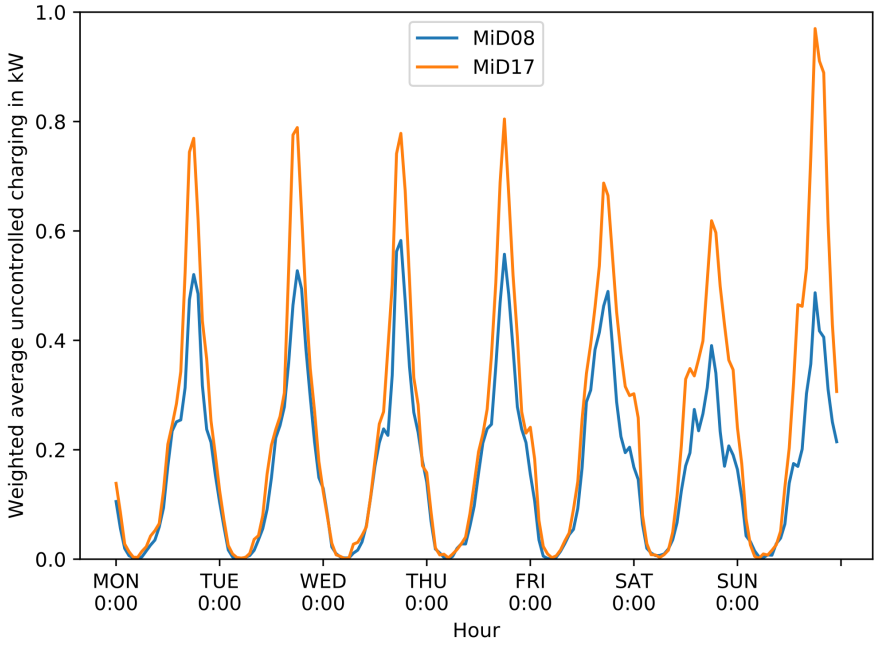


Figure 5. Weighted average uncontrolled charging in kW. Home charging with a capacity of 11 kW is assumed.

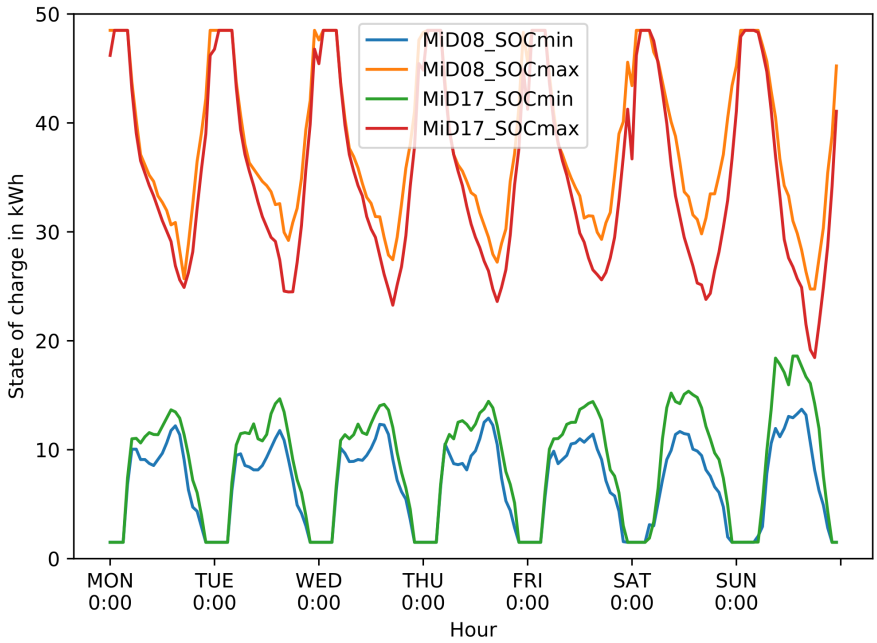


Figure 6. SoC min and max profiles of MiD08 and MiD17. Profiles are based on single-day min and max profile calculation and merged for this plot. For details, see Section 2.1.4. A 50 kWh battery is assumed for this case study.

4. Discussion

4.1. Situating VencoPy Simulation Results on the Background of Literature Results

Comparing VencoPy simulation results with results for EV fleet charging given in the literature is difficult due to different boundary conditions such as assumed battery

capacities and specific electricity consumption and infrastructure modeling detail. Still, the results presented above are described next to literature findings of three studies, even though a direct comparison cannot really be performed. Two of the studies follow a similar approach extrapolating fossil fuel vehicle mobility behavior to electric fleets [12,23] and a third one assessing empirically measured charging events [24], thus being more heterogeneous in the vehicle model range and used infrastructure. Table 5 gives an overview of the studies and assumptions.

Table 5. Literature studies calculating electric vehicle fleet profiles and respective assumptions taken.

Reference	Battery Capacity	Electric Consumption	Grid Modeling	Available Profiles
[23]	multiple [1]	multiple [1]	multiple [2]	$charge_{\mathrm{unc}}$, $p_{\mathrm{charge,\,max}}$, $drain_{\mathrm{elec}}$
[12]	70 $\frac{\mathrm{kWh}}{\mathrm{veh}}$	16 $\frac{\mathrm{kWh}}{100\ \mathrm{km}}$	9.1 kW for home charging	$charge_{\mathrm{unc}}$
[24]	multiple [3]	multiple [3]	multiple [3]	$charge_{\mathrm{unc}}$
Case study	50 $\frac{\mathrm{kWh}}{\mathrm{veh}}$	20 $\frac{\mathrm{kWh}}{100\ \mathrm{km}}$	11 kW	$charge_{\mathrm{unc}}$, $p_{\mathrm{charge,\,max}}$, $drain_{\mathrm{elec}}$

[1] 22 values for 13 different segments. [2] 3.7 kW for work, education and home charging, 22 kW for shopping and leisure. [3] Vehicle models see [24], charging up to 22 kW stations.

All profiles are compared on the basis of an average vehicle of the fleet on the basis of charging power and respective patterns throughout the day as well as the volume of charged energy as an aggregate measure.

4.1.1. Power and Patterns

Electricity consumption and uncontrolled charging power values are similar to literature values. VencoPy calculates electricity consumption values between 400 and 500 W for morning peaks at 7:00 and 500 and 600 W for evening peaks at 16:00 on workdays. On the weekend, electricity consumption peaks at 500–700 W around noon. Only Heinz provides electricity consumption estimates peaking at 500–550 W at 7:30 and 17:00 on average on workdays and at 400 W at 15:30 on weekend days [23].

VencoPy simulations yield uncontrolled charging evening peaks amounting to 700–800 W on workdays and 600–950 W on weekend days on average occurring at 18:00. Comparing evening peaks for uncontrolled charging, Ried finds evening peaks of 870 W on workdays and 480–550 W on weekend days peaking at 19:00–20:00 and 19:00, respectively [12]. Heinz finds peaks of 560 and 340 W occurring at 18:00 and 18:30 for workdays and weekend days, respectively [23]. Schaeuble et al. report a peak of 380 W on 18:15 on an overall average day, standardizing the profiles with an own calculation of daily charged energy based on the average daily driven distance of 39 km given in MiD [24].

Grid connection shares are given only by Heinz describing around 1.75 kW of 3.5 kW (50%) at its minimum occurring at 10:30 in the morning on an average workday for the home charging scenario [23]. On the weekend the minimum connected power increases to 2.7 kW (77%) at 11:00. VencoPy's grid connection shares are reduced to 40% on workdays and 55–70% on weekend days. The results are thus slightly lower throughout the week suggesting that the dataset used describes more mobile vehicle users.

4.1.2. Charged Energy Volumes in the Uncontrolled Charging Scenario

The total amount of energy charged is compared to two values. For one, ref. [24] discusses different daily energy volumes charged in the evaluated empirical data sets on the background of rule-of-thumb calculations using average distance travelled. The latter yields a charged energy of 5.4 kWh per day including losses compared to 4.4 kWh and 9.2–11.5 kWh depending on the respective measured data set with the latter's variation stemming from different weekdays. Heinz's published profiles enable a reproduction of charged energy for the calculated representative profile [23]. Assuming discretised 10-min power values yields average charging volumes of 4.9 kWh/day on workdays and

3.6 kWh/day on weekend days. VencoPy's charged energy demand for uncontrolled charging lies slightly higher with 5.4 kWh/day for the average vehicle at an average day than values from [23] but well in the range given in [24]. Two times higher values for daily charged energy volumes reported for the Get eReady study carried out between 2013 and 2015 in Stuttgart can be explained by non-representative vehicle users as 75% of survey participants were small to medium sized companies receiving a refund for their participation.

4.2. Limitations and Potential Improvements

A potential improvement in a future charging flexibility estimation would be to take into account charging probabilities and to sample grid connections to trip purpose-dependent stays based on a given probability [8]. In a next step, further dependencies such as regional charging availability could be assumed.

Moreover, the decision to plug in a vehicle when a charging point is available is not explicitly modeled and it is assumed that users always connect their vehicles when charging is available. A potential improvement could be to incorporate fitted models given, for example, for the case of public charging in [25]. Energy system models usually require annual profiles in hourly or sub-hourly resolution. VencoPy currently only supports annual calculations which are structurally fixed in the tools codebase. Temporal resolutions down to at least 10-min intervals may be supported by the data used in the case study (MiD08 and MiD17). Furthermore, seasonal influences on drain profiles such as temperature changes have been suggested by other authors and should be incorporated into the tool.

Aggregated profiles for fleet state-of-charge profiles have been shown to exaggerate the flexibility potential of fleets. Mathematically exact Minkowski sums have been proposed as a mean of representing fleets' aggregated load shifting potential, however applications to intervals greater than 2 h have been shown to be infeasible due to exponentially increasing calculations times.

The analysis of the mobility pattern is based on fossil fuel cars. There is evidence in the literature that EV users drive their cars differently. However, this change may currently be exaggerated with EV users still not being representative for the entirety of individual motorized vehicle users. However, future travel surveys may provide sufficient information to isolate EV users and thus run comparable analysis without this strong overarching assumption.

5. Conclusions

Changing mobility patterns described in detail by national travel surveys, such as 'Mobilität in Deutschland' for Germany, may imply changes in EV fleet electric load shifting potential estimations. For the interval between 2008 and 2017, a slight decrease in the number of trips per day and person from 3.4 to 2.9 and a strong increase in unweighted average distance travelled from 9.4 to 17 km per person/day for motorized individual vehicles is evident from the analysis.

The Open Source tool Vehicle Energy Consumption in Python (VencoPy) makes use of an interface to the data, filtering and evaluation algorithms to assess the consequences of these changes in high temporal resolution for an average week.

In a what-if scenario assuming an EV battery size of 50 kWh, a specific consumption of 20 kWh/100 km, only home charging and a maximum charging power of 11 kW, the effects of these mobility pattern changes on the average EV flexibility are assessed.

Slight increases in fleet charging capacity are found on workdays and slight decreases on weekends. The average electricity consumption flowing from the battery for driving is found to be higher for mobility data from MiD17 for daytime hours with a workday consumption peak on Tuesday evening and an overall consumption peak on Sundays due to increased Sunday travel activities.

An estimate of the average fleet battery limits show slightly decreasing flexibility (increased lower bounds and decreased upper bounds) in state-of-charge levels due to

the aforementioned effects. The average fleet battery limits vary from 50 kWh at night to around 15 kWh during workdays and only a few kWh on Sundays.

Uncontrolled home charging patterns are similar based on the two analysed samples. However, peak charging is higher based on the newer MiD17. A notion of low Friday and Saturday peaks, medium Monday through Thursday and high Sunday peaks is observed showing the exceptional role of increased travels on Sunday and their impact on EV charging.

The results of the simulations regarding power and time patterns throughout the day as well as the sum of daily charged and consumed electricity lie within the range of or close to literature values. The results demonstrate the value of analyzing the influence of detailed changes in mobility patterns on EV charging assessments. The influence of changing mobility patterns dependent on different weekdays is exemplified. Other variables can and should be analyzed such as household income, region type, employment status, age and gender since they can also be mapped to EV adoption groups. An increased validation of tools such as VencoPy by empirical EV mobility or charging station data is advised, a prospect towards which the first promising steps have already been undertaken. Validation experiments can yield insights if mobility pattern changes apply in the same way to EV users as they do to all vehicle users and if there are other EV specific pattern changes.

Author Contributions: Conceptualization, N.W.; methodology, N.W.; software, N.W.; formal analysis, N.W.; investigation, N.W.; resources, H.C.G.; data curation, N.W.; writing—original draft preparation, N.W.; writing—review and editing, N.W., F.M., H.C.G. & P.J.; visualization, N.W.; supervision, H.C.G. & P.J.; project administration, H.C.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the German Aerospace Center within the scope of the project EVer—Energie und Verkehr.

Data Availability Statement: Data analyzed in this study (MiD 2008, public use file and MiD 2017, B2 trip data set) are available from the Clearinghouse Transport (German: "Clearingstelle Verkehr") via https://daten.clearingstelle-verkehr.de/279/ behind a low paywall for research institutions. Results data can be obtained using the referenced repository or upon request to the corresponding author.

Acknowledgments: We thank the Energy Systems Modeling group at the Department of Energy System Analysis, Institute for Networked Energy System, DLR for providing valuable feedback and, infrastructure and the flexibility needed to work in these times. We thank Carsten Hoyer-Klick for providing funding for the project. We thank Moritz Bergfeld, Anton Galich and Claudia Nobis for fruitful discussions, input on the MiD data and sharing data. We thank the BMVI for providing the national travel survey at a low cost.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle (specifically battery electric vehicle)
MiD08	Mobilität in Deutschland 2008
MiD17	Mobilität in Deutschland 2017
RE	Renewable Energy
SoC	State of Charge
VencoPy	Vehicle Energy Consumption in Python

Appendix A. List of Required Trip Variables

The following Table A1 shows a list of the required variables, the VencoPy internal namings as well as the variable namings in the two case study data sets MiD 2008 and MiD 2017.

Table A1. Required trip variables from raw mobility travel surveys as a minimum requirement to serve as input to VencoPy. Shown are the VencoPy internal namings as well as the variable namings of the surveys MiD08 and MiD17 analyzed in the case study.

VencoPy Internal Variable Names	MiD 2008 Name	MiD 2017 Name
dataset	MiD08	MiD17
isMIVDriver	pkw_f	W_VM_G
hhID	hhid	H_ID_Reg
personID	pid	P_ID
hhPersonID	NA	HP_ID_Reg
tripID	wid	W_ID
tripWeight	w_gew	W_GEW
tripScaleFactor	NA	W_HOCH
tripStartClock	st_time	W_SZ
tripEndClock	en_time	W_AZ
tripPurpose	w04	zweck
tripDistance	wegkm_k	wegkm
travelTime	wegmin_k	wegmin_imp1
tripStartYear	stich_j	ST_JAHR
tripStartMonth	stich_m	ST_MONAT
tripStartWeek	stichwo	ST_WOCHE
tripStartWeekday	stichtag	ST_WOTAG
tripStartHour	st_std	W_SZS
tripStartMinute	st_min	W_SZM
tripEndHour	en_std	W_AZS
tripEndMinute	en_min	W_AZM
tripEndNextDay	en_dat	W_FOLGETAG
tripIsIntermodal	NA	weg_intermod

Appendix B. Detailed Description of Trip Diary Composition

In both MiD data sets, no explicit timestamp information for the survey time May 2016 to October 2017 is available, so we synthesize timestamps from the variables *ST_JAHR*, *ST_WOCHE*, *ST_WOTAG*, *W_SZS* and *W_SZM*. We use calendaric weeks to determine the month of the survey day. Timestamp for start and end are written to two separate columns. Afterwards, the end timestamp is updated to account for overnight trips where the arrival day is different from departure day. We then transform the data set, allocating trip distances to hours and potentially splitting the trip distances of reported trips to multiple hours. This follows the steps

1. The trip duration is calculated using the timestamp information
2. It is determined if the trip ends in the same hour as it starts
3. For 1-h trips the share of the start hour is set to one, for multi-hour trips the remaining minutes of the first trip hour are divided by the trip duration to determine the share of the first hour
4. For 1-h-trips, the end hour share is set to 0. For multi-hour trips, the end hour share is calculated by dividing the minute attribute of the end timestamp by the duration.
5. The number of full travel hours between start and end hours is calculated. Currently end-timestamps at exactly the full hour are allocated to fullHour trips if the trip duration exceeds 60 min. Thus, a trip starting at 11:30 and ending at 13:00 has a start hour share of 33%, an end hour share of 0%, one full hour of travel and a full hour share of 67%.

Table A2. Exemplary trip timestamps and respective conversions to shares of end and starting hours as well as number and trip length of full hours in the trip. The first row shows a single-hour trip, the second row a single-hour trip starting in a different hour than ending and the third row a multiple-hour trip.

Timestamp Start	Timestamp End	Start Hour Share	End Hour Share	No. of Full Hours	Full Hour Trip Length
2017-04-25 11:10:00	2017-04-25 11:35:00	1	0	0	0
2017-02-08 10:30:00	2017-02-08 11:05:00	0.86	0.14	0	0
2017-06-16 11:15:00	2017-06-16 13:50:00	0.29	0.32	2	110

After this procedure we created six additional variables for the same number of observations. However, due to formatting of input data, some inconsistencies still occur after this trip length allocation that have to be filtered out. Specifically, there are trips where the share of the start hour is not 1 but the share of end hour and the number of full hour trips are both equal to 0. This occurs for three trips due to a trip duration being 0 ($W_SZ = W_AZ$) resulting in a start hour share of *NA* or because of one overnight trip where the variable *W_FOLGETAG* was falsely set to 1. These three trips are filtered out. The clean base trip data set now consists of 414,683 trip entries.

Table A3. Exemplary output (first 9 observations) of daily travel diaries as input for VencoPy.

hhPersonID	*tripStartWeekday*	*tripWeight*	...7	8	9	10	11...	...17	18	19...
10001952	TUE	0.49	0.00	0.00	0.00	0.00	9.50	0.00	9.50	0.00
10002161	WED	0.24	0.00	9.50	0.00	8.14	1.36	0.00	0.00	0.00
10002341	SAT	0.11	0.00	6.18	1.43	0.00	0.00	0.00	0.00	6.18
10002422	THU	0.20	0.00	0.00	0.00	0.00	2.38	0.00	36.27	20.73
10003121	SAT	2.02	0.00	0.00	0.00	0.00	34.83	0.00	0.00	0.00
10003122	SAT	1.26	0.00	0.00	0.00	0.00	0.00	28.50	0.00	0.00
10003123	SAT	2.08	0.00	0.00	0.00	0.00	0.00	28.50	0.00	0.00
10003124	SAT	2.24	0.00	0.00	0.00	0.00	34.83	34.83	69.67	0.00
10003852	TUE	0.35	4.75	1.90	2.85	0.00	1.90	0.00	0.00	0.00

Since at the end of the parsing a data set is needed with explicit information of distance travelled in each hour, a new dataframe is created with one column for each hour and with the same ID column (Household-person ID) as the base data set. From a software-design point of view, this is performance intensive since the operation has to be applied to each row but to various columns. In the current version, this is solved by a callable class FillHourValues() and a function applying that class to each row of the empty dataframe. The callable class obtains all required attributes from the clean base trip data set.

Merging individual trips to daily travel diaries In the next step, the dataset is merged as shown in Figure A1. Thereby, individual trips of the same household and person are merged together to one travel diary with its respective unique ID.

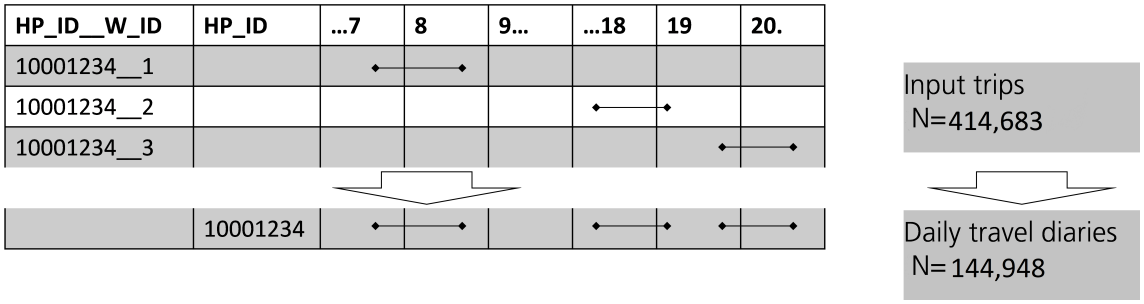


Figure A1. Merging of individual trips to travel diaries.

The daily trip diary now has 105,453 observations with the access to all geographical, temporal, technical and socio-economic information from the person and household data set through merging by the identifier. For the weekday and the weights, this is done by

default in the *flexibility estimation* for further analysis and scaling. The data set is then written in a .csv-file as an input into VencoPy:

The MiD2017 B2 trip data set contains a variable *zweck*, German for 'purpose', that differentiates the following trip purposes as shown in Table A4.

Table A4. Trip purpose descriptions in the data set MiD2017 and respective mappings to VencoPy internal trip categories.

Variable Value	German Description	English Description	Aggregated Identifier
1	Erreichen des Arbeitsplatzes	Reaching work	WORK
2	dienstlich/geschäftlich	Work trip	WORK
3	Erreichen dAusbildungsstätte/Schule	Reaching educational facility	SCHOOL
4	Einkauf	Shopping	SHOPPING
5	private Erledigung	Private errand	SHOPPING
6	Bringen/Holen/Begleiten von Personen	Bringing, fetching and accompanying persons	LEISURE
7	Freizeitaktivität	Leisure	LEISURE
8	nach Hause	Trip home	HOME
9	Rückweg vom vorherigen Weg	Trip back from trip before	HOME
10	anderer Zweck	Other purpose	OTHER
99	keine Angabe	Not available	NA

From the trip purposes we are able to learn the location category of a vehicle during the course of the day. This information can, together with assumptions of location-specific charging infrastructure distribution, yield the information whether a charging station is available or not at a respective location category e.g., HOME. We introduce an additional purpose 'DRIVING' to account for hours where vehicle holders are mainly driving and thus cannot charge. The filling of trip purposes follows these steps

1. Take the trip distance diary data set and replace all non-zero entries with 'DRIVING'.
2. We are foremost interested in setting inter-trip hours to specific purposes, and thus we have to go through each diary ID but also through each trip of the diary in its original data set (*W_ID*) in order to extract and correctly allocate the purpose.
3. All trips are assumed to start at HOME; thus, for the first trip, the hours from beginning to the hour of the trip are filled with 'HOME'. If the trip starts in the first half of an hour, that hour is not filled with 'HOME'; if it starts in the second half, it is. If it starts exactly at HH:30, this hour is set to 'DRIVING'.
4. For all other trips, the first hour, in which the purpose is not 'DRIVING' (or the previous purpose in case of <30 min trips) is identified based on a logical case differentiation schematically shown in the following Figure A2.

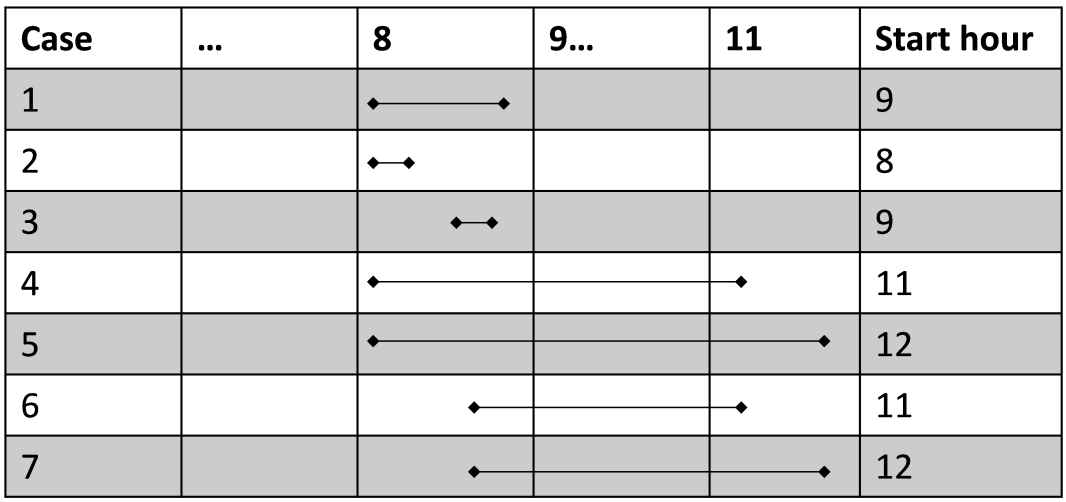


Figure A2. Differentiation of cases for the allocation of location purposes based on the trip purpose.

Ending hours are currently not differentiated in detail. Thus, the starting hour of the next trip is always determined by the duration of the next trip and the purpose between the two trips ends in the hours before the next trip starts regardless of the start being in the first or second half of the hour, e.g., someone drives to work from 7:30 to 8:20 and then home from 17:20 to 18:10, and thus hour 7 will be determined as 'DRIVING'; the hours 8–16 will be determined as 'WORK', hour 17 as 'DRIVING' and the hours from 18 onward will be determined 'HOME'.

References

1. Babrowski, S.; Heinrichs, H.; Jochem, P.; Fichtner, W. Load shift potential of electric vehicles in Europe. *J. Power Sources* **2014**, *255*, 283–293. [CrossRef]
2. Ried, S.; Dengiz, T.; Soldner, S.; Jochem, P. Aggregating load shifting potentials of electric vehicles for energz system models. In Proceedings of the Institute of Electrical and Electronics Engineers (IEEE) 17th International Conference on the European Energy Market, EEM, Stockholm, Sweden, 16–18 September 2020; Art.Nr. 9221974. Available online: https://ieeexplore.ieee.org/document/9221974 (accessed on 20 May 2021).
3. Luca de Tena, D. Large Scale Renewable Power Integration with Electric Vehicles. In *Long Term Analysis for Germany with a Renewable Based Power Supply*; University of Stuttgart: Stuttgart, Germany, 2014.
4. Jochem, P.; Szimba, E.; Reuter-Oppermann, M. How many fast charging stations do we need for European highways? *Transp. Res. Part D* **2019**, *73*, 120–129. [CrossRef]
5. Wulff, N.; Steck, F.; Gils, H.C.; Hoyer-Klick, C.; Van den Adel, B.; Anderson, J.E. Comparing Power-System and User-Oriented Battery Electric Vehicle Charging Representation and Its Implications on Energy System Modeling. *Energies* **2020**, *13*, 1093. [CrossRef]
6. GitHub—RAMP-Project/RAMP-Mobility: A RAMP Application for Generating Bottom-Up Stochastic Electric Vehicles Load Profiles. Available online: https://github.com/RAMP-project/RAMP-mobility (accessed on 23 April 2021).
7. Mangipinto, A.; Lombardi, F.; Sanvito, F.D.; Quoilin, S.; Pavičević, M.; Colombo, E. RAMP-Mobility: Time series of electric vehicle consumption and charging strategies for all European countries, in preparation.
8. GitLab—DIW EVU/Emobpy/Emobpy. Available online: https://gitlab.com/diw-evu/emobpy/emobpy (accessed on 23 April 2021).
9. Gaete-Morales, C.; Kramer, H.; Schill, W.P.; Zerrahn, A. An open tool for creating battery-electric vehicle time series from empirical data—Emobpy. *Sci. Data* **2021**, *8*, 152. [CrossRef] [PubMed]
10. Fischer, D.; Harbrecht, A.; Surmann, A.; McKenna, R. Electric vehicles' impacts on residential electric local profiles—A stochastic modelling approach considering socio-economic, behavioural and spatial factors. *Appl. Energy* **2019**, *233–234*, 644–658. [CrossRef]
11. Gnann, T.; Klingler, A.-L.; Kühnbach, M. The load shift potential of plug-in electric vehicles with different amounts of charging infrastructure. *J. Power Sources* **2018**, *390*, 20–29. [CrossRef]
12. Ried, S. *Gesteuertes Laden von Elektrofahrzeugen in Verteilnetzen mit hoher Einspeisung Erneuerbarer Energien. Ein Beitrag zur Kopplung von Elektrizitäts- und Verkehrssektor*; Karlsruher Instituts für Technologie (KIT): Karlsruhe, Germany, 2021.
13. Von Bonin, M. (Fraunhofer IEE, Kassel, Hesse, Germany). Personal communication, 2021.
14. Babrowski, S.; Jochem, P.; Fichtner, W. Electricity storage systems in the future German energy sector An optimization of the German electricity generation system until 2040 considering grid restrictions. *Comput. Oper. Res.* **2016**, *66*, 228–240. [CrossRef]
15. Luca de Tena, D.; Pregger, T. Impact of electric vehicles on a future renewable energy- based power system in Europe with a focus on Germany. *Int. J. Energy Res.* **2018**, *42*, 2670–2685. [CrossRef]
16. DLR / GitLab—VencoPy Code Repository. Available online: https://gitlab.com/dlr-ve/vencopy (accessed on 21 May 2021).
17. Infas, DLR, IVT and Infas 360: Mobilität in Deutschland —MiD. Ergebnisbericht. Available online: http://www.mobilitaet-in-deutschland.de/pdf/MiD2017_Ergebnisbericht.pdf (accessed on 13 April 2021).
18. Nobis, C.; Kuhnimhof, T.; Follmer, R.; Bäumer, M. Mobilität in Deutschland—Zeitreihenbericht 2002–2008–2017. Study by infas, DLR, IVT und infas 360 on behalf of the German Minister for Transportation and Digital Infrastructure (FE-Nr. 70.904/15). Bonn, Berlin. Available online: http://www.mobilitaet-in-deutschland.de/pdf/MiD2017_Zeitreihenbericht_2002_2008_2017.pdf (accessed on 23 April 2021).
19. Howells, M.; Rogner, H.; Strachan, N.; Heaps, C.; Huntington, H.; Kypreos, S.; Hughes, A.; Silveira, S.; DeCarolis, J.; Bazillian, M.; et al. OSeMOSYS: The Open Source Energy Modeling System. An introduction to its ethos, structure and development. *Energy Policy* **2011**, *39*, 5850–5870. [CrossRef]
20. Infas, DLR, IVT and Infas 360: Mobilität in Deutschland—MiD. Ergebnisbericht. Struktur—Aufkommen—Emissionen—Trends. Available online: http://www.mobilitaet-in-deutschland.de/pdf/infas_MiD2008_Abschlussbericht_I.pdf (accessed on 21 May 2021).
21. Nobis, C.; Köhler, K. Mobilität in Deutschland—MiD Nutzerhandbuch. Study by Infas, DLR, IVT und infas 360 on behalf of the German Minister for Transportation and Digital Infrastructure (FE-Nr. 70.904/15). Bonn, Berlin. Available online: http://www.mobilitaet-in-deutschland.de/pdf/MiD2017_Nutzerhandbuch.pdf (accessed on 23 April 2021).

22. Eggs, J.; Follmer, R.; Gruschwitz, D.; Nobis, C; Bäumer, M; Pfeiffer, M. Mobilität in Deutschland—MiD Methodenbericht. Study by Infas, DLR, IVT und Infas 360 on behalf of the German Minister for Transportation and Digital Infrastructure (FE-Nr. 70.904/15). Bonn, Berlin. Available online: http://www.mobilitaet-in-deutschland.de/pdf/MiD2017_Methodenbericht.pdf (accessed on 23 April 2021).
23. Heinz, D. Erstellung und Auswertung Repräsentativer Mobilitäts- und Ladeprofile für Elektrofahrzeuge in Deutschland. Bachelor of Science, Karlsruhe Institute of Technology, 16.04.2018. Available online: https://publikationen.bibliothek.kit.edu/1000086372/18281493 (accessed on 17 May 2021).
24. Schaeuble, J.; Kaschub, T.; Ensslen, A.; Jochem, P.; Fichtner, W. Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany. *J. Clean. Prod.* **2017**, *150*, 253–266. [CrossRef]
25. Flammini, M.G.; Prettico, G.; Julea, A.; Fulli, G.; Mazza, A.; Chicco, G. Statistical characterisation of the real transaction data gathered from electric vehicle charging stations *Electr. Power Syst. Res.* **2019**, *166*, 136–150. [CrossRef]

B.2. Paper II - Comparing Power-System and User-Oriented Battery Electric Vehicle Charging Representation and Its Implications on Energy System Modeling

energies

MDPI

Article

Comparing Power-System and User-Oriented Battery Electric Vehicle Charging Representation and Its Implications on Energy System Modeling

Niklas Wulff [1,*], Felix Steck [2], Hans Christian Gils [1], Carsten Hoyer-Klick [1], Bent van den Adel [3] and John E. Anderson [2]

1 Department of Energy Systems Analysis, Institute of Engineering Thermodynamics, German Aerospace Center, Pfaffenwaldring 38-40, 70569 Stuttgart, Germany; hans-christian.gils@dlr.de (H.C.G.); carsten.hoyer-klick@dlr.de (C.H.-K.)

2 Department of Passenger Transport, Institute of Transport Research, German Aerospace Center, Rudower Chaussee 7, 12489 Berlin, Germany; felix.steck@dlr.de (F.S.); john.anderson@dlr.de (J.E.A.)

3 Department of Vehicle Systems and Technology Assessment, Institute of Vehicle Concepts, German Aerospace Center, Pfaffenwaldring 38-40, 70569 Stuttgart, Germany; bentvdadel@googlemail.com

* Correspondence: niklas.wulff@dlr.de

Received: 18 January 2020; Accepted: 26 February 2020; Published: 2 March 2020



Abstract: Battery electric vehicles (BEV) provide an opportunity to balance supply and demand in future power systems with high shares of fluctuating renewable energy. Compared to other storage systems such as pumped-storage hydroelectricity, electric vehicle energy demand is highly dependent on charging and connection choices of vehicle users. We present a model framework of a utility-based stock and flow model, a utility-based microsimulation of charging decisions, and an energy system model including respective interfaces to assess how the representation of battery electric vehicle charging affects energy system optimization results. We then apply the framework to a scenario study for controlled charging of nine million electric vehicles in Germany in 2030. Assuming a respective fleet power demand of 27 TWh, we analyze the difference between power-system-based and vehicle user-based charging decisions in two respective scenarios. Our results show that taking into account vehicle users' charging and connection decisions significantly decreases the load shifting potential of controlled charging. The analysis of marginal values of equations and variables of the optimization problem yields valuable insights on the importance of specific constraints and optimization variables. Assumptions on fleet battery availability and a detailed representation of fast charging are found to have a strong impact on wind curtailment, renewable energy feed-in, and required gas power plant flexibility. A representation of fleet connection to the grid in high temporal detail is less important. Peak load can be reduced by 5% and 3% in both scenarios, respectively. Shifted load is robust across sensitivity analyses while other model results such as curtailment are more sensitive to factors such as underlying data years. Analyzing the importance of increased BEV fleet battery availability for power systems with different weather and electricity demand characteristics should be further scrutinized.

Keywords: electric vehicles; sector coupling; energy system optimization; renewable energy integration; REMix; charging behavior; marginal values

1. Introduction

1.1. Motivation

The Paris Agreement calls for a nearly carbon-neutral global energy and transport system by 2050 [1]. Furthermore, the European Commission announced that Europe will be climate-neutral

by 2050 [2]. In Germany, the transformation of the power system is well underway; however, the transition to a greenhouse gas (GHG) emission free transport system is far behind [3]. In order to achieve transport GHG emission goals, electric vehicles (EVs) are seen as a potential solution when combined with renewable energy sources (RES) [4]. This in turn requires a new integration of the energy and transport sectors.

Integrating the energy and transport sectors requires an alignment of power demand from EVs and power supply from fluctuating RES. In order to address this challenge, increasing flexibility of the power system is necessary to ensure demand is always met [5]. Measures to increase power system flexibility include an expansion of battery storage and sector coupling [6]. Sector coupling allows for the shifting of energy from different sectors such as heating or transport. Designing sector coupling requires a detailed analysis of the interactions and dependencies between the sectors.

Sector coupling in general and EVs in particular will create an additional load on the power system. At the same time, EVs often contain oversized batteries and offer an option for added flexibility in the energy system, assuming they can flexibly charge in contrast to uncontrolled charging [7] (p. 4). Daily demand patterns depend on individual transport demand, charging behavior, infrastructure availability, and differences between working day and weekend travel. Consequently, charging behavior will influence EVs' role in the electricity system. This serves as the motivation for developing an integrated user behavior focused modeling approach for the interactions between future EV fleets and the energy system.

1.2. Literature Review

In this section, we present a selection of literature related to the potential of integrating EVs in power systems within energy system optimization modeling and more transport related research assessing driving factors for demand patterns, charging dynamics, users' acceptance for controlled charging, and connection choices of EV users.

Integrating endogenous vehicle market development modeling into energy system modeling has been demonstrated by [8] for the case of the COCHIN-TIMES model for different drive-train technologies.

Transportation research has carried out various research to better understand EV charging related phenomena. The acceptance of utility controlled charging and its respective factors have been assessed for 1470 plug-in EV buyers in Canada [9]. The authors find general acceptance for utility controlled charging among one-half to two-thirds of the respondents interested in buying a plug-in hybrid electric vehicle. Turning more to transportation demand-oriented driving factors for EV charging, Sun et al. show that state-of-charge (SOC), interval in days before the next trip, and vehicle-kilometers to be traveled on the next day are the main predictors for deciding to charge or not [10]. Fischer et al. complement this finding by also mentioning location and comfortable range as determinants of recharge decisions and charging characteristics [7].

Another strand of studies examines the build-up of EV charging infrastructure. Gnann et al. utilized empirical charging data in a queuing model to estimate future fast charging infrastructure requirements [11]. Chakraborty et al. examine the influence of electricity costs on charging behavior and thereby on infrastructure needs [12]. Tian et al. similarly use analysis of charging behavior to optimize the location of charging stations in China [13]. As a final example, Hardman et al. conduct a review of charging preferences in relation to the build-up charging infrastructure [14]. Thus the main focus of charging behavior models and investigations has been on determining charging infrastructure to support the uptake of EVs.

Steck et al. simulate charging behavior of EV users to determine potential emission reductions from shifting charging events [15]. Taking into account user preferences and user specific alternatives, their results show that charging demand can be shifted away from demand peaks due to the price sensitivity of EV users. Schuller shows the impact of controlled charging on RES utilization for EVs. He describes a concentrating effect of charging events when decisions are taken based on power prices [16].

Energy system modeling has been incorporating partly flexible electricity demand by EVs in their models for some time. Brown et al. (2018) describe an over proportionally high increase in system cost with uncontrollable electricity demand from the transport sector. Controlling charging times of battery electric vehicles (BEVs) is described to provide a PV-integrating effect, reducing total system cost by 10% when 25% of the fleet is flexible for a study of the European power system with 95% GHG reduction targets for 2030 [4].

Michaelis et al. assess the role of controlled charging for the German power system in 2030 utilizing the models ALADIN and eLoad taking into account commercial and public charging stations. They reproduce the finding of Schuller et al. (2013) that price-based charging leads to a load concentration around noon in summer and a night and a day peak in winter. They find a 1.8 TWh reduction of RES curtailment and up to 2.2 GW reduction of peak load by controlled charging [17]. However, charging power is limited to a conservative value of 3.7 kW per vehicle. Furthermore, the power system setup is not described so results are hard to compare and the authors call for an assessment of different flexibility options.

Luca de Tena & Pregger assume an additional power demand of 49 TWh/a for EVs in Germany for 2050. In their analysis, system losses are reduced by 1.4 TWh/a in 2030 in the base scenario. Residual peak demand can be reduced by 1.2 GW in 2030 [18].

Gerhardt et al. assume German transport sector's power demand in 2050 amounting to approximately 120 TWh including light duty vehicles. They assume the vehicle fleet is comprised of 20% BEVs and 40% plug-in hybrid and range extended EVs. RES curtailment is reduced from 12.2 TWh to 10.7 TWh [19].

Taljegaard et al. assess implications of future BEV fleets on power system investments up to 2050 and on power system operation in 2030 for a geographical scope of Scandinavia and Germany. They find that the increase in needed power plant capacities for fulfilling increased electricity demand for the BEV fleet is lower than the increase in annual power demand through increased utilization rates of wind power (2–4%), thermal power plants, and grid interconnectors (increase of 10%), at the same time implying decreased cycling of thermal power plants. Furthermore, a potential EV fleet may decrease necessary peak power capacity by 13–15 GW by smoothing the net load curve reducing peak net load by 7 GW from 120 to 113 GW. Investments for solar power are drastically reduced by 22–42% due to PV feed-in competing with vehicle-to-grid feed-in in midday peak hours. Taking into account only the optimization of charging hours without feeding back to the grid, electricity costs from operation lies in the same order of electricity costs without optimization with slightly lower costs for an assumed 60% BEV fleet and slightly higher costs for a 100% BEV fleet [20].

Both strands of research, energy system analysis and transport research, provide valuable insights. However, the research fields of energy system analysis and transport research have been carried out in a fairly distinct manner, formulating the interest of each field's research to the other. So far, this gap has not been bridged to integrate BEV users' preferences in energy system analytical frameworks. At the same time, energy system model studies are hard to compare since model experiments cannot be reproduced, model scopes vary among the studies and energy system model sensitivities to different aspects of BEV charging has not been assessed in-depth.

Robinius et al. formalize the concept of sector coupling [6] and the challenge of describing different parts of both power and transport systems in adequate detail. They suggest an open model environment where sector and technology specific calculations are carried out in sub-models and interfaced with each other [21]. This approach is adopted in our paper. We use the two terms 'energy system' and 'power system'—differentiating power plants, stationary storage, grids, and power demand (power system) from power demand in the transportation sector (which is part of the energy system).

This paper contributes to the existing literature by providing a first step towards bridging the gap between detailed transport modeling tools and energy system optimization models. By comparing power-system-based and vehicle user-based charging decisions, we identify the most crucial aspects

that deserve high analytical detail when representing EV fleets as a potential load shifting option in power systems with high shares of fluctuating renewable energies.

1.3. Scope of This Work

Despite the fact that the flexibility related to the controlled charging of EVs is regarded as potentially highly relevant to the integration of fluctuating RES power generation, the role of EV user behavior, as well as a detailed modeling of charging infrastructure, has received relatively little attention in energy system modeling literature. We address this gap in the literature by specifically analyzing the limitations of charging flexibility related to individual decisions on when, where, and to what degree vehicles are charged. Furthermore, we evaluate the impact of representing these decisions on energy system optimization models results. By combining four models focused on vehicle buyers' decision making, BEV charging behavior, and the energy system, we answer the following research question:

How are energy system optimization modeling results affected by representing BEV charging based on a power-system oriented perspective vs. a more user-oriented perspective?

We assess this question with regard to annual energy system results such as annual curtailment, added capacities etc. (Section 3.2.1), cost-optimal charging of EV fleets (Section 3.2.2), show explanatory insights (Section 3.2.3), and test respective sensitivities (Section 3.3).

The paper is organized as follows. Section 2 gives a brief introduction into representing vehicle buyers' and EV users' decisions, as well as energy system modeling, how we interface the approaches, and the scope and boundary assumptions of our scenario study. In Section 3, we describe similarities and differences in the results of the two modeling approaches, and then explain and discuss them. In Section 4, we summarize our work and identify potential areas for future research.

2. Methodology

In the following, we describe the methodological framework for model coupling and give an overview on each model. This includes the model structure, implicit modeling assumptions, and the parametrization of the models. The four models are VECTOR21, VencoPy, CURRENT, and REMix. The models stem from both energy system analysis and transport research. We apply a stock-and-flow model, VECTOR21, to model technology diffusion as well as regional differentiation of vehicle fleets serving as harmonized boundary conditions for further analyses. Individual mobility demand, EV charging, and respective power system flexibility are represented by two tools. VencoPy is a data preparation tool that was developed for the application in the REMix analysis framework [22] and calculates maximum flexibility of a hypothetical fleet based on real German travel data. In a more detailed manner, CURRENT simulates charging decisions of each EV user depending on locational preferences, infrastructure availability, and the users' knowledge of their future trips. Both tools are based on the German travel survey from 2008 (MiD) [23]. The energy system is represented by the linear optimization model (REMix) comprising competing power system flexibility technologies including sector coupling [24]. The BEV fleet charging models and the energy system model are interfaced via five BEV fleet flexibility profiles. What they represent is described in the subsection describing BEV charging modeling while their form and function for the energy system is described in the subsection thereafter.

A baseline scenario (S0) acts as a reference and models the power system without additional demand and flexibility from an EV fleet. We then describe the model coupling framework and its application for two scenarios. In the first scenario (S1), the EV load shifting potential is calculated by VencoPy with the assumption that the fleet batteries are highly controllable by the power system. In the second scenario (S2), CURRENT simulates EV load-shifting potential with increased detail on user charging behavior, infrastructure, and variability of mobility between weekdays. Boundary conditions on technology, EV fleet, and transportation demand have been harmonized in both scenarios for comparability. Figure 1 provides an overview of the four models, their application in the scenario

study, the presentation of results, and the respective sections of this paper. The flexibility profiles (Section 2.2) are the only difference between S1 and S2. Both sets of flexibility profiles are model inputs for REMix and model outputs of VencoPy (S1) and CURRENT (S2). Due to their pivotal function for further analysis, they are described in Section 3.1.

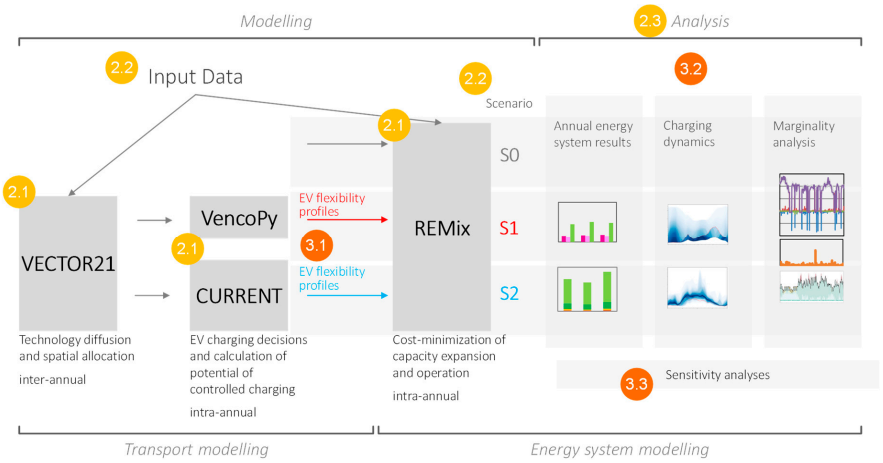


Figure 1. Overview of the four models used in the analysis (VECTOR21, VencoPy, CURRENT, and REMix), data flow, and paper structure. The numbers refer to the section of the paper where the item is discussed.

2.1. Model Descriptions

2.1.1. Vehicle Fleet Model (VECTOR21)

The model VECTOR21 (Vehicle Technologies Scenario Model) is a hybrid of an agent based and discrete choice market penetration model that assesses the competition between different powertrain alternatives. It simulates future passenger vehicles' market shares of powertrain technologies under effects of changing political and technological conditions in an annual resolution. The basis of the simulation is the customer purchase decision. Therefore, different customer profiles (agents) choose a powertrain with the highest perceived value in a predefined framework such as regional policies or energy prices. To calculate each utility, five unique customer preferences are been identified: purchase price, operating cost, range, CO_2-emissions, and maximum vehicle acceleration [25]. To take into account current market phenomena we implement boundaries for range anxiety, as well as the lack of charging infrastructure availability.

The model also incorporates various drivetrain technologies in three size segments (i.e., small, medium, large). In particular, the model differs between pure conventional internal combustion engines and minor electrification internal combustion engines both for diesel and gasoline. In addition, there are alternatives such as plug-in hybrid electric vehicle, battery electric vehicle, fuel cell electric vehicle, and combustion engine with compressed natural gas. Furthermore, VECTOR21 covers aspects like manufacturer strategies to comply with CO_2 regulations and the regulation's influence on the vehicle stock. Throughout the simulated year, customer purchase decisions affect the prices for new components (i.e., lithium-ion batteries, fuel cell systems) with a learning curve model.

In the second step, all new passenger vehicles are transferred into the stock model. The future evolution of a vehicle fleet is modeled based on segment specific survival rates [26]. The survival rate depends on the vehicle age and vehicle miles thus far traveled. As a result, the model offers analysis on a ZIP-code level to see stock alteration.

For our study, the penetration of battery EVs calculated for the year 2030 by VECTOR21 is aggregated to the two model regions considered in REMix (i.e., Northern Germany and Southern Germany).

2.1.2. Electric Vehicle Charging Models (VencoPy, CURRENT)

User-optimal BEV charging strategies are not necessarily system-optimal strategies [7]. Therefore, the consequence and differences of both approaches have to be considered in order to assess challenges and opportunities of high BEV-penetration scenarios and to draw conclusions on the detail of representing BEV charging for energy system optimization models.

In our paper, we compare two methods to simulate charging behavior of an electric fleet and then evaluate the influence of these different approaches on the energy system. First, we apply VencoPy (Vehicle Energy Consumption in Python), which is the original data preparation tool in the energy model REMix to simulate EVs and its load shifting potential in high temporal detail. VencoPy accounts for the electric demand of an electric fleet, but the charging decision and the average battery level of the fleet is determined by the power system. Second, we implement an existing transport model, CURRENT, which simulates charging behavior from a utility based approach, within the framework of REMix. This replaces the existing approach with VencoPy and accounts for detailed user behavior. We next present both models in detail. VencoPy does not directly calculate BEV charging but rather a best-case yielding high flexibility and a worst case yielding low flexibility for the energy system. Thus, when we talk about BEV charging in VencoPy's results, we mean charging in its two respective cases.

VencoPy calculates BEV flexibility profiles constraining fleet battery charging and discharging for controlled charging in hourly temporal resolution. Only home charging is assumed with vehicle segment-dependent power (small, medium, large, see Table 4). This approach is backed by empirical findings, showing a 72% of charging energy is from home charging [27]. Long-distance trips requiring fast charging events are excluded from the analysis. VencoPy calculates the hourly information of electric mileage, if a BEV is connected to the grid, and the maximum and minimum battery SOC possible to realize all travel demand. Demand data is taken from the trip dataset of the German travel survey for German household transportation demand (MiD) [23]. The maximum SOC level profile represents a case where BEVs always charge when possible with maximum SOC at beginning of the day, while the minimum battery level describes the opposite case of minimum SOC and only needed electricity for the next trips is charged before departure. A similar approach is described in e.g., [19]. Each vehicle profile is summed unweighted and normalized to a fleet profile for one day. The share of the BEV fleet that can shift its charging demand to conduct controlled charging is exogenously defined in REMix and used as a scaling factor for the normalized profiles (see next section).

CURRENT stands for "charging infrastructure for electric vehicles analysis tool" [28]. It is a microscopic charging demand tool for BEVs providing time and location-specific information about charging [15]. CURRENT gives information on the hourly electricity demand of an electric fleet over the course of a week and shows flexibility potential for controlled charging. The overview of the model is presented in Figure 2.

Two assumptions form the basis for CURRENT's calculations. First, BEV users do not significantly change their travel pattern. Second, users predominantly charge where they already park. These assumptions are consistent with other research [29,30] and the anticipated user behavior for a mass-market of EVs. For our case study, we use the 2008 German household travel survey (MiD) [23]. Next, we outline the workings of the model.

First, CURRENT takes the household travel dataset and creates 24-hour vehicle diaries with information for all trips and parking events for one day. Specific information for each vehicle is added to model it as an electric vehicle (e.g., electric range, charging power capacity). We then define the availability of charging infrastructure at different locations (e.g., home, work, shopping), available charging power, and a minimum parking time for a charging event. Using these assumptions and the vehicle diaries, every vehicle must run through the charging algorithm as a BEV. In the charging algorithm, every vehicle must complete every activity of the day (i.e., trip and parking event). Based on charging preferences and depending on charging opportunities during a day, a BEV is charged while parking or during a trip interruption at a fast charging station. At a fast charging event, a vehicle

is charged up to 80% of its battery capacity with an average charging power of 37.5 kW. This results in an aggregated charging demand per hour of the week and per location for an entire fleet of EVs.

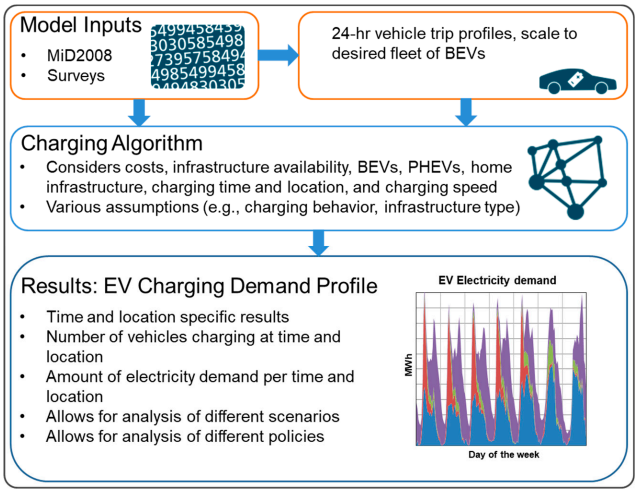


Figure 2. Overview of the transport model CURRENT (charging infrastructure for electric vehicles analysis tool).

A charging event occurs stochastically based on a multinomial logit approach. The model enables users to account for charging preferences in their decision algorithm. A utility-based approach gives the probability of charging at each activity of the day and also for interrupting the trip for a fast charging event. The utility function of each activity considers the preference of charging per location and price per kWh. The charging decision is made by a Monte Carlo simulation according to the charging probability at the charging point. In addition, the probability of finding available charging infrastructure differs for each location (i.e., home, work, shopping, leisure, other). For each household with a vehicle and a private parking spot at home, we assign a private charging infrastructure with a maximum charging power of 7.4 kW. When interrupting a trip for a fast charging event, the probability to find a fast charging station is 100 percent. Fast chargers have a maximum charging power of 50 kW. At all other locations normal charging infrastructure with a maximum charging power of 11.1 kW is assumed. Due to a lack of empirical information, we make assumptions on the probability of finding available charging infrastructure based on [28] and assigned the information for each parking event by a Monte-Carlo simulation.

As a vehicle user does not have to charge every day—the average German daily mileage of 40 kilometers is far below an electric range of a BEV—a non-choice opportunity of not charging the vehicle on the same day is included in the choice set of the charging decision in CURRENT. The non-choice opportunity gives a probability that a vehicle is not charged every day. By simulating every vehicle diary by several sequential runs, CURRENT can simulate charging events which do not occur daily. In the end, the utility based approach leads to charging events enabled by preferences for location, price, alternatives, and current SOC. These charging events do not occur every day and at every opportunity. The calibration of CURRENT aims to get the same average SOC for the fleet at the beginning and end of the week. Further detailed information on CURRENT, all assumptions, and the detailed algorithm are summarized in [15,28].

By using the 2008 German household travel survey (MiD) VencoPy and CURRENT use the same input data. The number of BEVs by segment and region differentiated for Northern Germany and Southern Germany are harmonized for both methods and based on the results of the aforementioned stock-and-flow model VECTOR21. Also, technological assumptions of BEVs such as battery capacity, consumption, and electric range are harmonized (see Section 2.2.1).

Both models differ in their degree of complexity regarding infrastructure, weekday differentiation, and users' preferences. In comparison to VencoPy, CURRENT calculations lead to fewer charging

events per day, but with the same amount of electric demand in total, and a lower number of vehicles connected to the grid because of BEV users charging and thus connecting their BEVs sufficiency-oriented in CURRENT. Also, fast charging during the trip generates a significant load due to the high charging power of each charging event and leads to high charging power during the day than in VencoPy yielding charging peaks during night hours. Fast charging events in CURRENT also give the energy system no potential to shift electricity demand, as charging time equals parking time. Since VencoPy only allows for charging at home nighttime charging is higher than during the day at other activities (i.e., work, during shopping). Allowing fast charging and charging apart from home in CURRENT, leads to more charging events during the day.

Deviating from VencoPy's interpretation of uncontrolled charging as connecting their EV after returning home, CURRENT's uncontrolled charging is a specific sub-part of the travel activities that require the BEV owner to recharge in order to reach sufficient SOC including fast-charging as an option of last resort. In CURRENT, minimum and maximum SOC levels of single profiles are determined via evaluating the charging time of an activity in comparison to the respective parking and thus connection time. Only if the latter is higher than necessary charging, minimum and maximum SOC profiles differ where maximum SOC represents direct charging after connection and minimum SOC the latest possible charging beginning. Thus, the power system has only little control over charging procedures under the condition of a user-oriented connection decision. This reduces the potential to shift charging demand as charging time is equal or almost equal to parking time during daytime and fast charging.

On a modeling level, a very relevant difference of the two models is their means of enforcing boundary conditions at the beginning and end of a day (VencoPy) and week (CURRENT). VencoPy assumes maximum and minimum SOC at beginning and end of a modelled day for SOC max and min respectively with a SOC security margin of 3% and secures meeting boundary conditions on each single profile basis, thus each profile and thus fleet has the same beginning and end SOC min and max. CURRENT on the other side calculates user specific SOCs for each profile under the assumption that the average BEV fleet SOC at beginning and end of the week is equal. Table 1 summarizes the main structural differences between BEV charging representation using VencoPy or CURRENT.

Table 1. Main differences between the BEV charging representation in VencoPy and CURRENT.

	VencoPy	**CURRENT**
Time horizon and weekday representation	1 day	7 days
BEV user representation	Demand has to be fulfilled	As in VencoPy plus temporal and activity based connection choice including non-choice option
Data and input assumptions	MiD 2008	MiD 2008
Infrastructure representation	Segment-specific rated power for home charging	Activity-specific rated power including fast-charging and availability probabilities
Boundary condition enforcement level	Single profile level	BEV fleet level

2.1.3. Energy System Optimization Model (REMix)

The main aim of REMix (renewable electricity mix) is to model future energy systems in high temporal and spatial resolution to adequately represent the influence of high shares of variable renewable energy sources. The model is composed of two sub models: the EnDat model for processing of input data and OptiMo to optimize the system design and operation. Figure 3 shows the main elements of the REMix model. One of the main pillars of REMix-EnDat is an inventory of renewable energy source data. It contains potentials of hourly renewable energy generation and maximum installable capacities. The model and its database are described in detail in [31]. The optimization model REMix-OptiMo relies on a linear optimization approach, which is formulated in the General Algebraic Modeling System (GAMS). The energy system is described in a system of linear equations and inequalities. The model optimizes both the hourly operation of the system during one year and the investment in additional capacities if needed to balance the energy demand. The objective function

to be minimized contains the variable operational costs of all considered assets, including fuel as well as optional CO_2 emission costs, and the annuities and fixed operational costs of all endogenously added capacities.

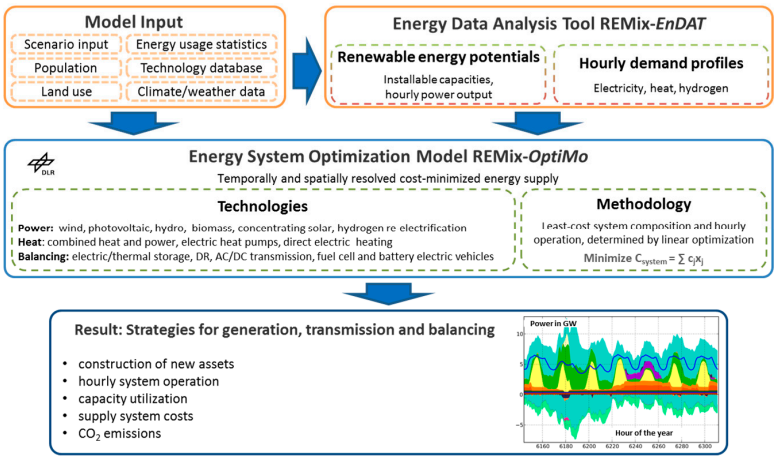


Figure 3. Overview of the REMix model for energy system optimization. Source: [32].

REMix-OptiMo is a multi-node model, which implies that power generation, demand, and transmission are aggregated to predefined regional model nodes. The most important boundary condition is the power balance, which assures that power demand and supply are equal in each time step and model region. Power generation, storage, and grid technologies are represented by their cost, efficiency, availability, and maximum installable capacity. A detailed description of the general modeling approach and fundamental equations can be found in [33]. Building upon the basic model setup introduced there, REMix-OptiMo has been continuously enhanced in its scope to not only include the power sector, but also the most relevant links to the heating and transport sectors as described in [34].

The representation of EVs was originally developed within [22] and has been developed further for this work. Due to REMix' modular structure, the sets, variables, parameters, and equations of the module representing BEVs can easily be activated or deactivated for the optimization model of minimizing the overall system cost.

In order to represent load shifting, REMix-OptiMo requires five hourly input profiles, defining optimization constraints for charging of BEV fleet batteries. These time series input profiles contain information as follows:

1. The power demand in the case of uncontrolled charging;
2. The electric power demand required to fulfill mobility demand;
3. A maximum fleet battery state-of-charge level (SOC Max);
4. A minimum fleet battery state-of-charge level (SOC Min);
5. The maximum rated power of the vehicle fleet connected to the grid;

More details are given in [22]. Profiles can either be given in normalized or absolute figures in units of GW and GWh. Scaling of normalized profiles to optimization input constraints is carried out in REMix's pre-calculation phase with additional assumptions on battery capacity, vehicle numbers, charging efficiencies, and BEV segment-specific rated connection power. Non-linear effects such as the degradation of batteries depending on cycling frequency cannot be accounted for within REMix.

In [22], Venco provided normalized profiles with battery capacity and vehicle consumption given as input parameters. These profiles were then scaled by regional technology specific vehicle numbers, battery sizes, and consumption rates in the data preparation stage of REMix. For S1, this approach is adopted with harmonized technical and fleet-size assumptions. For S2 on the other hand, scaling

from single-profile level to fleet level as well as infrastructure assumptions are endogenous parts of CURRENT calculations, thus the scaling step is skipped.

2.2. Linking the Models and Description of the Scenario Study

2.2.1. Linking the Models

Coupling the above described models requires a harmonization of dimensionality of the models, input assumptions, and at least a partial harmonization of the models' scopes. This requires parallel runs of the lower resolution model across the higher resolution model dimension, aggregating results of the higher resolution model or selecting a relevant subset of the high-resolution dimension. Additionally, data processing steps—such as normalization, scaling, and reformatting—are needed. Harmonizing the model scope is the most challenging harmonization technique since often model endogenous specifics have to be adjusted. Table 2 shows the model dimensionality and harmonization approaches for respective model dimensions.

Table 2. Model dimensionality and respective harmonization approaches.

Dimension	VECTOR21	REMix	CURRENT	Harmonization Approach
Spatial horizon	Germany	Germany plus neighboring countries	Germany	-
Spatial resolution	ZIP code areas	Germany in 2 nodes, others in 1 each	1 node	Aggregation of ZIP code areas to 2 nodes in Germany
Temporal horizon	2010–2050	1 year in 2030	7 days in 2030	Filtering for 2030, cloning CURRENT output for REMix
Temporal resolution	Annual	Hourly	Activity/hourly	No model harmonization between VECTOR21 and the other models, CURRENT-adaption to hourly output
Technological resolution	3 drivetrain technologies, 3 vehicle sizes	Transport: 6 technologies, Power: X technologies	1 technology	Filtering BEV, parallel CURRENT runs for each REMix-technology
Infrastructure resolution	Input to agent's preference	1 plug power value per transport technology	Probability distributions of plug power availability depending on places	No harmonization with VECTOR21, REMix-adaptation to be able to model CURRENT output

VECTOR21 model output is relevant for both REMix and CURRENT calculations, as it is taken as a quantitative input for estimating vehicle fleets of BEVs in Germany in 2030. Dimensionality mismatches are treated by either filtering or aggregation.

Cloning of CURRENT output is conducted to transfer the time horizon of a week to a full year for REMix, thereby neglecting effects of seasonal mobility behavior changes and holidays [35]. Filtering and separate runs are carried out for model regions. REMix models Germany and its neighboring countries, while surrounding countries are not relevant for modeling BEV charging decisions within Germany.

In the first scenario, S1, the BEV flexibility profiles are calculated based on the method described in [22] assuming that 94% of battery capacities of the BEV fleet are available to the power system as a battery storage. Thus, in extreme cases, each vehicle's battery is available as battery storage with hourly varying capacity, described by profiles 3 and 4 and charge power described by profile 5 (see Section 2.1.3). In scenario S2, BEV flexibility profiles are calculated based on a harmonized CURRENT run, taking into account agent's preferences with regard to charging location and the SOC.

2.2.2. Description of the Scenario Study

This section summarizes the main structural and quantitative model assumptions for our case study of a hypothetical German power system in 2030 including its neighboring countries. We start by describing the model scope and continue to present the main assumptions on the EV fleet and its power demand as well as techno-economic assumptions. The REMix parametrization builds upon assumptions and data given in [36].

We apply a model setup with two model regions for Germany (North and South) and its neighboring countries (i.e., Austria, Belgium, the Czech Republic, Denmark, France, Luxembourg, the

Netherlands, Norway, Poland, Sweden, and Switzerland). The division into Northern Germany and Southern Germany is done to analyze the impact of the different renewable power plant portfolios. Southern Germany is dominated by wind power with approximately twice as high wind than PV installations while this relationship is inversed in Southern Germany with PV fluctuating in diurnal day and night patterns. Total fluctuating RES capacities before optimization are more than three times higher in Northern Germany compared to Southern Germany. The division of Germany is based on 21 sub-control zones of the four German transmission system operators (TSOs) [37]. Since our focus lies on differences in representation of a hypothetical EV fleet and their respective impacts on power system modeling, the German neighboring countries are taken as constant boundary conditions, even though investments in power plants and storage are allowed. Grid transmission capacities are based on [38,39]. Power system dispatch is cost-optimized for the scenario year 2030 in hourly resolution and with perfect foresight over the overall time horizon. Fluctuating RES time series are taken on the basis of calculations in [24,31,40].

We implement five conventional power plant technologies, six renewable energy technologies, as well as three storage and one transmission grid technologies as shown in Table 3. Technology expansion is optimized in a brownfield approach based on existing capacities with the option to invest in a technology expansion to meet the power demand. Power demand from other sectors is considered only with regard to passenger BEVs.

Table 3. Technology resolution of power plant, grid, storage, and EV technologies in REMix. Rows are not related to each other.

Power Plant Technologies		Grid Technologies	Storage Technologies	Electric Vehicle Technologies
Fluctuating renewable energies	Photovoltaic, wind onshore, wind offshore, run-of-the-river hydro	HVDC	Stationary lithium-ion batteries	Small BEVs
Controllable renewable energies	Reservoir hydro dam power		Pumped hydro storage	Medium BEVs
Thermal power plants	Hard coal steam turbine, lignite steam turbine, natural gas combined cycle gas turbine, natural gas gas turbine		Hydrogen underground caverns	Large BEVs

The annual electricity demand data are taken from the European Network of Transmission System Operators (ENTSO-E). Values are disaggregated by German ENTSO-E profiles to yield hourly time series of electricity demand in order to account for the difference between weekend and weekday electric demand which is taken into account for BEV flexibility profiles in S2 as well.

In the following, we describe the quantitative basis for modeling the power system flexibility of a future EV fleet. For scenarios S0 and S1, the annual power demand from the BEV fleet has to be explicitly given and scaled in the pre-processing phases of REMix, while for scenario S2 the total EV fleet power demand is an implicit result of CURRENT. Thus, S0 and S1 input assumptions have to be harmonized in order to assure comparability across all scenario calculations. Results of the harmonization are shown in the fourth column in Table 5.

Technical assumptions that are constant for all model regions for scenario S1 are shown in Table 4. Battery capacity assumptions are compared to historic values, ranges given in the IEA EV Outlook 2018, and to literature assumptions on prospective values in Figure A2.

We assume that two-thirds of the vehicles can be charged by controlled charging following an upper-bound assumption from [9], limiting the flexible charging demand to approximately 18 TWh/a. A REMix-endogenous model decision regarding the investment enabling controlled BEV charging is not considered as we are foremost interested in intra-annual implications of user behavior and increased detail of representing infrastructure. A harmonization of BEV fleet shifting capabilities will be presented in a sensitivity analysis.

Table 4. Technology assumptions for EVs for scenario S1 and respective degree of harmonization with scenario S2 input assumptions. Battery capacity values are assumed based on a comparison of historic battery sizes and literature projections from [18,20,28,41,42].

Name		Unit	Value	Degree of Harmonization
Battery capacity (gross)	BEV-S	kWh	40	harmonized
	BEV-M	kWh	70	
	BEV-L	kWh	100	
Charging capacity	BEV-S	kW	3.7	Not harmonized
	BEV-M	kW	7.4	
	BEV-L	kW	22	
Electric demand	BEV-S	kWh/km	0.15	harmonized
	BEV-M	kWh/km	0.20	
	BEV-L	kWh/km	0.25	
Share of controlled charging		%	67	Not harmonized
Efficiency of vehicle charging (plug to battery)		%	95	harmonized
Variable operation and maintenance costs of controlled charging		€/MWh	5	harmonized

Table 5 presents VECTOR21 results for the BEV vehicle fleet aggregated to REMix model nodes for 2030. For matching geographical boundaries data from [43] was used. With a cumulated BEV fleet of 8.8 million vehicles in 2030, we assume a stronger BEV adoption than the one given in the scenarios for the European 10-year network development plan of 2.6–5.4 million EVs for Germany [44].

Table 5. EV fleet spatially dependent parameters as aggregated results from VECTOR21 scenario.

Model Node	Vehicle Size	Number of Vehicles in Units of 1000 Vehicles	Annual Electric Demand in TWh/a
Northern Germany	BEV-S	414	1.31
	BEV-M	3365	10.68
	BEV-L	215	0.68
Southern Germany	BEV-S	492	1.52
	BEV-M	4078	12.61
	BEV-L	213	0.66
Sum	-	8777	27.47

In scenario S1, we assume two-thirds of the BEV fleet as flexible fleet battery that can be mostly charged controlled top-down by the power system needs within the given SOC min and SOC max profiles as described in Section 2.3. In S2, we describe the charging patterns and behavior-related decisions of representative agents and thus the BEV fleet only provides a load shifting potential at times where the parking duration exceeds the charging duration.

Charging connection power of size specific BEV fleets and the share of controllable charging procedures of the fleets are not harmonized between scenarios S1 and S2. Since CURRENT simulates both infrastructure availability and user preference to connect a respective vehicle to the grid at a given location, plug power, and the controlled charging share are both determined endogenously and resulting hourly week-profiles are cloned to the annual timescale and formatted taking into account weekday specificities for adjustment of BEV profiles to other sectors' electricity demand profiles.

2.3. Analytical Methods

We analyze the effects of differing BEV charging representation on annual energy system modeling results, on detailed sub-annual BEV charging characteristics and shed light on the changing role of the BEV fleet throughout the year by analyzing the marginal values of model equations and variables.

Since energy system optimization modeling results are sensitive to GHG ambitions, the underlying weather and demand data and techno-economic assumptions, we then calculate the same model setup with three additional degrees of GHG ambitions, six additional weather and electric demand years between 2006 and 2012, and two other sets of capital expenditures for fluctuating RES technologies. With this, we test the robustness of shifted energy and annual energy system results. In this section, we describe our methodological approach to analyze REMix model results.

REMix model results are partly transformed in its post-calculation phase, yielding .gdx files. These are again aggregated using a Python script, writing pivot-table data to excel files. For analysis, multiple result files are then combined in an analysis file giving tabular data with filtering, aggregation and different visualization methods. These files are used for the analysis of REMix results on an annual basis. Peak load and information about imports and exports are extracted individually from the .gdx files.

A separate evaluation framework is set up for the analysis of sub-annual BEV fleet charging characteristics. The calculation of shifted load is carried out in this framework since the shifted load is calculated slightly different in S1 and S2. In S1, the shifted power is calculated as shown in *powerShiftVP*

$$\text{shifted power (S1)} = \sum_{t=1}^{8760} R(t) - \Psi_{CC}(t) \qquad powerShiftVP$$

with $R(t)$ being the cumulative charged energy of the vehicle fleet in each hour in the case of uncontrolled charging and $\Psi_{CC}(t)$ being the real electric vehicle fleet charging energy. In S2, shifted power is calculated taking into account two of the BEV flexibility profiles, uncontrolled charging, and the maximum battery SOC

$$\text{shifted power (S2)} = \sum_{t=1}^{8760} [(C_{unc}(t) + \mathrm{L}_{max}(t) - \mathrm{L}_{max}(t-1)) - \Psi_{CC}(t)] \qquad powerShiftCU$$

with:

C_{unc}: Uncontrolled charging (battery inflow) of BEV fleet;
Ψ_{CC}/Ψ_{V2G}: Controlled charging of BEV fleet battery in the case of only controlled charging (CC) or with the option to feed electricity back to the grid (V2G);
Φ_{V2G}: Electricity fed-back to the grid from the fleet battery;
P_{drive}: Exogenously given electricity demand for driving in each hour;
$\Lambda(t)$: Battery level in hour t.

In linear optimization, results comprise not only the value of variables at the optimal solution, but also the value of marginal changes of variables and constraints. These values are referred to as marginal values of variables and marginal values of equations (equalities and inequalities). Generally, the marginal value of an inequality is only unequal 0 if the formulated constraint is bounded, for example if the SOC is at its maximum level. Equalities are transformed to two inequalities, thus equalities are always bounded.

Marginal values of variables and equations are shortly described using the battery level balance equation in REMix where Latin letters describe exogenous parameters and Greek letters optimization variables. For clarity, the parameters' and variables' dependency on the model region and the vehicle segment are ignored. The equation *batLevBal* is

$$C_{unc}(t) + \Psi_{CC}(t) + \Psi_{V2G}(t) - \Phi_{V2G}(t) - P_{drive}(t) = \Lambda(t) - \Lambda(t-1) \qquad batLevBal$$

The battery level constraints limiting the SOC of the BEV fleet are given by the equations *maxBatLev* and *minBatLev*

$$\Lambda(t) \leq L_{max}(t) \qquad maxBatLev$$

$$\Lambda(t) \geq L_{min}(t) \qquad minBatLev$$

Finally, controlled charging must not be higher than the currently connected charging power of the EV fleet given by the equation *maxCC*

$$\frac{\Psi_{CC}(t)}{\eta_{GtV}} \leq P_{charge,\,avail}(t) \qquad maxCC$$

with

η_{GtV}: Charging efficiency between the grid and the vehicle battery.

Each equation has a marginal value in the solution for each hour corresponding to the increase of total system cost if the sum of all non-variable terms is increased by 1 unit in the respective unit of the equation. For the *maxBatLev* equation this implies increasing $L_{max}(t)$. by 1 GWh and for *batLevBal* increasing $P_{drive}(t) - C_{unc}(t)$ by 1 GW, respectively.

Since there are only two variables for each hour, namely the battery level and the amount of controlled charging, the marginal values of the equations are tightly coupled to each other. When the EV fleet battery SOC is not bounded, the marginal of the battery level balance equation has the value of the last time that it was constrained minus the marginal value of either the *maxBatLev* or the *minBatLev* equation if it was at upper or lower bound respectively. Since *maxBatLev* marginal are always negative and *minBatLev* marginal always negative, the marginal value of the *batLevBal* equation increases by the negative value of the marginal of *maxBatLev* and continues on this level until the SOC reaches another constraint.

3. Results and Discussion

We now present the scenario study results as per Figure 1 and described in the previous sections. We start with an introductory quantitative and qualitative description of the differences between scenarios S1 and S2 (Section 3.1). Specifically, we examine the amplitudes and temporal distributions of the five EV flexibility profiles introduced and described in Sections 2.1.2 and 2.1.3. We exemplify the profiles and identify three major and three minor differences in the two approaches of representing EV charging dynamics and constraints. Building on this, we describe the results of the scenario study on an annual scale compared to benchmark scenarios (Section 3.2.1) and differences in intra-annual EV charging characteristics between S1 and S2 (Section 3.2.2). We then present an analysis of the marginal values of the main equations and variables of the BEV module in REMix, providing deeper explanatory insights into the specific importance of different model details. Section 3.3 assesses the sensitivity of the insights with regard to GHG reduction ambitions, historic weather and load years, and assumed techno-economic parameters of power-plant technologies.

3.1. Comparison of BEV Flexibility Profiles (Intermediary Results)

As a basis for comparison, scenario S0 calculates benchmarking values without additional power demand and load-shifting flexibility from BEVs. The consecutive scenarios S1 and S2 assume a penetration of 8.8 million BEVs in Germany, implying an additional annual power demand of around 29 TWh including 5% electricity losses during charging procedures increasing the electricity demand given in Table 5.

Table 6 provides an overview on quantitative implications of the two different methods of modeling BEV charging characteristics aggregated for Northern Germany and Southern Germany, as well as for all vehicle sizes. The hourly load shifting potential range describes the difference between the minimum and maximum BEV fleet SOCs in a specific hour. It is significantly reduced in S2. Explicitly

modeling a non-choice and a fast-charging option leads to a reduction of the fleet connection share of the BEV fleet from a range between 33–59 GW in S1 to 3–8 GW in S2. The share of uncontrolled charging is an exogenous assumption in scenario S1, while it is a result of CURRENT's microsimulation in scenario S2.

Table 6. Summary of fleet power demand flexibility characteristics in the three scenarios considered (S0, S1, and S2). Cumulative power demand includes losses during charging. SOC range gives the minimum and maximum difference between SOC max and SOC min. Fleet connection share includes uncontrollably charging BEVs. For SOC and fleet connection ranges, VencoPy daily minimum and maximum hours, for CURRENT weekly minimum and maximum hours are used.

EV Charging Model (Scenario)	Cumulative Power Demand from BEV Fleet in TWh/a	SOC Range Available to Power System Load-Shifting in GWh	Fleet Connection Share Range in GW	Share of Uncontrolled Charging in %
- (S0)	0	0	0	-
VencoPy (S1)	29	272–419	33–59	33%
CURRENT (S2)	29	5–10	3–8	70%

The following Table 7 systematizes the above described structural differences in BEV charging modeling.

Table 7. Structural differences in BEV charging representation between VencoPy and CURRENT. Shown are structural differences in the models VencoPy and CURRENT.

	Number	Representation Detail	Quantitative Effect on BEV Flexibility Profiles
Major structural differences	1	Weekly boundary conditions for BEV fleet SOC	Reducing available aggregated BEV fleet battery capacity for load shifting from minimum 272 GWh to maximum 10 GWh
	2	Taking into account users' sufficiency-oriented charge connection	Reducing grid connection of BEVs from 33 GW min to 8 GW max
	3	Including fast-charging	Reduction of controllable charging by 16.2 TWh/a
Minor structural differences	4	Possibility to charge at other locations than home	Shifts charging availability from night to daytimes
	5	Accounting for non-availability of private home charging infrastructure	Reduction of total charging availability and shifting charging to daytime
	6	Accounting for weekday-specific travel patterns	Effects on all profiles (see text)

Including fast charging in CURRENT in comparison to VencoPy leads to an increase in uncontrolled charging since charging time is always as long as parking time for fast charging. The additional degrees of detail that were added to the simulation in CURRENT are other charging locations such as work and shopping, more realistic probabilities of availability of home charging infrastructure, as well as a differentiation between weekday-specific travel patterns. The expansion of time horizon from one model day in VencoPy to a week in CURRENT affects all profiles. Uncontrolled charging and grid connection are shifted to later times in the day during weekends. BEV owners drive more during the day and less during the morning and evening, which shifts electric demand to daytime hours. Load shifting potential increases during daytime hours on the weekend due to more BEVs being parked at home and available for load-shifting. EV flexibility profiles are depicted in Figure 4 for S1 and S2.

Constraining BEV fleet SOC profiles are shown in Figure 4A. There is a significant reduction in BEV fleet battery capacity available to the power system for load shifting from 270–420 GWh in S1 to 5–10 GWh in S2. This reduction is mainly explained by the first major effect of different boundary condition enforcement and aggregation procedures in VencoPy and CURRENT (see Section 2.1.2 and Table 7).

In Figure 4B, the influence of effects 3, 4, and 5 can be seen. Uncontrolled charging is shifted to daytime hours through fast charging and other charging locations and a probability that no charging option is available at home. Additionally, the influence of working day and weekend transportation demand is shown in the CURRENT profiles resulting in a 2:00 p.m. peak on Saturdays while

uncontrolled charging reaches a slightly-decreasing plateau between 8:00 a.m. and 7:00 p.m. on working days.

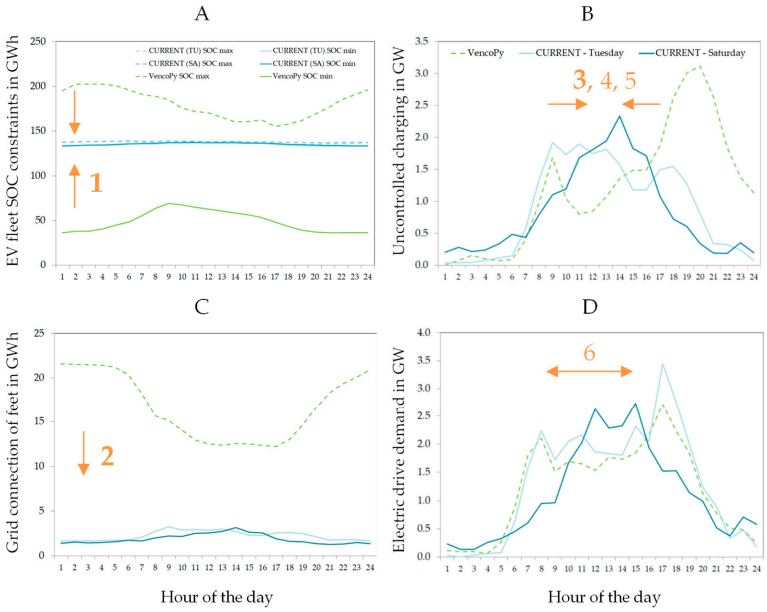


Figure 4. EV profiles for the case of a power system-oriented charging approach (VencoPy, green lines) and a user-behavior-oriented charging approach (CURRENT, turquoise lines) for the case of medium-sized BEV in Northern Germany. Arrows and numbers illustrate the effects of structural differences given in Table 7. CURRENT profiles are given for a working day (TU: Tuesday, light turquoise) and a weekend day (SA: Saturday, darker turquoise). (**A**) SOC min and max profiles. Dashed lines give maximum SOC and solid lines minimum SOC. (**B**) Uncontrolled charging profiles. Legend relates to plots B–D. (**C**) Fleet connection share profiles. (**D**) Profiles for the electricity demand for driving.

The difference in charge connection profiles shown in Figure 4C originates from two causes. VencoPy assumes, that only home charging is allowed, but that BEV users connect their vehicles as soon as they arrive home with the rated connection capacities given in Table 4. This leads to a high fleet charge availability during night hours and an approximately 50% fleet charge availability from ~10:00 a.m.–6:00 p.m. when users start returning home. In CURRENT on the other hand, BEV users only connect their vehicle when it is required by their respective trip purposes, thus adjusting their grid connection to their respective mobility needs. This explains the overall lower fleet connection share. The reversed course of the graphs in Figure 4C is due to a more detailed non-vehicle-size-dependent infrastructure modeling in CURRENT. Fast charging is taken into account which amounts to 59% of the total charged electricity and thus significantly shifts vehicle connection from nighttime to daytime hours. Additionally, probability distributions are assumed for the charge connection availability at the places home, work, shopping, and other activities.

Electric driving demand profiles are found to be similar as shown in Figure 4D. Slight differences evolve from CURRENT's differentiation in weekdays as well as the consideration of weights of representativeness that are given in the dataset both of which are neglected in VencoPy aggregation procedures from individual profiles to BEV fleet aggregates.

The analyses of the two methods (power system-oriented approach versus user-behavior-oriented approach) have some limitations. First, the results rely on conventional travel patterns. We assume that electric vehicle users do not alter their travel patterns. This assumption is supported by the literature, but we are also limited by the lack of data on detailed travel information of electric vehicle users [29,30]. Second, electricity demand from BEVs is temperature and seasonally dependent, which was not considered in this model experiments but suggested, e.g., in [4]. Third, assumptions for

user-preferences are based on a specific study from Australia [45]. Fourth, capacity limits of medium and low voltage distribution grids connections are not taken into account. Fifth, CURRENT makes very conservative assumptions on grid connections, which are only taken from the driver's perspective and when charging is needed.

Future work should focus on isolating each effect given in Table 7, thus giving the chance of decisively quantifying the implications of integrating each aspect into BEV charging modeling. Additionally, empirically measured charging behavior of BEV users could be taken into account to gain insights on real BEV users' behavior. Additional inter-seasonal effects such as electricity demand by vehicle heating and cooling [4,7] as well as travel behavior due to holidays [35] should be evaluated on their respective importance to load shifting potential of future BEV fleets.

3.2. Implications of Structural Differences in Representing BEV Fleets

In this section, we give three key implications of the different model approaches on annual energy system model results, intra-annual BEV charging, and on intra-annual importance of the respective equations. Each main insight is given at the beginning of each section and then described and discussed in the following for easier readability. All results are available as .gdx files in the data Appendix A.

3.2.1. Energy System Implications on an Annual Basis

In the following, we describe the results of three scenarios (S0, S1, and S2) and thus the implications of the different modeling approaches on energy system modeling results. We find that fast charging and the reduced BEV fleet battery capacities have the strongest influence on energy system results, significantly reducing BEV fleet flexibility provision from 24 TWh in S1 to 8 TWh in S2 shifted load. Other flexibility options such as curtailment (+31% curtailed energy) and gas power plants (+5% in capacity additions) compensate for lower BEV fleet load shifting potential.

Table 8 shows the results of the scenarios S0, S1, and S2 including two intermediary benchmarking scenarios *S1a* and *S2a*, where additional BEV electricity demand occurs without any load shifting potential for the same scenario study boundary conditions and temporal VencoPy and CURRENT profiles (green lines in Figure 4) respectively.

Table 8. Overview on scenario definitions and main annual results of the four main scenarios under analysis. Total system costs are given for the complete system boundary while all other values are given for Germany. Difference in total system costs between *S2a* and S2 is more than an order below numbers shown. Source: Own calculations.

	Scenario Definitions					**Results**									
Scenario	**Annual Electricity Demand from BEV Fleet in TWh**	**Controllable Share in %**	**Total System Costs in bn. €**	**Shifted Load by German BEV Fleets in TWh**	**Peak Load in GW**	**Installed Capacities of Power Plant Park in GW**	**Installed Fluctuating RES Capacities in GW**	**Fluctuating RES Capacity Additions in GW**	**Gas Power Plant Capacity Additions in GW**	**Annual Power Generation in TWh**	**Annual Fluctuating RES Power Generation in TWh**	**VRE Share in Total Power Generation in %**	**Annual VRE Curtailment in TWh**	**Imports to Germany in TWh**	**Exports from Northern G to Southern G in TWh**
S0	0	-	68.4	0	83.9	214	153	46.2	31.3	501	279	55.7	2.9	45.9	64.7
S1a	*27*	*0*	*71.7*	*0*	*91.1*	*224*	*156*	*49.0*	*39.0*	*525*	*284*	*54.1*	*3.6*	*50.3*	*62.9*
S1	27	66	71.2	24.2	86.3	223	159	51.5	35.5	526	291	55.3	2.6	51.3	65.1
S2a	*27*	*0*	*71.7*	*0*	*93.5*	*223*	*156*	*48.8*	*37.9*	*524*	*284*	*54.2*	*3.5*	*51.6*	*62.4*
S2	27	30	71.7	8.4	87.6	222	156	48.8	37.2	524	284	54.2	3.4	51.6	62.2

Total system costs increase by approximately 5% induced by an additional electricity demand from German BEV fleets. This increase can be reduced to 4% by controllable BEV charging with high control through the power system. Total system cost values for uncontrolled and user-behavior constrained charging are similar. In S1, additional load is compensated by both gas turbine and onshore wind power capacity expansions that can be well balanced by the fleet shifting potential. A higher peak demand occurs when introducing additional BEV electricity demand. Complete inflexibility increases peak demand by 7.2 GW or 9.6 GW in *S1a* and *S2a* respectively. Assuming BEV fleets' controlled charging decreases the peak load by 4.8 GW (S1) and 5.9 GW (S2).

Due to lower flexibility especially on an 3–4-day timescale, in S2 5% lower onshore wind capacity expansions (−2.7 GW) have to be compensated by increased gas turbine expansions of 5% (+1.7 GW) reducing the RES share in power generation slightly from 55% to 54%. Gas turbine additions are around twice as high in northern Germany. Reducing the BEV fleets' flexibility further increases gas power plant needs by 0.7 GW in Southern Germany and around 1 GW in Northern Germany. At the same time, curtailment is increased from 2.6 TWh in S1 to 3.4 TWh in S2 indicating that despite 2 TWh lower wind power feed-in, the decreased charging controllability leads to a significant amount of hours in the year where wind oversupply cannot be stored in the BEV fleet.

Import levels are comparable in S1 and S2 and lie around 12% above the benchmark values. Main importers of electricity to Germany are France, Sweden, Switzerland, and Norway. Germany exports electricity to Poland and the Czech Republic. Inner-German electricity transport is high at above 60 TWh from Northern Germany to Southern Germany in all scenarios. It is higher in S1 due to lower power generation from conventional power plants in the south (−4 TWh) but also in the north (−2 TWh).

Especially the decreased BEV fleet battery capacity available for load shifting leads to a significant reduction in quantity and quality of flexibility provision of BEV charging. Load in S2 can only be shifted diurnally within a day thus diminishing the BEV fleet's potential to balance wind power feed-in. This effect of future BEV fleets as a complementary PV balancing option has already been described by [4,46]. Coal power plant generation is slightly increased in Northern Germany by 1.3% and 1% for coal and lignite plants respectively and reduced by 2% for coal power plants in Southern Germany.

Curtailment reductions found in [17] are lower even in S1 when high flexibility is assumed. Peak load reductions are higher which can be explained by the assumptions of very high BEV penetration rates, considering their 40 kWh BEV battery as the smallest size with the majority being at 70 kWh. The different assumptions in charging power of our 3.7, 7.4, and 22 and fast-charging is supposedly not very relevant because of the unimportance of the charge connection constraint (see next section).

Future work should take into account BEV fleets in neighboring countries, empirical indications of BEV users' adoption of controlled charging and respective economic incentives as well as feedback of power generation costs to the users to assess to what degree BEV users could be incentivized to system-friendly charging by price signals.

3.2.2. Energy System Implications on Charging Dynamics

Charging dynamics vary significantly between S1 and S2 as well as Northern Germany and Southern Germany as shown in the following. Reduced BEV fleet battery capacity has the strongest influence on charging profiles resulting in a significantly reduced variability. Including fast charging, the non-choice option and other daytime charging options lead to higher daytime charging peaks. Accounting for differences in weekday travel patterns lead to increased weekend daytime hour charging in Northern Germany (+40%) and Southern Germany (+12%) and to a sharper peak at 1 p.m.

For the power system, three main implications result from BEV usage. First, the mileage of an electric fleet imposes an increased electric demand in each hour for the energy system. Secondly, BEV charging events and the respective fleet grid connection power available are subject to temporal dynamics. Thirdly, controlled charging may occur when the time that a vehicle is connected to the grid

is longer than the time required for a complete charging process and thus, the beginning of a charging event can be shifted to a later point in time.

As CURRENT differentiates each day of a week, the BEV electricity demand differs in particular from working days and weekend. For example on Sunday only 54% of the vehicles are used, while during the week the share of vehicles with a minimum distance driven is 70%. Not only the number of vehicles used is different for each day of a week, also travel pattern and time of travelling, which results in different time and location a charging event occurs.

Figure 5 shows the daily charging patterns for all working days of the year differentiated in charging in Southern Germany and Northern Germany for a cost-optimal charging with high controllability by the power system (S1) on the left and lower flexibility (S2) on the right-hand side.

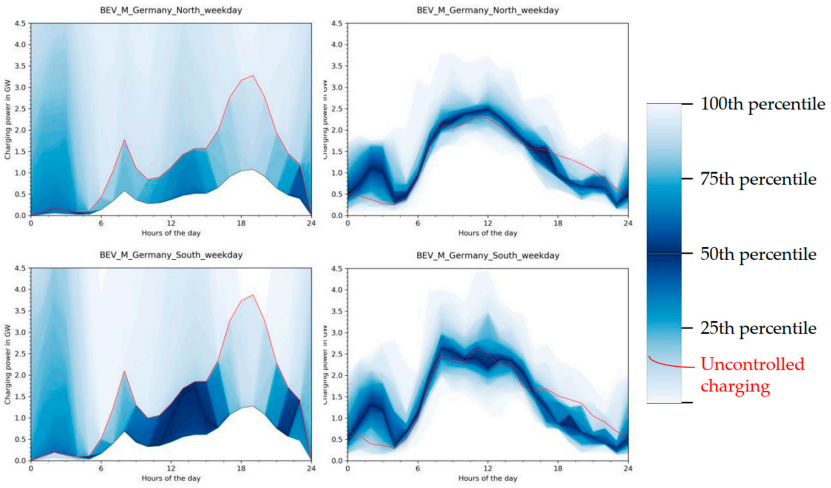


Figure 5. Annual distribution of total charging on weekdays in cost-minimal power system operation. The red line indicates how charging would take place in case of uncontrolled charging. The black line indicates the median value for charging in each hour (not the median profile). Figures on the left are the distributions for Northern Germany and Southern Germany for the medium sized BEV fleets for scenario S1 (VencoPy profiles). Figures on the right side depict charging distributions in scenario S2.

Even though uncontrolled charging input profiles are very different, a few similarities can be observed. Generally, electricity demand is shifted from morning and evening hours to midday and nighttime hours. In S2, the reduced BEV fleet battery capacity leads to a sharply reduced variability of controlled charging power from up to 14 GW (beyond y-axis cutout of S1) to around 4.5 GW.

Between 6:00 and 9:00 a.m. the median of controlled charging is at its minimum in both scenarios. For evening hours, this is true for the timeframe between 5:00 and 9:00 p.m. for the high fleet flexibility since the evening load peak occurs in the same time interval (compare Figure 4). For scenario S2 the median is not as sharp at the bottom, which is due to varying weekday-dependent travel patterns but generally up to 1 GW below uncontrolled charging. From midnight on, charging occurs to a higher degree than in the uncontrolled charging case although uncontrolled charging reaches its minimum around 4:00 a.m.

The controlled charging median is much higher in S2 (1.1 GW in Northern Germany and 1.4 GW in Southern Germany) compared to 0.2 GW in S1 due to many working day nights in S1 where charging is not needed at all, even though electricity load is low. A strong alignment of controlled charging to PV feed-in can be observed in Southern Germany versus Northern Germany for S1. For S2, this effect is also observable, yet not as strong and complimented by generally broader charging behavior during daytime in Southern Germany compared to Northern Germany.

The results indicate the increasing importance of controlled charging at midday in sunny regions with high shares of solar energy. More charging at nighttime is seen in the north, especially if higher fleet capacities are available. This valley-filling effect has already been observed by other authors,

e.g., [47]. In S1 where home charging is available to all BEV users and the whole fleet capacity is available to the power system, the variability of nighttime controlled charging procedures is higher with the median of controlled charging being at no charging power. This shows that controlled charging balances wind feed-in when available in S1, while in S2 nighttime hours are utilized in more than 90% of working days. Both aspects motivate stronger home charging infrastructure expansion in Northern Germany compared to Southern Germany.

Weekend and working day charging differences are described comparing Figure 5 and the same depiction for weekends, Figure A8. In S1, there is a general trend to more charging on the weekends across all hours increasingly making use of lower electricity demand from other sectors and showing increased load shifting times compared to S2. This effect is much stronger in Southern Germany where total BEV charging load is higher than uncontrolled charging in the vast majority of the hours except for the time between 4:00 and 11:00 p.m. where load peaks occur in the general electricity demand. In northern Germany, the charging median follows the uncontrolled charging profile except for between 4:00 and 11:00 p.m. with two frequently occurring charging peaks between 1:00 and 7:00 a.m. as well as between 11:00 a.m. and 3:00 p.m. On weekend days in S2, nighttime hour charging peaks are diminished and in Southern Germany shifted to 9:00 to 11:00 p.m. where mean charging amounts to 1.4 GW. In northern Germany, no nighttime charging peaks occur on the weekends. Weekend daytime hour charging peak is increased from 2.5 GW at working days to 3.5 GW in Southern Germany and 2.8 GW in Northern Germany on weekends and occur more sharply at 1:00 p.m. in both model regions.

Of the driving factors, mentioned in Table 7, setting a boundary condition on the fleet level rather than the single profile level has the strongest effect on cost-optimal charging characteristics, diminishing wind power balancing potential and limiting EV fleets' load shifting to diurnal load-shifting. An additional fast charging option in S2 reduces the evening peak in uncontrolled charging shifting it to midday. Differentiating between weekend and working days does have a strong impact on BEV fleet charging as described above.

Results from [17] showing a season-dependent concentration of BEV fleet charging is reproduced by our analysis as can be seen in Appendix B Figure A5, Figure A6, Figure A7. However, Southern Germany shows a daytime peak in winter as well in S1. When BEV user preferences are taken into account, this concentration effect cannot be shown, thus providing insights to what degree the "technical potential" estimate in [17] will supposedly be limited by BEV users' decisions.

After having presented the most important differences between S1 and S2 in a descriptive way we will now explain the quantitative reasons for differences and draw more abstract conclusions for representing transportation demand in power system models.

To what degree charging connections limit load shifting in both scenarios will be discussed in the next section. The higher degree of modeling charging infrastructure availability depending on different types of locations has a strong effect on the profiles shown in Section 3.1. Its respective impact on energy system models can be estimated by the marginal value of the charge connection constraint equation.

3.2.3. Linear Optimization Marginality Analysis

Based on the description of marginal values of equations and variables in Section 2.3, we compare the marginal values of the relevant REMix equations that model a partly flexible power demand of BEV charging in the following section. From a comparison of absolute marginal values and temporal dynamics within the power plant dispatch, we provide explanatory insights on the importance of different components of BEV modeling and their respective implications for energy system optimization modeling. Here, we present the key insights of the marginality analysis; the detailed analysis is laid out in the respective section of Appendix B.

In scenario S2, an increase of electricity demand for driving generally leads to a more direct pass through of power generation costs. BEV fleet batteries expand the availability of otherwise curtailed fluctuating RES to hours (and in scenario S1 to days) before and after low residual load situations occur.

This can be observed in scenario S1, in which a load increase or charging decrease does not always lead to power system cost increases due to possible shifting of fluctuating RES feed-in as shown in the period between mid-November and mid-December in Figure A10. However, in these periods, controlled charging has a pivotal role for expanding periods of low residual load.

The number of hours in which the marginal value of an equation is above a fixed threshold makes it possible to compare the importance of that constraint for total power system cost in each scenario S1 and S2 as well as between the two model regions. Table 9 gives the numbers of hours for which the marginal value of the grid connection constraint *maxCC* of the medium-sized BEV fleet is above the thresholds given in the first column. Two cutoff values are compared in order to reflect the presence of peak marginal values. Their value corresponds to the increase of the total system costs that originate from an increase in electricity for driving or a decrease of uncontrolled charging (or a mixture of both) by 1 GW. For S2 compared to S1, the constraint gets more important in northern and less important in Southern Germany. Increases in Northern Germany occur due to higher peaks in S2 and narrower SOC bands, necessitating steeper charging at times of low residual load at decreased BEV fleet charge connection compared to S1. Decreasing number of hours in S2 in Southern Germany occur due to increased utilization of other flexibility options such as gas power plants and imports. The effect of extending low cost electricity availability can be observed in the third row of Table 9 showing the number of hours in which the marginal value of the battery balance equation *batLevBal* is low. While this effect does not occur in Southern Germany due to low wind availability, in Northern Germany the constraint is below the threshold in twice as many hours in S1 compared to S2.

Table 9. Number of hours in which the marginal value of the constraints *maxCC* (BEV fleet charging connection) and *batLevBal* (battery balance) is higher or lower than the cutoff-values given in the second column. All numbers are only given for the fleet of medium-sized BEVs.

Constraint	Cutoff Marginal Value	S1 GER-N	S1 GER-S	S2 GER-N	S2 GER-S
maxCC	**>1000€**	6	88	90	63
	>1€	34	227	185	126
batLevBal	**<1000€**	1135	0	500	0

3.3. Sensitivity Analysis

In order to test the robustness of the results, a sensitivity analysis has been carried out varying the GHG reduction ambitions, the weather years for load and fluctuating RES feed-in profiles as well as capital expenditure assumptions of wind and PV power plant technologies. Weather and electricity demand data for the years 2006–2012 are based on the analysis in [36]. Specific capital expenditure is varied based on two independent sets of values given by [48] and [49]. Tables A8, A10 and A11 present annual energy system model results of all carried out sensitivity scenario calculations. In scenarios b–d, the German greenhouse gas emission limits have been reduced to 80, 50 and 0 Mt per year. In scenarios e–j, weather and electric demand data years have been varied taking into account data from 2006 to 2012. Scenarios k and l correspond to two deviating specific fluctuating RES technology investment costs sets. Scenario m reduces the load shifting potential in S1 to 30% of flexible charging as in S2.

Sensitivity run results are shown as difference between a model result e.g., system cost between S1x–S2x in a sensitivity scenario x e.g., b compared to the baseline difference S1–S2. Equation *sens* shows the definition.

$$sensitivity_{Result} = \frac{Result_{S1x} - Result_{S2x}}{Result_{S1} - Result_{S2}} \qquad sens$$

Figure 6 shows the resulting sensitivities. The four input sensitivity types are clustered via color. Differences in BEV fleet load shifting between S1 and S2 are robust to all tested sensitivities except

for scenario run S1m, in which a reduction of the share of controlled charging from 66% to 30% is exogenously given. However, despite the reduction of the charge control by more than half, the load shifting only drops by 20%. Differences of total system cost are quite robust. The peak load reduction achieved by shifted BEV charging is notably affected by almost all input parameters variations, which can be explained by the changes in the fluctuating RES capacities and power generation as well as load profiles heavily affecting the balancing requirements. Differences in power plant installations are increased in all sensitivity scenarios except for k where lower costs lead to increased PV installations in Southern Germany reducing the importance of the BEV fleets for wind power balancing. Differences in RES capacity additions are generally increased except for scenario d, the 0 t CO_2 emission limit. Here, more needed expensive flexibility options such as battery storage reduces the importance of the BEV fleet as a balancing option. Differences in gas power plant capacity additions are inverted for sensitivity scenario m, where the share of uncontrolled charging is harmonized. Thus, in S1m more gas power plant capacities are needed than in S2, which can be explained partly by better alignment of charging to PV feed-in in S2 due to available daytime and fast charging infrastructure. Annual fluctuating RES power production is increased by 7 TWh in the baseline. In most sensitivity scenarios, this is not the case and S2 model runs have between 7 and 12 TWh more RES production due to significantly increased inner-German transmission, imports from neighboring countries, and lower curtailments. The specific capital expenditure sensitivity runs drastically change the fluctuating RES portfolio. This explains that while fluctuating RES shares are 1.1% higher in S1 in the baseline runs, they are around 3% lower in sensitivity scenario k utilizing global cost assumptions. This is due to 10 GW more PV and 5 GW more onshore wind power plant capacities in S2k compared to S1k also implying increased battery capacities in S2k.

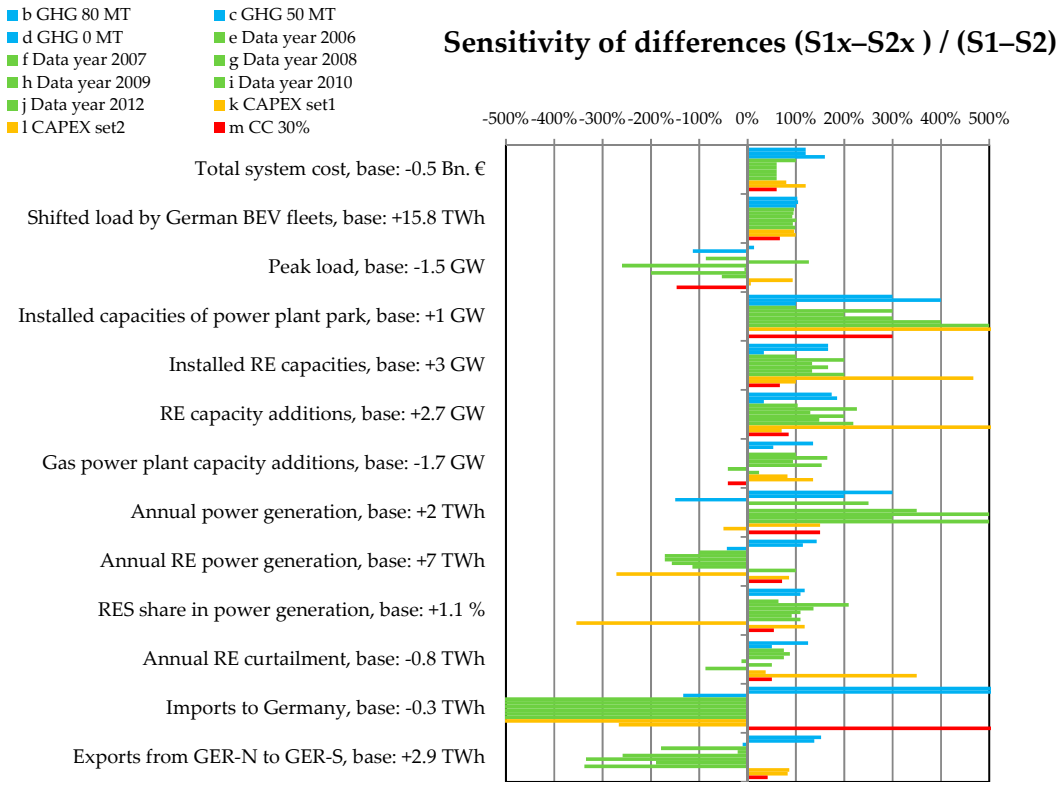


Figure 6. Sensitivity of the difference of REMix model results (categories) between S1 and S2 on German GHG ambitions (**b**–**d**, blue), different underlying weather and electric demand data (**e**–**j**, green), CAPEX assumptions (**k**–**l**, yellow) and controlled charging in S1 (**m**, red). Values between 0 and 100% indicate decrease in difference, values above 100% indicate increased difference, and values below 0 indicate an inversion.

Annual curtailment of fluctuating RES is strongly sensitive to all tested input variations. Especially for varying specific capital expenditures this is due to changes in the power plant portfolio that can be observed between the baseline scenarios S1 and S2 on the one hand and the sensitivity runs k and l, introducing increased shares of PV. These effects also imply changes in transmitted power from Northern Germany to Southern Germany. While these are highly sensitive to weather and demand year variations, imports to Southern Germany are less but still sensitive to GHG limitations with a maximum of 44% increase in the 0 t CO_2 scenario.

These analyses show the robustness of BEV fleet as a load-shifting option in different model setups. Also, fluctuating RES and gas power plant capacity additions, fluctuating RES shares and annual curtailment of solar and wind power feed-in have the same effect direction as in the baseline scenarios S1 and S2. At the same time, in some sensitivity scenario calculations, energy system model results are inverted within similar sensitivity scenario calculations motivating further analyses of underlying intra-annual profile data as well as specific capital expenditure assumptions.

4. Conclusions and Outlook

Strengthening the bridge between energy systems modeling and transport research, we compare the load shifting potential of power-system controlled battery electric vehicle charging modeling with a user-preference oriented charging modeling approach. In a scenario study for Germany, implications of both approaches on cost-optimizing power system investment and dispatch modeling are presented.

The first major finding of the paper is that taking a user centric view and more charging options especially fast charging into account significantly reduces the load shifting potential of electric vehicles compared to a simplified approach to charging flexibility. Main drivers affecting electric vehicle load shifting characteristics are including fast charging, the consideration of sufficiency-oriented charging decisions, and boundary constraint enforcements for electric vehicle fleet state of charge to be equal at beginning and end of the transport model time horizon. Minor factors are weekday-specific travel patterns. By considering these drivers, the hourly electric vehicle fleet battery capacity availability to the power system is reduced by roughly 98%. Similarly, the hourly fleet connection power is reduced by about 90% which does not have a significant effect on electric vehicles' load shifting capabilities for the power system.

The second major finding of the paper is that load shifting patterns relate to the prevailing weather patterns of fluctuating renewable energy grid feed-in. More shifting towards night hours occurs in northern Germany, where wind energy is the dominating fluctuating renewable energy source. In more solar-energy dominated Southern Germany, there is a shift of electric vehicle fleet charging towards midday when solar energy is strongest. This effect is driven by flexibility provision in a power-system oriented charging modeling while it is mainly driven by inflexible fast-charging in a more user-oriented charging modeling.

The third major finding of the paper is that wind integration capabilities are significantly affected by the way of modeling electric vehicle fleet charging. While wind power curtailments are reduced by 10% in a power-system controlled electric vehicle fleet, curtailment is increased by 17% in the case of user-oriented charging modeling compared to the benchmark scenario that assumes neither additional load nor load shifting from electric vehicles. In the first case, larger electric vehicle fleet batteries are capable of shifting wind feed-in across multiple days, day-by-day releasing its energy to the electricity demand for driving. On the other hand, electric vehicle load-shifting reduces peak load in both scenarios significantly compared to benchmark runs since multi-day flexibility is less important for decreasing peak load. Compared to inflexible additional electric vehicle electricity demand, necessary gas power plant additions can be reduced by up to 9%.

Load shifting reductions from a power system centered to a user-preferences oriented electric vehicle fleet charging are highly robust across all sensitivity runs. Also, the way a changed electric vehicle charging modeling affects the required power plant capacities, fluctuating RES share in total power generation and curtailments is shown to be quite robust. However, charging modeling induced

changes in annual RES power generation and electricity transmission to and within Germany is found to be sensitive to changes in emission limits, underlying weather years and specific capital expenditure assumptions.

One limitation of the paper is that we use today's driving patterns for the analysis, not taking into account that travel behavior may change in the future to reduce the overall traffic of individual cars. Similarly, analyzing the effect of ridesharing or gig economies may become increasingly important, depending on the geographical scope of the analysis. We use simplified assumptions on the charging behavior, as users always connect their car when they reach their home in one case or only when they need charging in the other. The use of periodic boundary conditions for the state of charge limits long-term balancing of wind feed-in in the case of user-oriented charging modeling.

Further research needs to systematically isolate factors, reducing the load shifting potential in both types of charging modeling. Identifying driving factors to increase the willingness of electric vehicle users to participate in power system-friendly charging is deemed important to support the integration of renewable energy sources even if there is no urgent need to charge the car. Also, vehicle user preference modeling needs to be expanded beyond a week to allow for longer load balancing of wind feed-in, which tends to have longer weather dependent cycles.

The model coupling setup provides promising analytical opportunities. Electric vehicle user preferences for power prices are already implemented but not yet time-dependent, thus charging sensitivity to power system price feedbacks are yet to be addressed. Also, the potential of feeding electricity back to the grid has been shown to significantly impact energy modeling results. Since the energy system model used does not assess electricity distribution below a voltage level of 220 kV, a plausibility of model results on a single vehicle profile basis by disaggregation would further validate the modeling approach. Furthermore, assessing dynamic vehicle adoption pathways through a stronger incorporation of VECTOR21 into the proposed model framework seems promising for assessing the interrelations of charger availability at a household level and its respective implications for electric vehicle adoptions.

The combination of a central planner energy system model with a user-oriented electric vehicle charging model shows a significantly reduced potential for load shifting of electric vehicles for the energy system. However, impacts depend on specific temporal dynamics and are specific to the model parametrization. Marginal values of equations and variables are rarely explicitly analyzed in energy system analysis studies but offer the opportunity to assess temporal dependencies especially in relevant RES fluctuation dynamics in detail and can be interpreted as an indicator for sensitivity of the model setup. We call for thorough investigations of the dependency between different availabilities of electric vehicle fleet battery capacity for power systems on the one hand and historic weather and electric demand patterns on the other side. Expanding the marginality analysis to all equations and variables to identify specific constraints and variables that are most important may yield deeper insights. It also seems promising to look at characteristic residual load developments across different temporal ranges and identify respective flexibility demands. We took the first steps in this direction.

Author Contributions: Conceptualization N.W., F.S., and C.H.-K.; Methodology, N.W. and F.S.; Software, N.W., F.S., H.-C.G., and B.v.d.A.; Data curation and parametrization, N.W., F.S., H.C.G., and B.v.d.A.; Writing—original draft preparation, N.W. and F.S.; Writing—review and editing, N.W., J.E.A., H.-C.G., and C.H.-K.; Visualization: N.W.; Funding acquisition and project administration: C.H.-K. and J.E.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded through the following projects: DLR internal funds EVer (CURRENT and REMix enhancements and coupling), BMBF E-Navi (Funding number 03SFK4D1), BMWi MuSeKo (Funding number: 03ET4038B, REMix model enhancement), and BMWi RegMex (Funding number: 0325874C, base model parametrization).

Acknowledgments: We thank Benjamin Fuchs for providing support of scripting architecture and Manuel Wetzel for scripting of the statistical charging dynamics plots. We thank Karl-Kien Cao for support in the REMix architecture. We thank Karl-Kien Cao and Jannik Haas for fruitful discussions. We thank the whole REMix team at DLR for maintaining and cleaning up the code for publication.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Assumptions, Scenario Study, and Results

Model Description and Parametrization

Regarding the model set-up and scope, the main characteristics are summarized in Table A1 below.

Table A1. Model characteristics of REMix as used in this case study.

Optimization type	Target year optimization
Optimization method	Linear programming
Objective function	Total cost including CAPEX of all endogenously added capacities, OPEX of all capacities, and penalty costs for unsupplied load
Temporal resolution	Hourly (8760 timesteps)
Geographical horizon and resolution	13 nodes: Germany in two nodes plus neighbors
Optimization variables	Investment in power plant capacities and flexibilities as well as technology dispatch
Energy demand sectors	Power, transport
Transport mode	Private passenger road transport
Transport technology resolution	3 battery electric vehicle (BEV) fleets (S, M, L)
Variation of wind and PV power feed-in patterns	2006–2012 yearly
Variation of load patterns	2006–2012 yearly

Scenario Study Assumptions

Overarching assumptions regard the following points:

- Power demand stays the same in quantity and in its hourly variability as in the underlying data years (2011 for baseline runs and 2006–2012 for sensitivity scenarios e–j)
- Weather patterns stay the same as in the historic years considered
- Socio-economic development: The populations in Germany and its neighboring countries develop according to assumptions in the ENTSO-E TYNDP [38]
- For REMix: The flexibility options are chosen solely based on a (total) cost basis, disregarding power grid phenomena occurring at sub-minute time-scale, import dependency, acceptance of grid- or power plant expansion, etc.

Assumptions regarding technical transfer capacities between all model nodes considered in the case study are based on the German "Netzentwicklungsplan" (NEP) [39] (p. 110), the ENTSO-E TYNDP [38] (p. 30), and older data. The capacities are assumed to be equal to the given capacities as "before 2035". Except for the connection from Germany to Sweden these are equivalent to the capacities given in the NEP.

The largest differences in export and import capacities are for the links between Belgium and France, Belgium and Luxembourg, Denmark and Sweden, France and Switzerland, Germany and Poland as well as Germany and Switzerland.

Assumptions had to be made on the model link length between Northern Germany and Southern Germany, which is assumed to be 150 km and the link length between Belgium and Luxembourg which is assumed to be 100 km. Other link lengths are averaged over given data in the TYNDP.

Power Demand

Power demand for Germany and its neighboring countries are based on the "Sustainable Transition" scenario of the TYNDP 2018. It includes power demand from heat and transport sector. Power demand of a 2030 EV fleet was approximated based on data given in [38] and subtracted for Germany in order to avoid double counting. The German power demand is disaggregated based on population census data from 2011 [43] yielding disaggregation factors of 53% for Northern Germany and 47% for Southern Germany. Historic development of power demand as well as projections are shown below in Figure A1.

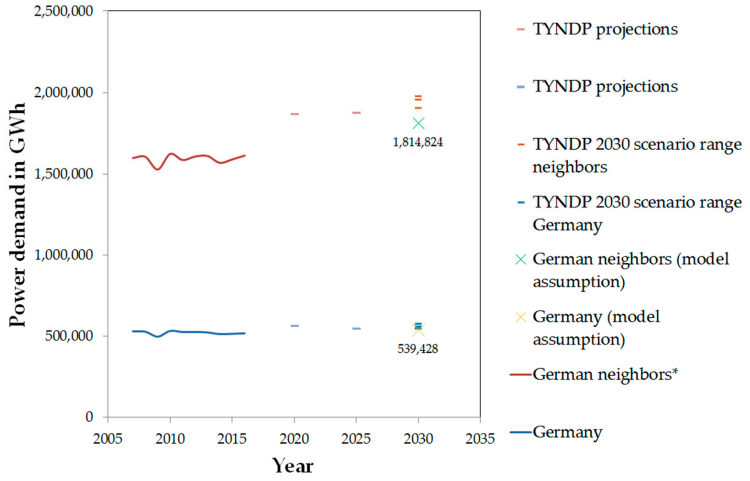


Figure A1. Historic power demand, TYNDP best estimates for 2020 and 2025 as well as scenario values for the scenario "Sustainable Transition" for 2030. The three markers in 2030 present the variety of two TYNDP scenarios, "Sustainable Transition" and "Distributed Generation" as well as an EUCO scenario. Green and orange crosses show the here assumed values from the scenario "Sustainable Transition" corrected by an approximated power demand of the 2030 PEV fleet.

Power Plant Park

The existing power plant park is used based on REMix-parametrization from the INTEEVER project [36]. There, a base run for 2030 was carried out to quantify a base power plant, grid and storage park in a first step as a quantitative basis for the next step of optimizing the expansion of different flexibility options. INTEEVER model results that are assumed for this study are shown in Table A2 and contrasted with the TYNDP 2030ST scenario assumptions.

Table A2. Quantitative assumptions for the existing power supply capacities as an input for the scenario study runs, aggregated for Germany and its neighboring countries. Pumped hydro power is not shown. All values in GW.

	Parameter	TYNDP 2030ST [36]		Own Assumptions	
		Germany	German Neighbors	Germany	German Neighbors
	Conventional thermal power plants *	66	141	61	134
Fluctuating renewable energies	PV	66	69	47	26
	Wind onshore	59	82	50	36
	Wind offshore	15	26	6	12
	Hydro run-of-river	4	24	4	27
Controllable renewable energies	Biomass power **	0	2	0	0
	Hydro reservoir	11	95	1	70

* Including oil and other conventional power plants in [38]. ** "Biofuels" in [38].

Flexibility Options

One strength of REMix is the modeling of different competing flexibility options to balance fluctuating renewable energy power generation. REMix optimizes the investment in and the operation of different flexibility options, e.g., power plants or energy storage. We consider the following flexibility options:

- Gas power plants (CCGT and OCGT);
- Curtailment of wind and PV power generation;
- Controllable renewable energies;
- Import and exports;
- Battery storage and hydrogen caverns;

- BEV fleet controlled charging;

The need for balancing renewable energy feed-in is mainly determined by the power balance constrained in a few hours of the lowest fluctuating renewable energy power feed-in. These hours differ from model node to model node and depend on the respective residual load curve.

Similar to power plant capacities, we apply a brownfield approach implying that certain flexibility capacities are already installed in the power system before optimization. Flexibility options' expansion restrictions are shown in Table A3 and are only set for PV, wind and hydro power plant capacities as well as for hydro power technologies and hydrogen caverns. The expansion of BEVs is not modelled REMix-endogenously but fleet values are taken from the more specialized stock and flow model VECTOR21. Thus, investments in the fleet are not possible but only the utilization of the vehicle fleet battery is optimized subject to annual constraints such as state-of-charge (SOC) limitations, charging infrastructure availability, and electric power outflow from the battery due to driving (see main document for more details).

Table A3. Quantitative and qualitative flexibility options' restrictions. Sources given in last column.

Flexibility Option	Technology	Unit	Expansion Constraint		Operational Constraint		Source
			Northern Germany	Southern Germany	Northern Germany	Southern Germany	
Thermal power plants	CCGT, GT	GW	-	-	-	-	
Surplus VRE and curtailment	PV	GW	1316	505	Hourly feed-in timeseries		
	Wind power onshore	GW	1172	452	Hourly feed-in timeseries		
	Wind power offshore	GW	210	0	Hourly feed-in timeseries		
	Hydro run-of-river	MW	1044	388	Daily feed-in timeseries		
Controllable RE	Biomass	MW	-	-	-	-	
	Hydro reservoir	TWh	0.043	0.488	-	-	
Power storage	Pumped hydro	GWh	24	14	-	-	
	Lithium ion batteries		-	-	-	-	
	Hydrogen caverns	GWh	113639	1395	-	-	
EV fleet controlled charging	BEV (S, M, L)		-	-	Hourly flexibility profiles (see below)		[20]

Table A4. Net transfer capacities from and to Germany.

Node	Technology	Value	Source
Northern Germany to neighbors	HVAC 380 kV	23.3 GW	[38]
	DC	4.7 GW	[38]
Southern Germany to neighbors	HVAC 380 kV	15.23 GW	[38]
	DC	0 GW	[38]
Northern Germany to Southern Germany	HVAC 380 kV	14.3 GW	[39]
	DC	10 GW	[39]

Techno-Economic Assumptions on BEVs

Historic battery electric vehicle battery capacities as well as literature projection and our own scenario assumptions are shown below in Figure A2.

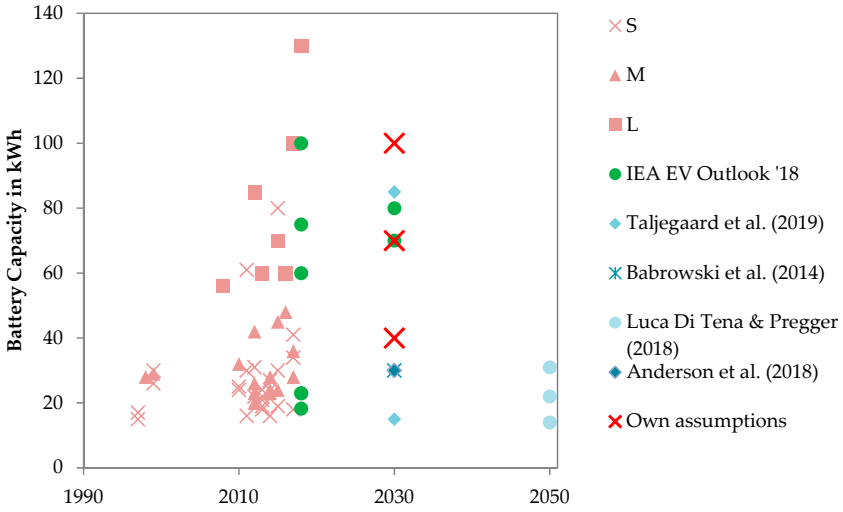


Figure A2. Historic development, prospective values from literature and own assumptions of BEV battery capacity values in kWh. Historic values are given in light red and differentiated between small (S), medium (M) and large (L) BEV models. Historic values are not weighted by sales or stocks. Ranges given in the IEA EV Outlook for 2018 as well as average fleet ranges for 2030 are given in green. Literature projections for 2030 and 2050 are given in light blue as indications. Own assumptions for the REMix model runs 0 and 1 are given as dark red crosses. Sources: Own composition based on [18,20,28,41,42].

Fluctuating RE and Electricity Demand Profiles

Dispatch optimization in REMix is carried out taking into account hourly profiles for the target year for each node for power demand and VRE feed-in (four separate profiles). In Figure A3, we show the load duration curves of the here utilized 2011 load series as well as simulated feed-in of the four fluctuating RE technologies for Northern Germany, Southern Germany, and the German neighbors.

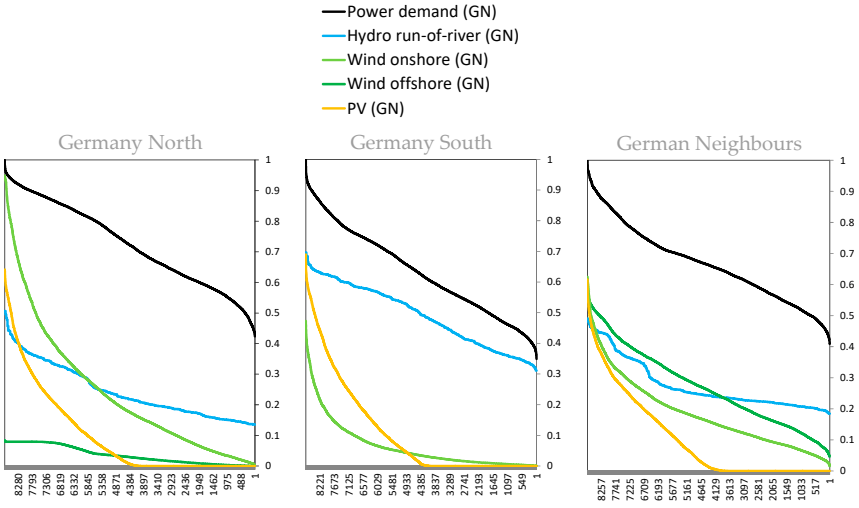


Figure A3. Duration curves of power demand and feed-in series of the four fluctuating RE power plant technologies. Hydro run-of-river profiles are given in 24-hour resolution. Fluctuating RE profiles are given based on the respective rated capacity. Power demand was normalized with the respective peak load in the model node. Source: Own composition based on [24,31,40].

Emission Targets

Emission targets used are based on an 80% GHG reduction target for Germany up to 2050 compared with 1990. In the three sensitivity scenarios b–d, these will be varied between this moderate

political target and a 0 t CO_2 emission power system (d). CO_2 costs of 60 €/t CO_2 are assumed. All assumptions are shown below in Table A5.

Table A5. Emission targets for Germany and its neighboring countries as well as CO_2 costs.

	Node	Unit	Value	Source
Emission reduction targets	Germany	MT CO_2	123 + sensitivity scenarios (b–d)	
	Cumulated emission target of neighboring countries	Mt CO_2	193	
CO_2 costs	all	€/t CO_2 emitted	60	

Overview Table of All Model Runs Carried out in the Scenario Study

Table A6. Overview on model runs and respective scenario acronyms

Scenario Acronym	Varied Value and Unit	Amount of Variation
S0	Electricity demand from BEV fleet in TWh	To 0
S1		
S2		
a	Maximum share of controlled charging in %	To 0
b	Max climate targets in Germany in Mt	Changed from 122 Mt to 80 Mt
c		Changed from 122 Mt to 50 Mt
d		Changed from 122 Mt to 0 Mt
e	Varied underlying weather and electricity demand data years	2006
f		2007
g		2008
h		2009
i		2010
j		2012
k	Specific investments of fluctuating RE technologies	See Table A9
l		See Table A9
S1m	Share of controlled charging of BEV fleet	30%

Transparency Checklist—List of Secondary Data Sources

Table A7. Secondary sources for the transparency checklist.

Dataset		Source
Annual power demand of non-transport sectors		Assumption based on [38]
Power demand, wind and PV time series		[24,31,40]
Disaggregation base: Census data		[43]
Power plant park		[36]
Net transfer capacities		[38,39]
Techno-economic assumptions of power plant technologies		Data sheets Leitstudie 2010 https://elib.dlr.de/69139/1/Leitstudie_2010.pdf
Techno-economic assumptions of storage		Data sheets Leitstudie 2010 https://elib.dlr.de/69139/1/Leitstudie_2010.pdf
CO2 emission targets		assumption
CO2 costs		assumption
Techno-economic assumptions of BEVs	Battery size, consumption,	Own assumptions based on [18,20,28,41,42]
BEV electricity demand in 2030		[38]

Appendix B. Results of Scenario Study Modeling Runs

Annual Distributions of Daily Charging Dynamics

Full Year

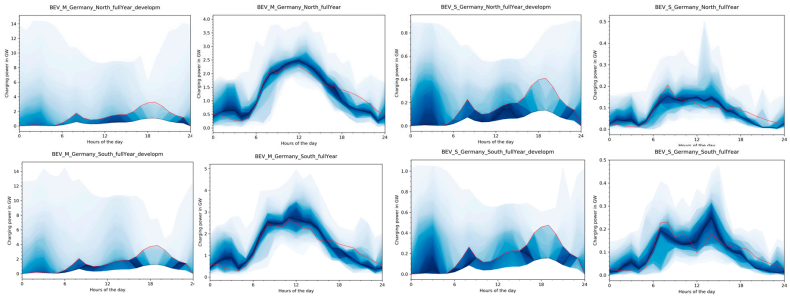


Figure A4. Daily probability distributions for total charging (controlled and uncontrolled) of medium and small sized BEV fleets in Northern Germany (**top row**) and Southern Germany (**bottom row**). The first and the third column show S1 results and the second and third column show S2 results. A case of completely uncontrolled charging is shown as red line.

Summer Hours

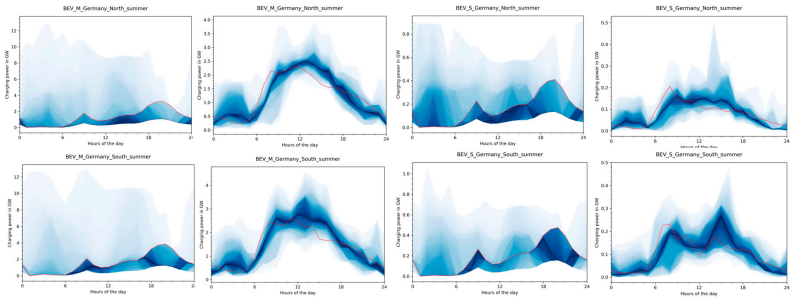


Figure A5. Daily probability distributions for total charging (controlled and uncontrolled) of medium and small sized BEV fleets in Northern Germany (**top row**) and Southern Germany (**bottom row**) in summer hours (3600–5760). The first and the third column show S1 results and the second and third column show S2 results. A case of completely uncontrolled charging is shown as red line.

Winter Hours

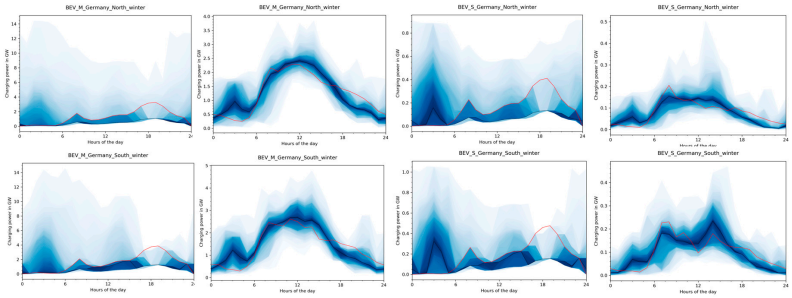


Figure A6. Daily probability distributions for total charging (controlled and uncontrolled) of medium and small sized BEV fleets in Northern Germany (**top row**) and Southern Germany (**bottom row**) in winter hours (1–2160 and 7920–8760). The first and the third column show S1 results and the second and third column show S2 results. A case of completely uncontrolled charging is shown as red line.

Intermediary Season Hours

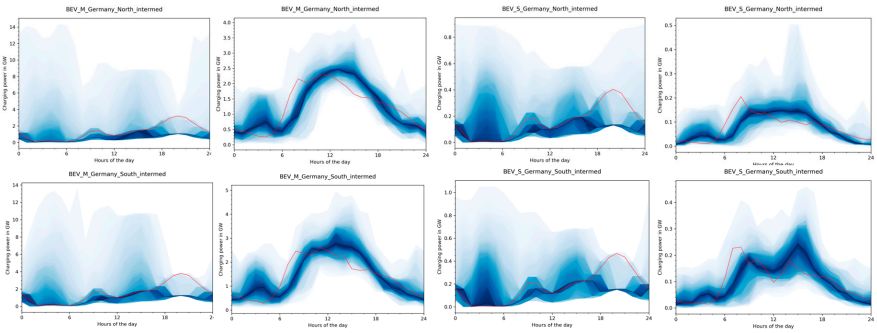


Figure A7. Daily probability distributions for total charging (controlled and uncontrolled) of medium and small sized BEV fleets in Northern Germany (**top row**) and Southern Germany (**bottom row**) in winter hours (1440–3600 and 5760–7920). The first and the third column show S1 results and the second and third column show S2 results. A case of completely uncontrolled charging is shown as red line.

Weekend

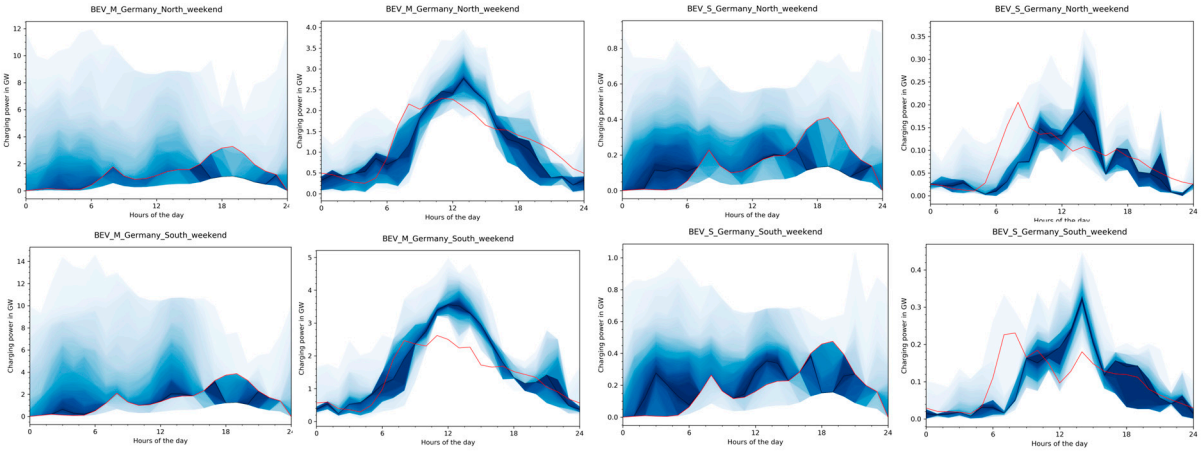


Figure A8. Daily probability distributions for total charging (controlled and uncontrolled) of medium and small sized BEV fleets in Northern Germany (**top row**) and Southern Germany (**bottom row**) on weekends. The first and the third column show S1 results and the second and third column show S2 results. A case of completely uncontrolled charging is shown as red line.

Marginality Analysis

For our case of controlled charging without feeding electricity back to the grid, $\Psi_{V2G} = 0$ and $\Phi_{V2G} = 0$ hold true and bringing all variables to the left-hand and all parameters to the right hand side of the *batLevBal* equation (see Section 2.3 for all equations), yields

$$\Psi_{CC}(t) - \Lambda(t) + \Lambda(t-1) = P_{drive}(t) - C_{unc}(t)$$

The marginal value of this equation corresponds to the increase of the total system costs that originate from an increase of the right-hand side of the battery level balance equation by 1. Since the equation is formulated in units of GW, in this case, we can interpret the marginal value of the equation by either an increase of electricity for driving or a decrease of uncontrolled charging (or a mixture) by 1 GW. The three other relevant equations are the battery level constraints for minimum (*minBatLev*) and maximum (*maxBatLev*) SOC as well as the equation limiting controlled charging by the fleet connection

power to the grid (*maxCC*). Additionally, the marginal value of power generation is shown since it presents the cost of an additional unit (GWh) of electric demand for the German power system.

The analysis will be carried out on two different timescales to show effects on a weekly and a monthly timescale. The marginal values of the equations for the full year are given in Figures A9 and A10. Two time intervals were chosen for a more in-depth analysis of the marginal values since they provide an interesting array of load and feed-in situations. Figure A9 shows BEV fleet battery operation and marginal for the first 15 days while Figure A10 shows the same quantities for the last 42 days of the year.

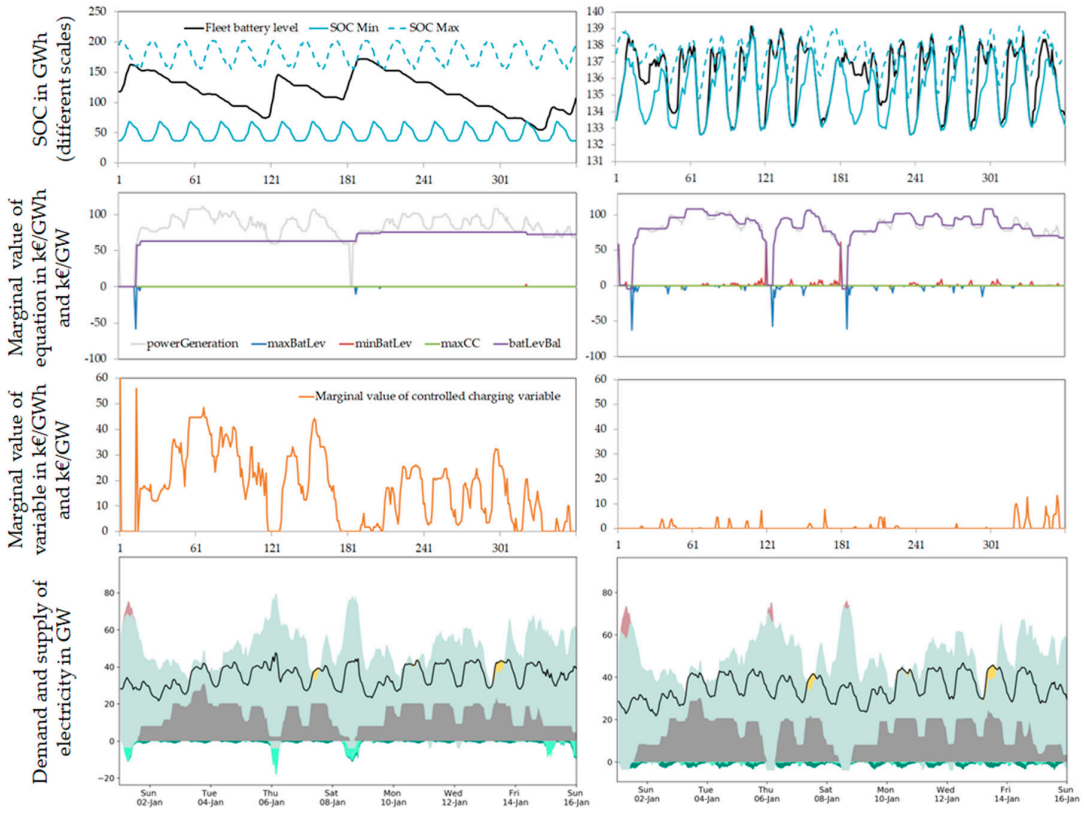


Figure A9. Marginality analysis of first 15 days (360 h) in the scenario for 2030 comparing scenario S1 (VencoPy input) (**left**) and scenario S2 (CURRENT input) (**right**) for Northern Germany. In the first row, EV fleet SOC constraints (turquoise) and levels (black) are depicted. The second-row plots show the marginal values of the equations of the REMix module and the power generation marginal for Northern Germany. The third row shows the marginal value of the controlled charging variable. The fourth row shows the power plant dispatch in Germany with fossil power plant dispatch in grey, renewables in shaded green, and curtailment in shaded red, imports in yellow. Uncontrolled charging is in dark turquoise while controlled charging is in light turquoise. The demand line comprises both electricity demand by households, industry, and service sector as well as EV charging demand. Duration curves of all marginal are shown in Figures A12–A14.

SOC constraints (model input parameters), levels (model solutions), marginal values of equations and variables as well as the power plant dispatch are given in Figure 6 for the first 15 days of the model year for scenarios S1 (left) and S2 (right).

The SOC plots on the top of Figure A9 show the implications of the reduced BEV fleet battery potential. In S1, the fleet battery is always discharged during daytime and charged every 3–7 days at times of low residual load. This can be observed on the dispatch plot on the bottom left. This concentrating effect of charging has been shown for the concentration from a relatively continuous charging power to hours of night and partly of daytime [17]. In scenario S2, the difference between the

SOC min and SOC max constraints is significantly decreased to 5–10 GWh. Since the axes of the SOC plots have a different scaling, the effect is even larger than visualized (compare Figure 4). Especially on weekday evening hours, the load shifting potential is almost completely diminished. In the dispatch plot for S2, both increased uncontrolled charging occurring on a daily pattern basis and the diurnal characteristic of controlled charging is depicted. Adjustment to high fluctuating RE feed-in still occurs but to a significantly lower degree.

Turning to the marginal values of BEV charging constraint equations, Figure A9 reveals a correlation between the marginal of the battery balance equation (in violet) with the power generation marginal. This correlation is higher for the case of lower flexibility indicating a more direct pass through of an increased electric driving demand or decrease of uncontrolled charging to total system costs at the respective cost of hourly power generation. BEV fleet batteries expand the availability of otherwise curtailed fluctuating RE to hours (and in S1 days) before and after low residual load situations occur. This can be seen in scenario S1, in which a load increase or charging decrease does not always lead to power system cost increases due to possible shifting of fluctuating RE feed-in as can be seen in the period between November 20 and December 14 in Figure A10. However, in these periods, controlled charging has a pivotal role in balancing wind feed-in as can be seen by the marginal value of the controlled charging variable in the same time frame.

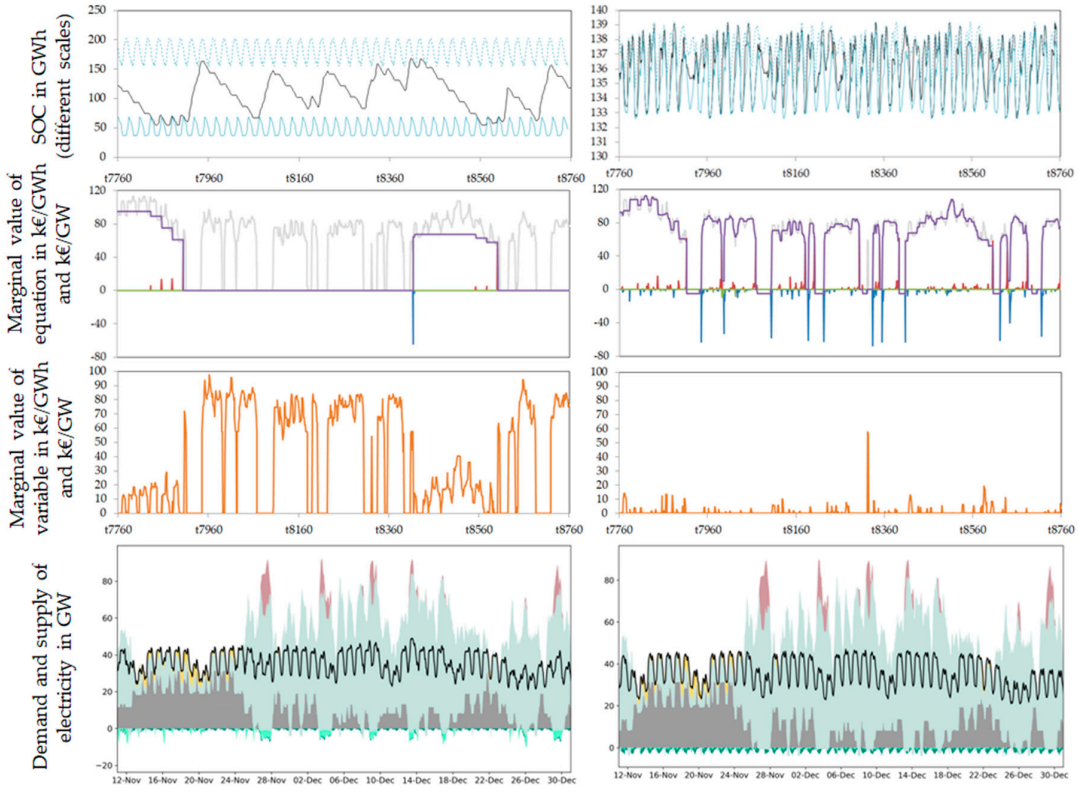


Figure A10. Marginality analysis for the last 42 days of the year.

The marginal value of the battery balance equation increases by the negative value of the marginal value of the constraint equation (*batLevMax* or *batLevMin*) at the last point in time where charging or discharging was constrained by SOC constraints (compare Section 2.3). For S1, the marginal value of *batLevBal* shows a lower temporal dynamic and an overall lower absolute value which is exemplified in Figure A10, where over the course of three weeks, a RE fluctuation characteristic occurs that lies in the range of the BEV fleet load shifting potential. Thus, in this time, increasing electric driving demand does not affect total system costs.

In some times in S2, the marginal value of the battery level equation becomes negative, indicating a potential reduction in total system cost if exogenous discharging increases. As can be seen in Figure A10 on November 19, this effect cannot be explained by either curtailment or the BEV fleet SOC being at its bounds. Supposedly, this is correlated with time intervals in which the relative BEV fleet SOC significantly increases, although this cannot be observed on November 20.

In general, the marginal value of controlled charging is drastically reduced in S2 in comparison with S1 indicating its decreased importance to overall system cost in S2. The higher importance to overall system cost can also be observed by the larger area under the duration curve of the marginal value of the controlled charging variable for S1 compared to the same area for S2 given in Figure A15.

Controlled charging has a more important role for the power system in the case of higher flexibility. This is due to a two-fold effect of reduced flexibility from BEV load-shifting. For one, BEV charging load occurs more often in peak load situations as can be seen by increased peak load demand in S2 compared to S1 (see Table A8). Secondly, general balancing is strongly limited to approximately a day thus diminishing the balancing effect of the BEV fleet battery for wind power feed-in. More costly flexibility options such as curtailment and increased gas power plant capacities are necessary in S2. Through the investment need in especially gas power plants and their respective availability, marginal value of controlled charging is reduced.

Upper and lower bounds of the BEV fleet battery state-of-charge are less often important in S1. The effect is shown in the duration curve of the marginal values of the two battery limitation constraints for the full year in Figure A13. The main determinants for the difference between the SOC min and max profiles in CURRENT are the difference between parking time and necessary charging time as well as the users' option not to charge. This motivates increased charging powers resulting in shorter charging periods and incentivizing users to connect their cars to the grid over-sufficiently in order to increase connected parking periods.

Marginal values of the charging connection constraint (*maxCC*) are generally low and constraints occur in general not very often as shown in Table A8. In these hours, the full connected capacity is utilized for charging the BEV fleet, usually in hours of curtailment. In the case of a higher detail of modeling BEV users' connection behavior with a sufficiency-oriented BEV connection, this constraint gets more important in Northern Germany and less important in Southern Germany. Increases in Northern Germany can be explained by higher peaks in S2 and narrower SOC bands, necessitating steeper charging at times of low residual load. Decreasing number of hours in S2 in Southern Germany occur because of increased utilization of other flexibility options such as gas power plants, imports, and curtailment.

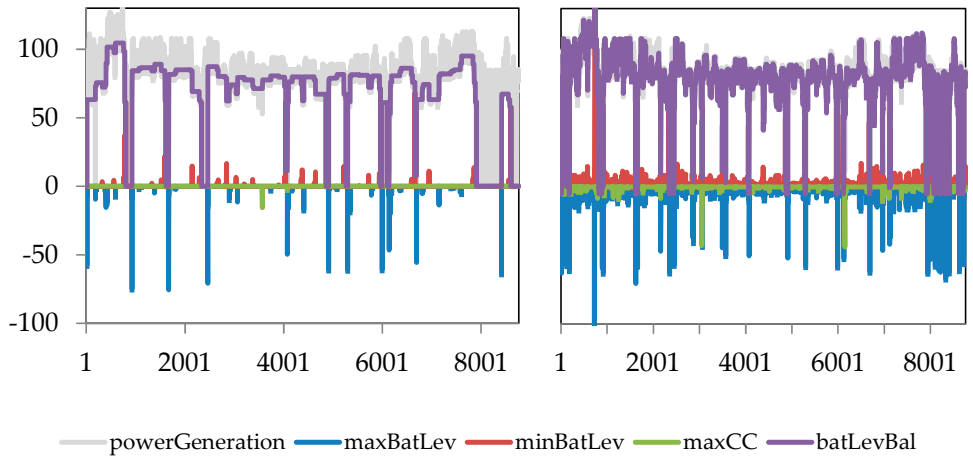


Figure A11. Marginal values of equations of the BEV modeling equations in REMix for the full year for scenario S1 (**left**) and S2 (**right**).

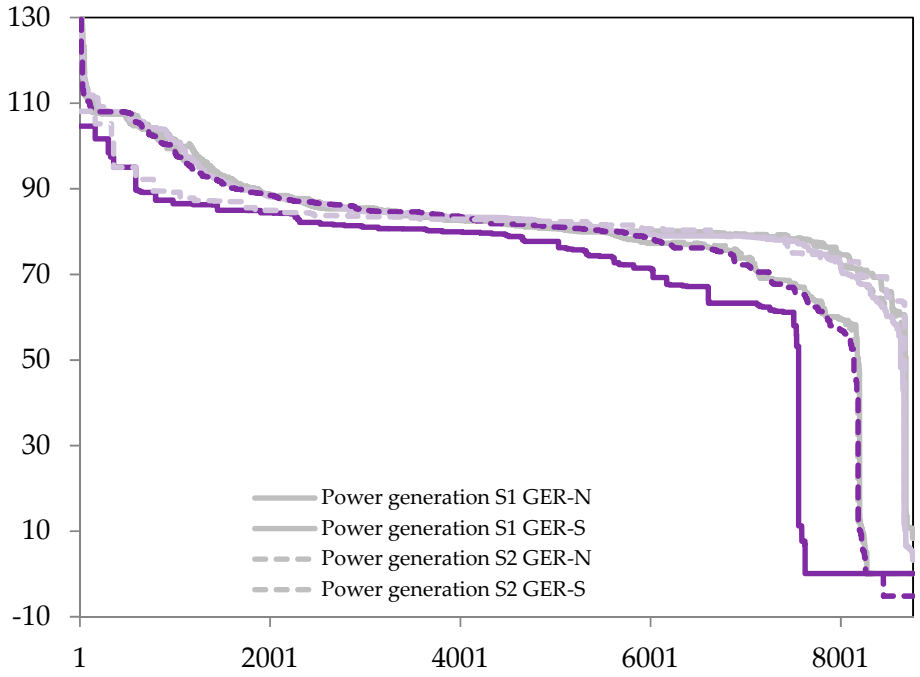


Figure A12. Duration curve of the marginal value of the battery balance equation (violet) compared to the load duration curve of the power generation marginal (grey). Solid lines show scenario S1 results and dashed lines scenario S2 results. Values for Southern Germany are given in light violet.

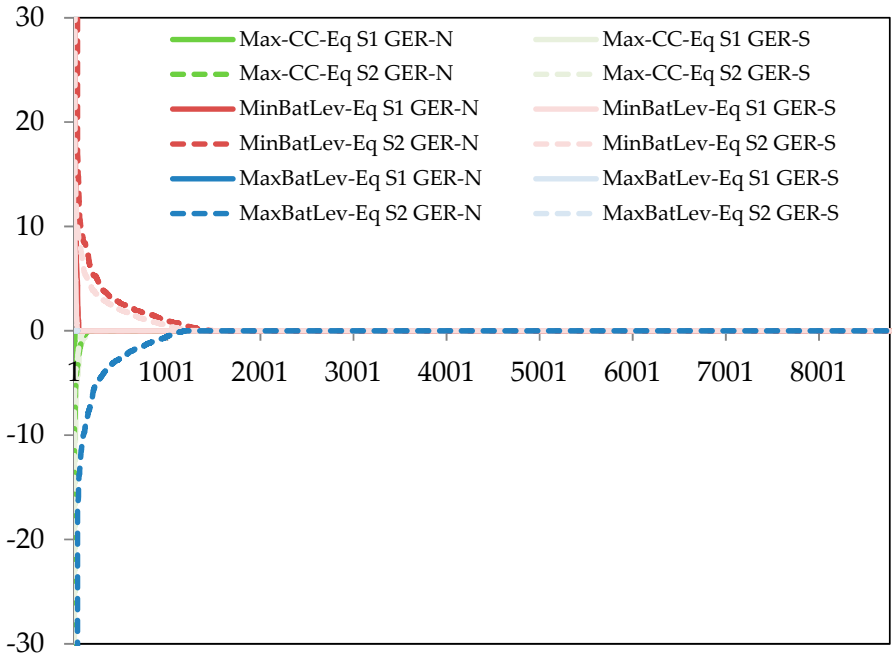


Figure A13. Duration curves of marginals of constraint equations. Max-CC: Equation constraining the power of controlled charging because of grid connection of EV fleet. MinBatLev: SOC min constraint. MaxBatLev: SOC max constraint. Curves are given solid for scenario S1 and dashed for scenario S2. Results for Southern Germany are given in light colors.

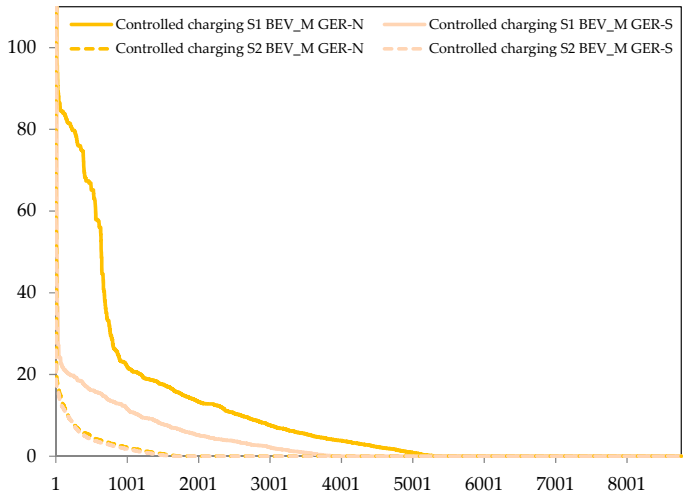


Figure A14. Duration curves of the marginal value of controlled charging for medium-sized BEV in Germany-North and -South.

Sensitivity Analysis

In the following, result tables of the annual energy system model results of the sensitivity scenarios b-m are given for GHG emission ambitions (scenarios b–d), weather and electric demand years (scenarios e–j), specific power plant technology investments (scenarios k and l) and controlled charging share (scenario m).

Table A8. Overview on scenario definitions and main annual results of the sensitivity analysis on the CO_2 emission limit and historic weather year used. Total system costs are given for the complete system boundary while all other values are given for Germany.

	Scenario Definitions												Results				
Scenario	Annual Electricity Demand from BEV Fleet in TWh	Controllable Share in %	GHG limitation for G Power System in Mt	Data Year for Load and VRE Feed-in	Total System Cost in Bn. €	Shifted load by German BEV Fleets in TWh	Peak Load in GW	Installed Capacities of Power Plant Park in GW	Installed RE Capacities in GW	RE Capacity Additions in GW	Gas Power Plant Capacity Additions in GW	Annual Power Generation in TWh	Annual RE Power Generation in TWh	VRE Share in Total Power Generation in %	Annual RE Curtailment in TWh	Imports to Germany in TWh	Exports from Northern G to Southern G in TWh
S0	0	-	122	2011	68.4	0	83.9	214	153	46.2	31.3	501	279	55.7	2.9	45.9	64.7
S1	27	66	122	2011	71.2	24.2	86.3	223	159	51.5	35.5	526	291	55.3	2.6	51.3	65.1
S2	27	30	122	2011	71.7	8.4	87.8	222	156	48.8	37.2	524	284	54.2	3.4	51.6	62.2
S1b	27	66	80	2011	71.4	24.6	87.4	222	166	59.0	26.4	453	309	68.2	4.9	124.0	77.6
S2b	27	30	80	2011	72.0	8.4	87.6	219	161	54.3	28.7	447	299	66.9	4.9	130.3	73.2
S1c	27	66	50	2011	72.1	24.9	89.3	237	187	79.6	21.3	431	331	76.8	6.3	147.1	77.3
S2c	27	30	50	2011	72.7	8.4	87.6	233	182	74.6	22.2	427	323	75.6	7.3	150.8	73.3
S1d	27	66	0	2011	79.4	24.2	87.4	304	274	167.1	0	497	494	99.4	5.5	105.8	89.3
S2d	27	30	0	2011	80.2	8.4	87.4	303	273	166.2	0	500	497	99.4	5.9	105.4	89.6
S1e	27	66	122	2006	72.2	23.6	90.8	211	155	47.8	27.0	510	268	53.9	1.4	54.9	65.7
S2e	27	30	122	2006	72.7	8.4	89.5	210	152	45.0	28.7	505	275	53.2	2.0	50.7	70.9
S1f	27	66	122	2007	67.9	23.4	87.6	225	165	57.6	31.2	541	309	59.4	6.7	70.2	34.4
S2f	27	30	122	2007	68.2	8.4	89.5	222	159	51.5	34.0	541	321	57.1	7.4	67.6	35.0
S1g	27	66	122	2008	68.8	23.0	91.8	213	160	52.6	24.2	535	290	56.5	4.8	68.5	40.3
S2g	27	30	122	2008	69.1	8.4	87.9	211	156	49.1	25.8	528	302	55.0	5.4	65.8	47.8
S1h	27	66	122	2009	74.8	24.3	88.0	226	165	57.8	32.0	519	273	54.8	2.2	60.1	56.4
S2h	27	30	122	2009	75.1	8.4	87.9	223	160	52.4	34.6	509	284	53.6	2.1	55.7	66.1
S1i	27	66	122	2010	77.4	23.2	94.2	226	169	61.6	28.4	516	275	54.8	2.4	54.9	58.4
S2i	27	30	122	2010	77.7	8.4	91.2	222	165	57.6	27.7	510	283	53.8	2.8	50.0	63.9
S1j	27	66	122	2012	74.4	24.0	88.4	224	164	57.3	30.9	525	291	55.0	4.8	54.9	50.7
S2j	27	30	122	2012	74.7	8.4	87.6	219	158	51.4	31.3	515	284	53.8	4.1	50.0	60.5

CAPEX Sensitivity

Capital expenditure sensitivities are carried out taking into account two alternative data sources. The first are the IRENA projections for 2025 [48] but assuming respective values for 2030 assuming slower but effective political dynamics needed to leverage cost reduction potentials for the production of PV and wind power technology. This yields the values given in Table 9 assuming an average exchange rate of 0.9 2015 €/2015 USD. It represents the global weighted average of an optimistic cost reduction for PV and wind power technologies. The second set is based on an analysis by the Danish Energy Agency and Energinet [49] and better reflects European projections. All values in Table 9 are given rounded to 10 €/kW.

Table A9. Specific CAPEX sensitivity assumptions based on [48,49].

		PV	Wind Onshore	Wind Offshore
Scenario assumptions	€/kW	860	1100	1800
CAPEX sensitivity set [1] [14]	USD/kW	790	1370	3950
	€/kW	710	1230	3560
CAPEX sensitivity set [2] [15]	€/kW	660 [1]	1040	1800 [2]

[1] PV specific installation costs assumed to be the average of small (870 €/kW), medium (800 €/kW) and large scale plants with large scale plants being made up half of tracking (310 €/kW) and half of non-tracking (300 €/kW) systems; [2] Offshore wind plants assumed to be half near shore (1660 €/kW) and half offshore (1930 €/kW).

Table A10. Overview on scenario definitions and main annual results of the sensitivity analysis on specific capital expenditure assumptions for fluctuating RE technologies. Total system costs are given for the complete system boundary while all other values are given for Germany.

															Results			
Scenario	**Annual Electricity Demand from BEV Fleet in TWh**	**Controllable Share in %**	**CAPEX PV in k€/MW**	**CAPEX Wind Onshore in k€/MW**	**CAPEX Wind Offshore in k€/MW**	**Total System Cost in Bn. €**	**Shifted Load by German BEV Fleets in TWh**	**Peak Load in GW**	**Installed Capacities of Power Plant Park in GW**	**Installed RE Capacities in GW**	**Fluctuating RE Capacity Additions in GW**	**Gas Power Plant Capacity Additions in GW**	**Annual Power Generation in TWh**	**Annual Fluctuating RE Power Generation in TWh**	**Fluctuating RE Share in Total Power Generation in %**	**Annual RE curtailment in TWh**	**Imports to Germany in TWh**	**Exports from Northern to Southern G in TWh**
S0	0	-	857	1100	1800	68.4	0	83.9	214	153	46.2	31.3	501	279	55.7	2.9	45.9	64.7
S1	27	66	857	1100	1800	71.2	24.2	86.3	223	159	51.5	35.5	526	291	55.3	2.6	51.3	65.1
S2	27	30	857	1100	1800	71.7	8.4	87.8	222	156	48.8	37.2	524	284	54.2	3.4	51.6	62.2
S1k	27	66	711	1233	3555	73.1	23.6	88.3	263	203	136.4	30.4	539	302	56.0	0.4	38.6	25.6
S2k	27	30	711	1233	3555	73.5	8.4	89.7	250	189	122.0	31.8	536	321	59.9	0.7	36.2	23.1
S1l	27	66	660	1040	1800	57.9	24.1	87.4	248	195	115.6	23.9	537	407	75.8	10.7	40.1	112.3
S2l	27	30	660	1040	1800	58.5	8.4	87.5	248	192	113.7	26.2	538	401	74.5	13.5	39.3	109.9

S1m with 30% Load Flexibility

An additional model run tests the exogenous assumption of S1 of 66% of the electric demand being flexible. In scenario S1m, this share is reduced to CURRENT's share of flexible charging of 30%.

Table A11. Sensitivity scenario results of scenario S1m in comparison with all reference and baseline scenarios S0–S2. Total system costs are given for the complete system boundary while all other values are given for Germany.

Scenario	Annual Electricity Demand from BEV Fleet in TWh	Controllable Share in %	Total System Cost in Bn. €	Shifted Load by German BEV Fleets in TWh	Peak Load in GW	Installed Capacities of Power Plant Park in GW	Installed RE Capacities in GW	RE Capacity Additions in GW	Gas Power Plant Capacity Additions in GW	Annual Power Generation in TWh	Annual RE Power Generation in TWh	Fluctuating RE Share in Total Power Generation in %	Annual RE Curtailment in TWh	Imports to Germany in TWh	Exports from Northern G to Southern G in TWh
S0	0	-	68.4	0	83.9	214	153	46.2	31.3	501	279	55.7	2.9	45.9	64.7
S1a	27	0	71.7	0	91.1	224	156	49.0	39.0	525	284	54.1	3.6	50.3	62.9
S1	27	66	71.2	24.2	86.3	223	159	51.5	35.5	526	291	55.3	2.6	51.3	65.1
S2a	27	30	71.7	0	93.5	223	156	48.8	37.9	524	284	54.2	3.5	51.6	62.4
S2	27	30	71.7	8.4	87.8	222	156	48.8	37.2	524	284	54.2	3.4	51.6	62.2
S1m	27	30	71.4	18.9	90.0	225	158	51.1	37.9	527	289	54.8	3.0	48.4	63.4

Relative Sensitivity

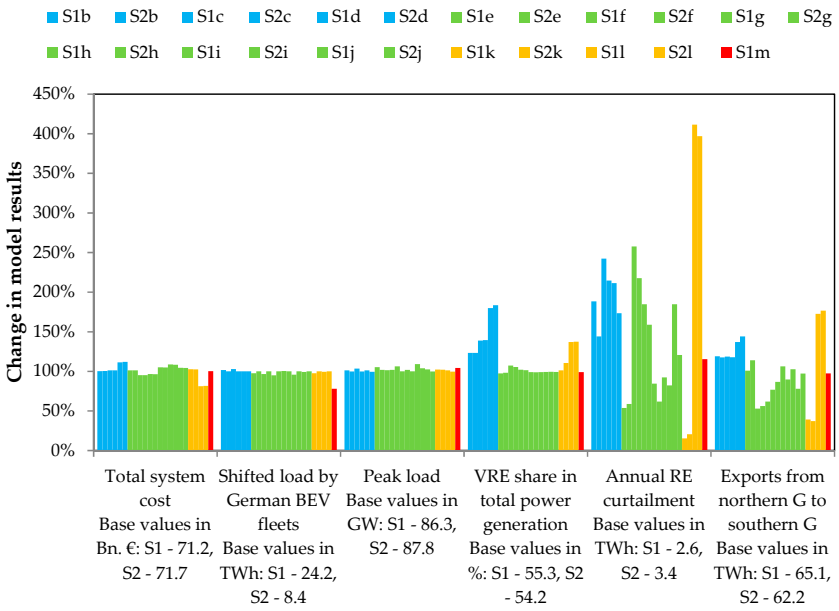


Figure A15. Relative sensitivity of annual energy system model results analyzed in Section 3.2. Each result value (of S1x, S2x) is divided by result values of baseline (S1, S2) values respectively. Blue bars show the results for the model runs with lower CO_2 limit, green those with different weather years, yellow those with different fluctuating RE specific investment assumptions and red that with lower BEV charge control availability.

References

1. United Nations. *Paris Agreement*; United Nations: Paris, France, 2015; p. 27.

2. European Commission. *Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions. The European Green Deal*; Publications Office of the European Commission: Brussels, Belgium, 2019.
3. German Federal Environment Agency. *National Inventory Report for the German Greenhouse Gas Inventory 1990–2017*; Federal Environmental Agency: Dessau, Germany, 2019; p. 565.
4. Brown, T.; Schlachtberger, D.; Kies, A.; Schramm, S.; Greiner, M. Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable European energy system. *Energy* **2018**, *160*, 720–739. [CrossRef]
5. Huber, M.; Dimkova, D.; Hamacher, T. Integration of wind and solar power in Europe: Assessment of flexibility requirements. *Energy* **2014**, *69*, 236–246. [CrossRef]
6. Robinius, M.; Otto, A.; Heuser, P.; Welder, L.; Syranidis, K.; Ryberg, D.S.; Grube, T.; Markewitz, P.; Peters, R.; Stolten, D. Linking the Power and Transport Sectors—Part 1: The Principle of Sector Coupling. *Energies* **2017**, *10*, 957. [CrossRef]
7. Fischer, D.; Harbrecht, A.; Surmann, A.; McKenna, R. Electric vehicles' impacts on residentail electric local profiles—A stochastic modelling approach considering socio-economic, behavioural and spatial factors. *Appl. Energy* **2018**, *233–234*, 644–658. [CrossRef]
8. Ramea, K.; Bunch, D.S.; Yang, C.; Yeh, S.; Ogden, J.M. Integration of behavioral effects from vehicle choice models into long-term energy systems optimization models. *Energy Econ.* **2018**, *74*, 663–676. [CrossRef]
9. Bailey, J.; Axsen, J. Anticipating PEV buyers' acceptance of utility controlled charging. *Transp. Res. Part A* **2015**. [CrossRef]
10. Sun, X.-H.; Yamamoto, T.; Morikawa, T. Charge timing choice behavior of battery electric vehicle users. *Transp. Res. Part D* **2015**, *37*, 91–107. [CrossRef]
11. Gnann, T.; Funke, S.; Jakobsson, N.; Plötz, P.; Sprei, F.; Bennehag, A. Fast charging infrastructure for electric vehicles: Today's situation and future needs. *Transp. Res. Part D Transp. Environ.* **2018**, *62*, 314–329. [CrossRef]
12. Chakraborty, D.; Bunch, D.S.; Lee, J.H.; Tal, G. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. *Transp. Res. Part D Transp. Environ.* **2019**, *76*, 255–272. [CrossRef]
13. Tian, Z.; Hou, W.; Gu, X.; Gu, F.; Yao, B. The location optimization of electric vehicle charging stations considering charging behavior. *Simulation* **2018**, *94*, 625–636. [CrossRef]
14. Hardman, S.; Jenn, A.; Tal, G.; Axsen, J.; Beard, G.; Daina, N.; Figenbaum, E.; Jakobsson, N.; Jochem, P.; Kinnear, N.; et al. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. *Transp. Res. Part D Transp. Environ.* **2018**, *62*, 508–523. [CrossRef]
15. Steck, F.; Anderson, J.E.; Kuhnimhof, T.; Hoyer-Klick, C. Comprehensive transportation and energy analysis: A price sensitive, time-specific microsimulation of electric vehicles. In Proceedings of the Transportation Research Board 98th Annual Meeting, Washington, DC, USA, 13–17 January 2019; p. 18.
16. Schuller, A. Electric Vehicle Charging Coordination. Economics of Renewable Energy Integration. Ph.D. Thesis, Karlsruhe Institute for Technology, Karlsruhe, Germany, 2013.
17. Michaelis, J.; Gnann, T.; Klingler, A.-L. Load Shifting Potentials of Plug-In Electric Vehicles—A Case Study for Germany. *World Electr. Veh. J.* **2018**, *9*, 21. [CrossRef]
18. Luca de Tena, D.; Pregger, T. Impact of electric vehicles on a future renewable energy-based power system in Europe with a focus on Germany. *Int. J. Energy Res.* **2018**, *42*, 2670–2685. [CrossRef]
19. Gerhardt, N.; Jentsch, M.; von Bonin, M.; Becker, S.; Böttger, D. *Entwicklung des Strassenverkehrs und Rückkopplung mit dem Energiesystem in -95% THG-Klimaszenarien. Teilbericht*; Technical Report; Fraunhofer IEE: Kassel, Germany, June 2018.
20. Taljegard, M.; Göransson, L.; Odenberger, M.; Johnsson, F. Impacts of electric vehicles on the electricity generation portfolio–A Scandinavian-German case study. *Appl. Energy* **2019**, *235*, 1637–1650. [CrossRef]
21. Robinius, M.; Otto, A.; Syranidis, K.; Ryberg, D.S.; Heuser, P.; Welder, L.; Grube, T.; Tietze, V.; Stolten, D. Linking the Power and Transport Sectors—Part 2: Modelling a Sector Coupling Scenario for Germany. *Energies* **2017**, *10*, 957. [CrossRef]
22. Luca De Tena, D. *Larce Scale Renewable Power Integration with Electric Vehicles. Long Term Analysis for Germany with a Renewable Based Power Supply*; University Stuttgart: Stuttgart, Germany, 2014.

23. Follmer, R.; Gruschwitz, D.; Jesske, B.; Quandt, S.; Lenz, B.; Nobis, C.; Köhler, K.; Mehlin, M. *Mobilität in Deutschland 2008. Ergebnisbericht. Struktur—Aufkommen—Emissionen—Trends*; Infas Institute for Applied Social Sciences & German Aerospace Center, Institute for Transport Research: Berlin/Bonn, Germany, February 2010.
24. Scholz, Y.; Gils, H.C.; Pietzcker, R.C. Application of a high-detail energy system model to derive power sector characteristics at high wind and solar shares. *Energy Econ.* **2017**, *64*, 568–582. [CrossRef]
25. Redelbach, M. *Entwicklung Eines Dynamischen Nutzenbasierten Szenariomodells zur Simulation der Zukünftigen Marktentwicklung für Alternative PKW-Antriebskonzepte*; University Stuttgart: Stuttgart, Germany, 2016.
26. Schimeczek, C.; Klötzke, M.; Kugler, U.; Schmid, S. *Report on Enhanced model Algorithm and model Calibration. EMAP Project Deliverable D6.1*; Institute for Vehicle Concepts, German Aerospace Center: Stuttgart, Germany, 2015.
27. Neaimeh, M.; Salisbury, D.S.; Hill, G.A.; Blythe, P.T.; Scoffield, D.R.; Francfort, J.E. Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy* **2017**, 474–486. [CrossRef]
28. Anderson, J.E.; Steck, F.; Kuhnimhof, T. Can Renewable Energy Sources Meet Electric Vehicle Charging Demand Today and in the Future? A Microscopic Time-Specific Travel Demand Analysis for Germany. In Proceedings of the 97th Annual Meeting of the Transportation Research Board, Washington, DC, USA, 7–11 January 2018; p. 15.
29. Hu, L.; Dong, J.; Lin, Z. Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach. *Transp. Res. Part C Emerg. Technol.* **2019**, *102*, 474–489. [CrossRef]
30. Wolbertus, R.; Kroesen, M.; van den Hoed, R.; Chorus, C.G. Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. *Transp. Res. Part D Transp. Environ.* **2018**, *62*, 283–297. [CrossRef]
31. Scholz, Y. *Renewable Energy Based Electricity Supply at Low Costs. Development of the REMix Model and Application for Europe*; University Stuttgart: Stuttgart, Germany, 2012.
32. Gils, H.C.; Simon, S.; Soria, R. 100% Renewable Energy Supply for Brazil—The Role of Sector Coupling and Regional Development. *Energies* **2017**, *10*, 1859. [CrossRef]
33. Gils, H.C.; Scholz, Y.; Pregger, T.; Luca de Tena, D.; Heide, D. Integrated modelling of variable renewable energy-based power supply in Europe. *Energy* **2017**, *123*, 173–188. [CrossRef]
34. Gils, H.C.; Simon, S. Carbon neutral archipelago—100% renewable energy supply for the Canary Islands. *Appl. Energy* **2017**, *188*, 342–355. [CrossRef]
35. Fattler, S.; Pichlmaier, S.; Schulz, M. Charge Optimization Of Privately And Commercially Used Electric Vehicles And Its Influence On Operational Emissions. In Proceedings of the IAEE Conference on Transforming Energy Markets, Groningen, The Netherlands, 10–13 June 2018; pp. 1–18.
36. Cao, K.K.; Pregger, T.; Scholz, Y.; Gils, H.C.; Nienhaus, K.; Deissenroth, M.; Schimeczek, C.; Krämer, N.; Schober, B.; Lens, H.; et al. Analyse von Strukturoptionen zur Integration erneuerbarer Energien in Deutschland und Europa unter Berücksichtigung der Versorgungssicherheit (INTEEVER). *Schlussbericht*. 2019. Available online: https://elib.dlr.de/126264/1/Endbericht_INTEEVER%20final.pdf (accessed on 28 February 2020).
37. EnBW Transportnetze AG; E.ON Netz GmbH; RWE Transportnetze Strom GmbH; Vattenfall Europe Transmission GmbH. Übersicht über die Voraussichtliche Entwicklung der Installierten Kraftwerksleistung und der Leistungsflüsse in den Netzgebieten der Deutschen Übertragungsnetzbetreiber (Regionenmodell "Stromtransport 2012"). Berlin, Germany, 2012. Available online: https://www.diesteckdose.net/download/file.php?id=4541 (accessed on 2 March 2020).
38. Chaniotis, D.; Schmitt, L.; TYNDP 2018. ENTSO Scenario 2018 Generation Capacities. Data File. 2018. Available online: https://www.entsog.eu/sites/default/files/entsog-migration/publications/TYNDP/2017/entsos_tyndp_2018_Scenario_Report_draft_edition.pdf (accessed on 12 December 2019).
39. Rippel, K.M.; Wiede, T.; Meinecke, M.; König, R. *Szenariorahmen für den Netzentwicklungsplan Strom 2030 (Version 2019). Entwurf der Übertragungsnetzbetreiber*; 50Hertz Transmission GmbH, Amprion GmbH, TenneT TSO GmbH, TransnetBW GmbH: Berlin/Dortmund/Bayreuth/Stuttgart, Germany, 2018; p. 121.
40. Gimeno-Gutiérez, R.M.; Lacal-Arántegui, R. *Assessment of the European Potential for Pumped Hydropower Energy Storage. A GIS-Based Assessment of Pumped Hydropower Storage Potential*; European Commission, Joint Research Centre, Institute for Energy and Transport: Petten, The Netherlands, 2013.

41. Turk, D.; Cazzola, P.; Bunsen, T.; Gorner, M.; Paoli, L.; Scheffer, S.; Schuitmaker, R.; Tattini, J.; Teter, J. *Global EV Outlook 2018. Towards Cross-Modal Electrification*; International Energy Agency (IEA): Paris, France, 2018.
42. Babrowski, S.; Heinrichs, H.; Jochem, P.; Fichtner, W. Load shift potential of electric vehicles in Europe. *J. Power Sources* **2014**, *255*, 283–293. [CrossRef]
43. Schwochow, M. Postleitzahlen Deutschland. 2019. Available online: https://www.suche-postleitzahl.org/downloads (accessed on 12 December 2019).
44. Chaniotis, D.; Schmitt, L.; TYNDP 2018. Europe's Network Development Plan to 2025, 2030 and 2040. 2018. Available online: https://www.entsog.eu/sites/default/files/2018-12/ENTSOG_TYNDP_2018_Executive%20Summary_web.pdf (accessed on 12 December 2019).
45. Jabeen, F.; Olaru, D.; Smith, B.; Braunl, T.; Speidel, S. Electric vehicle battery charging behaviour: Findings from a driver survey. In Proceedings of the Australasian Transport Research Forum, Brisbane, Australia, 11–13 October 2013; p. 15.
46. Gils, H.C. *Balancing of Intermittent Renewable Power Generation by Demand Response and Thermal Energy Storage*; University of Stuttgart: Stuttgart, Germany, 2015.
47. Babrowski, S.J.P.; Fichtner, W. Electricity storage systems in the future German energy sector. An optimization of the German electricity generation system until 2040 considering grid restrictions. *Comput. Oper. Res.* **2016**, 228–240. [CrossRef]
48. Taylor, M.; Ralon, P.; Ilas, A.; Dieckmann, S.; Dersch, J.; Lüpfert, E.; Pitz-Paal, R.; Giuliano, S. *The Power to Change: Solar and Wind Cost Reduction Potential to 2025*; International Renewable Energy Agency (IRENA): Bonn, Germany, 2016; p. 108.
49. Danish Energy Agency and Energinet. *Technology Data for Energy Plants for Electricity and District Heating Generation*; Danish Energy Agency and Energinet, 2016. Available online: https://ens.dk/sites/ens.dk/files/Analyser/technology_data_catalogue_for_el_and_dh_-_aug_2016_upd_oct18.pdf (accessed on 10 January 2020).



© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

B.3. Paper III - Energy system implications of demand scenarios and supply strategies for renewable transportation fuels

Energy Strategy Reviews 58 (2025) 101606

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Energy system implications of demand scenarios and supply strategies for renewable transportation fuels

Niklas Wulff [a,*], Danial Esmaeili Aliabadi [b], Samuel Hasselwander [c], Thomas Pregger [a], Hans Christian Gils [a], Stefan Kronshage [a], Wolfgang Grimme [d], Juri Horst [e], Carsten Hoyer-Klick [a], Patrick Jochem [a]

[a] German Aerospace Center (DLR), Institute of Networked Energy Systems, Curiestr. 4, 70563 Stuttgart, Germany
[b] Helmholtz Centre for Environmental Research - UFZ, Permoserstraße 15, 04318, Leipzig, Germany
[c] German Aerospace Center (DLR), Institute of Vehicle Concepts, Wankelstr. 5, 70563 Stuttgart, Germany
[d] German Aerospace Center (DLR), Institute of Air Transport, Linder Höhe, 51147 Köln, Germany
[e] IZES gGmbH, Altenkesseler Straße 17, Geb. A1, 66115 Saarbrücken, Germany

ARTICLE INFO

Dataset link: https://doi.org/10.5281/zenodo.14203522

Keywords:
Energy system analysis
Sector-coupling
Transport sector
Synthetic fuels
Biofuels
Fuel imports

ABSTRACT

Reducing greenhouse gas emissions in the transport sector is among the hardest challenges in transforming energy systems to zero emissions. Transport energy demands are driven by an interplay of social behavioral, technical factors, political decisions and economic conditions, motivating detailed transport demand modeling.

In Germany, transport energy supply – increasingly from electricity – is expected to challenge the energy supply infrastructure. Recent studies assume large shares of imported clean energy carriers and proclaim global renewable fuel import potentials. Simultaneously, sustainable biofuels' impacts on required electricity supply infrastructure is yet not well understood.

We assess the impact of climate ambition, indirect electrification shares and biofuel availability on energy supply infrastructure in 8 demand scenarios. Coupling the European energy system model REMix with the biofuel allocation model BENOPTex, we calculate cost-minimal energy supply infrastructure for each scenario. This high detail of integrated transport sector and biofuel modeling is novel to energy system analysis.

We find that incorporating user preferences in sales decisions clearly narrows the range of transport energy demand. As the German renewable energy potential is exhausted, higher clean fuel demand is covered by imports. Still, the use of these fuels drives the required power grid expansion, and especially electrolysis and fuel production capacities. Biofuel availability may significantly reduce e-fuel demand reducing cost-optimal hydrogen production capacity in the medium term and necessary grid expansion within Germany beyond 2030.

The model outcome is limited by assumptions on costs and availability of import options. Future work should further address modal shift transport scenarios.

1. Introduction

Cutting Greenhouse Gas (GHG) emissions in the transport sector is among the greatest challenges of clean energy supply [1]. The high energy densities of fossil fuels are a perceived requirement due to range expectancies, limited vehicle space and individual travel patterns. The associated habituation to the technical and economic possibilities of today's mobility leads to a reluctance towards behavioral changes, especially sufficiency. In addition, there is generally no option to carry out carbon dioxide (CO_2) capture, except for large ships, where anthropogenic carbon cycles are being discussed in research. Large parts of transport sector final energy demands are likely to be transformed to electricity based on RES. However, some modes of transport require the chemical-physical properties of hydrocarbons, such as aviation and shipping [2].

Final energy demand shares between electricity, H_2 and hydrocarbons are shaped by political choices. Vehicle stock mainly depends on fleet emission limits and support schemes. Infrastructure expansion is often managed by natural monopolies largely affected by policy-making and international trade relationships are limited or enabled by trade regulations on national or regional level. For hydrocarbons, sustainably produced biofuels may be important alternatives to electricity-based liquid or gaseous fuels referred to as e-fuels. Especially in industrialized

* Corresponding author.
E-mail address: niklas.wulff@dlr.de (N. Wulff).

https://doi.org/10.1016/j.esr.2024.101606
Received 15 October 2024; Received in revised form 22 November 2024; Accepted 5 December 2024
Available online 24 January 2025
2211-467X/© 2025 German Aerospace Center (DLR), Institute for Networked Energy Systems. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

Nomenclature

AC	Alternating Current
AEL	Alkaline ELectrolysis
BAU	Business-as-usual
BBS	Berlin, Brandenburg Saxony-Anhalt
BEV	Battery Electric Vehicle
BESS	Battery Energy Storage Systems
BECCS	Bioenergy with CCS
BLS	Bremen, Lower-Saxony
CCGT	Combined-cycle gas turbine power plant
CCS	Carbon Capture and Storage
CCU	Carbon Capture and Utilization
CH_4	Methane
CHP	Combined Heat and Power
CO_2	Carbon dioxide
CSP	Concentrating Solar Power
DAC	Direct Air Capture
DC	Direct Current
DEL	Direct electrification scenario
DEL_bio	DEL with biofuel availability
DH	District heating grid
EU	European Union
ExCCGT	Backpressure combined cycle gas turbine with heat extraction
FCEV	Fuel Cell Electric Vehicle
FT	Fischer Tropsch fuel production facility
GHG	Greenhouse Gas
GT	Gas turbine power plant fired by various fuels
H_2	Hydrogen
HSH	Hamburg, Schleswig-Holstein
HVAC	High-voltage alternating current transmission line
HVDC	High-voltage direct current transmission line
HYD	Hydrogen scenario
HYD_bio	HYD with biofuel availability
ICE	Internal Combustion Engine
Ind	Industrial
LIB	Lithium-Ion Battery
LP	Linear Programming
MENA	Middle East and North Africa
MVP	Mecklenburg-Vorpommern
NRW	North Rhine-Westfalia
OM	Operation and maintenance
PEMEL	Proton Exchange Membrane
PHEV	Plugin Hybrid Electric Vehicle
PtX	Power-to-X
PV	Photovoltaics
RED	Renewable Energy Directive
REF	Reference scenario
RES	Renewable Energy Sources
RFNBO	Renewable Fuels of Non-Biological Origin
SAF	Sustainable Aviation Fuel
ST	Steam turbine power plant fired by different primary energy carriers
SYN	Synthetic fuel scenario
SYN_bio	SYN with biofuel availability
TFC	Total Final Consumption
TH	Town heating grid
WACC	Weighted Average Capital Costs

countries with high population densities and limited solar and wind power potential, biomass may provide an additional source of primary energy.

The supply of electricity, hydrogen and other energy carriers requires different conversion stages from primary energy sources such as wind and solar energy. Increasing use of synthetic fuels, first hydrogen and then downstream synthetic products, which we refer to as increasing conversion depth, implies efficiency losses due to the second law of thermodynamics [3]. These energy losses are highly relevant in the assessment of different options, as the integration of the conversion steps into the energy system requires different infrastructure development. However, the techno-economic challenges and required fuel properties might demand pursuing deeper pathways.

Additionally, technical, political and user-specific factors interact and can result in varying fuel demand developments. As this also places various demands on the supply structure, integrated modeling must provide important insights into cost-relevant effects and the possible solutions at system level. To investigate the systemic impacts, the modeling for this paper focuses on the replacement of fossil fuels with the low-emission alternatives hydrogen, biogenic or electricity-based hydrocarbons based on RES complementary to direct electrification.

1.1. Motivation

Three transport sub-sectors have particular challenges in the transformation to carbon-neutrality: Road, aviation and navigation. The road sector, and specifically passenger cars, have the greatest share in transportation energy demand and emissions [4,5]. Aviation contributes less to final energy demands but is among the hardest to abate because direct electrification and hydrogen use can only substitute limited shares of persons and goods transported and respective technological concepts have not yet been introduced on a commercial scale [2]. Navigation also faces major challenges when switching to green fuels due to the high energy density required for heavy-duty and long-distance transport and high investments in propulsion systems with a long service life. Thus, shipping is also a candidate for the utilization of considerable quantities of clean synthetic fuels.

Different strategies for GHG reduction in transport are discussed. Decarbonization through direct electrification describes a replacement of internal combustion engines by Battery Electric Vehicle (BEV). Defossilization on the other hand means a change of primary energy source from fossil crude oil to RES based H_2. Also referred to as indirect electrification [6], this strategy requires electricity based on RES for supplying gaseous or liquid clean fuels, unless biomass is used as a primary energy carrier. Wind and solar power have to provide the major share of this, especially in countries such as Germany that have limited hydropower potential combined with high energy demands [7,8]. Irrespective of the strategy, the role of renewable energy as a primary energy carrier in transportation is expected to drastically increase, with well-known challenges.

The intermittent nature of wind and solar energy requires flexibility options to balance load and intermittent generation, and to ensure security of supply and system adequacy [9]. To assess intermittent RES integration into energy systems, both a high temporal resolution for short-term fluctuations and long horizons for seasonal effects must be considered [10]. Advanced energy system models need to be applied in order to analyze resulting systemic needs and implications

along the chain of electricity supply, transmission, distribution, storage and consumption. It must be taken into account that the national electricity grids in Europe are intertwined which leads to spatial flexibility. Moreover there is both, scientific evidence [11] and political targets [12] that European electricity markets and infrastructure are becoming increasingly integrated.

The role of biogenic energy carriers in substituting fossil fuels and thus limiting electricity demand increase for electric fuels is still not well understood. This gains importance because increasing sector-coupling [13] of transport, heat and industry is expected to require fast expansions of intermittent RES capacities. However, sustainable biomass potentials for the energy sector are also limited [14] due to competing demands from food production [15], for basic chemical productions [16] and for heating purposes [17].

Nowadays, all European countries except Norway are net energy importers [18], especially of crude-oil for transport fuel demands and fossil gas. Because of the limited resource potential for intermittent RES, especially in densely populated countries such as Germany, imports of clean fuels from world regions with higher resources such as Australia, South America or North Africa are discussed [19]. As with biofuels, imported Renewable Fuels of Non-Biological Origin (RFNBO) can relieve countries of the challenge of rapidly expanding intermittent RES capacities in order to produce RFNBO themselves at higher cost. However, import dependence also has major challenges. First, the consequences of the Ukraine war has shown the disadvantages of European countries' energy import dependence, which pushed the European Union (EU) to introduce the REPowerEU plan [20], aiming at increasing Europe's energy sovereignty [21]. Secondly, importing from countries in the global south to the EU bears the risk of reproducing and strengthening postcolonial trade relations as described as barrier for renewable electricity trade between Europe and its southern neighbors [22]. It is therefore necessary to scrutinize the evidence base of trade-offs between domestic RFNBO, imported RFNBO and biofuels.

1.2. Literature review

From the vast body of literature on reaching energy system climate neutrality, we focus on studies that describe fully sector-coupled clean energy supply systems. From those, studies were selected that explicitly describe German transport sector fuel demands and their implications on energy supply infrastructure. Both, target year and transformation pathway studies are considered. To enrich the discussion by a broader perspective, we cite individual sources with a global scope.

Bu et al. propose two demand scenarios with one achieving net zero passenger transport for China in 2050 [23]. However, the supply of energy forms is not assessed. Combining top-down and bottom-up modeling, this shortcoming is addressed by [24] analyzing environmental and economic benefits. The authors' analysis focus on medium-term transformations with an energy system model setup that does not have sufficient temporal resolution for modeling fully sector-coupled energy systems beyond 80% intermittent RES.

Transport sector CO_2 emission reduction strategies are highly intertwined with socio-economic factors. Emodi et al. mention population growth, fewer government regulations, weak traffic demand management and low investment in public transport infrastructure among others as drivers of transport emissions [25] in countries of the global south. Although other mentioned factors, e.g. freight activities of fossil fuel vehicles and low penetration of zero-energy vehicles are shared globally, the before mentioned factors are not as relevant to most European countries.

1.2.1. Demands of clean transport scenarios

Fuel and electricity demands of a GHG neutral German transport sector have been reviewed by Wiese et al. [26] and Ruhnau et al. [6] and further detailed by Gnann et al. [27] and Sensfußet al. [28]. Fuel demands could imply electricity equivalents of 700–1000 TWh/a with liquid fuels for aviation and navigation contributing more than half of that primary energy demand across all scenarios [27]. In a global defossilization study, Teske et al. [29] show that following at least a 2 °C pathway requires an average share of 50% direct electrification of global transport demand.

1.2.2. The role of biomass for energy system GHG neutrality

Wiese et al. show that the use of biomass for energy supply – around 300 TWh in 2018 – is reduced only in 5 of 20 reviewed scenarios. In 8 scenarios, the consumption is comparable to today's consumption, while 7 scenarios require a biomass increase by 100–400 TWh/a for a climate neutral energy supply. The reciprocity of biomass supply and RFNBO imports is exemplified in a scenario without RFNBO that requires a doubling of biomass supply (650 TWh) [26]. Please see Appendix A for a critical reflection of clean fuel import potential quantification studies.

Incorporating feedbacks between biomass and electricity supply is demonstrated by Aliabadi et al. in a proof-of-concept [30]. The soft-coupling of the bioenergy model BENOPTex and energy system model REMix focuses on biofuels and alternative fuels. It is shown that the German transport sector requires imports for comprehensive defossilization under the EU Renewable Energy Directive (RED) policy framework. Two projects in Germany examined the relationship between biofuels and synthetic fuels, highlighting the significance of timing for biofuels as bridging technologies [31]. As the demand for biomass is anticipated to rise its availability [32] and the support for energetic use [33,34] remains uncertain.

1.2.3. The role of imports for energy system GHG neutrality

Wiese et al. show that imports of both RFNBO and electricity are among the largest uncertainties across the 20 reviewed scenarios with 0–140 TWh for electricity and 0–820 TWh for RFNBO [26]. Net electricity imports and exports are found from −9% (export of 102 TWh/a) to 13% (imports of 176 TWh) by Sensfußet al. [35]. Exports occur in the T45-PtG scenario that assume large amounts of imported RFNBO.

They show volumes of 800–1600 TWh/a of electricity equivalents, imported in the form of fuels across the scenarios with the electricity oriented scenario at the lower and the hydro-carbon oriented scenario at the upper bound. In total, import dependence is found to be reduced to 30%–40%. Of the 360–690 TWh/a of German H_2 demand, 190–270 TWh/a are domestically produced leading to an H_2 import share between 49 and 61% [28].

1.2.4. Infrastructure for GHG neutral energy supply

Focussing on energy supply infrastructure capacities in literature, Gong et al. find around 1000 GW of cumulative solar and wind power under "economic-wide carbon neutrality in 2045" (approximately 300 GW wind and 700 GW solar power) [36] compared to 290–770 GW under GHG neutrality found in a comprehensive review [26]. Sensfußet al. show fairly similar transformation pathways cumulating to 630–672 GW of solar and wind power capacity in 2045.

Gong et al. find 37–45 GW of electrolysis and around 40 TWh of H_2 storage capacity under GHG neutrality [36]. Sensfußet al. on the other side show 58–77 GW of electrolysis and 244–413 TWh of H_2 storage capacity [35]. The authors call for electricity transmission grid expansion surpassing current planned capacities as per the German grid extension plan by 60%–100% with major shares before 2035.

Major uncertainties persist in the current body of literature on German transport emission reduction and respective energy system infrastructure transformation. Since subsector demand specifics are often neglected, the range of uncertainty of fuel demand is still found to be large and driven by authors' exogenous assumptions. The same holds true for the case of the role of biomass in transport emission reduction. Clean fuel imports are also mostly assumed as fix values before modeling, neglecting trade-offs between biofuel use, domestic production and imported hydro-carbons.

1.3. Research question and structure

On the background of the latest scientific literature reviewed, we arrive at the overarching research question: What are energy-system trade-offs between domestically produced RFNBO, imported RFNBO and biogenic fuels for transport sector defossilization in Germany? We will answer it, divided in three sub-questions:

- How large is the primary clean energy demand of a GHG neutral transport sector?
- How do the differences in conversion depth affect cost-optimal energy system compositions and build-up dynamics?
- To what degree alleviates biofuel availability sharp gradients in electricity and hydrogen supply infrastructure build-up?

The objective of the study is to show the impacts of policy driven fuel demand scenarios and biofuel availability on energy system transformation pathways up to greenhouse gas neutrality. In the following Section 2, we describe the research design, and data, while Section 3 describes, analyzes and discusses the results of eight scenarios. We conclude in Section 4 and identify the most relevant open questions.

2. Research design and data

One of the main uncertainties of future GHG neutral energy supply is the degree of direct and indirect electrification [6]. Mainly political decisions on infrastructure, climate ambition and energy independence will shape these futures which we consider via four scenarios in scope 1: A Reference scenario (REF) failing political targets on GHG reduction ambitions and three target scenarios focusing on direct electrification (Direct electrification scenario (DEL)), the use of H_2 as a final energy carrier (Hydrogen scenario (HYD)) and increased synthetic fuel demands (SYN). In scope 2, each of these four scenarios is complemented by a scenario allowing for biofuel supply of energy carriers, e.g. SYN_bio for SYN, resulting in a total of eight scenarios.

A scenario is a relevant possibility [37]. It constructs a set of coherent descriptions and parameters with the aim to operationalize an uncertain future that can never be known. For quantifying the above mentioned storylines, we leaned as much as possible on values from Senssfußet al. [35] The scenarios differ in political decisions taken (e.g. eligibility of drop-in fuels in fleet emission regimes), in techno-economic developments (costs of batteries, vehicles, fuel cells) and in infrastructure availability. For REMix specifically, the main differences between the scenarios are the shares of final energy forms of electricity, hydrogen and clean fuels as described in Appendix C.1.

We describe the results of transport sector demand modeling for road and aviation in Section 2.1 and for all other sectors in Section 2.2 for answering research question 1. Our assumptions on cost-potential of electricity-based fuel imports are described in Section 2.4. With the 3 demand models and REMix we answer research question 2 in scope 1. Assumptions on biofuel availability are described in Section 2.3. A bilateral model coupling between REMix and BENOPTex is then used in scope 2 to answer research question 3. A brief overview over the models REMix and BENOPTex, the data flow and the interfaces between the models are summarized in Section 2.5. Fig. 1 shows the data flow between the demand models and the bilateral model coupling of REMix and BENOPT. The model coupling was first introduced in [38].

We contribute to the body of scientific literature in three ways: We provide a set of four technology-driven scenarios of GHG-neutral transport in Germany with varying conversion depth. Secondly, we combine transport demand models with sector-coupled energy system models. Thirdly, we apply an iterative model coupling of two system models with two perspectives and analysis focus: The electricity system model REMix and the resource allocation model BENOPTex. This allows us to investigate feedback effects between optimal biofuel allocation and optimal energy supply infrastructure expansion and dispatch. All data described below except for the 33 national energy balances are published in a data appendix including all interface and plotting data routines.

2.1. Detailed sub-sector demand scenarios

From road, aviation and navigation sectors, the authors' demand models were used to create target-compliant energy demand paths for road and aviation modes as part of this analysis. Navigation was considered in the following via demand developments derived from other studies but is an interesting pursue for demand modeling in future research.

2.1.1. Road

Road passenger and freight vehicle energy demand is based on the scenario and market analysis software VECTOR21 [39]. The tool simulates the market development of vehicle technologies of newly registered cars and trucks until 2050, the stock development and the resulting energy demand.

The scenarios incorporate not only policy instruments such as passenger vehicle fleet quota or blends but also user-preferences in purchasing vehicles depending on price, infrastructure availability, acceleration, range and other factors. More details on the modeling logic, input assumptions and resulting final energy demands are given in Appendix B.4.

2.1.2. Aviation

The aviation energy demand estimation is based on DLR's traffic forecast, which includes passenger demand and aircraft movements up to 2050. The scenario is characterized by an increasing energy demand, as it assumes that traffic demand growth will outpace efficiency improvements in aircraft technology. In the scenarios REF and SYN, for geographical Europe, jet fuel demand is expected to grow from 66 Mt to 113 Mt between 2019 and 2050.

The actual demand for RFNBO will be determined by the blending quota from the RefuelEU Aviation initiative. According to the latest regulation of the European Commission, the blending quota will increase from 0.7% in 2030 to 35 % in 2050 [40]. In the scenarios DEL and HYD, a European-wide jet fuel demand of 65 Mt is expected in 2040, and 61 Mt in 2045, respectively. Jet fuel demand declines over time as the phase-in of hydrogen aircraft progresses.

Hydrogen accounts for 12.3% of energy consumption in aviation, as flights beyond 2780 km will still be operated with conventional aircraft. As electric flight will be limited to the segment of aircraft with a maximum of 19 seats, demand for electricity for direct use in aviation will be limited to about 600 MWh in Europe in 2050. Further details can be found in Appendix B.5.

2.2. National energy balances

The energy demand for other sectors has to be taken into account in order to capture systemic interactions and implications on energy supply and grid infrastructure in future system developments. For the transport sector, this includes shipping and rail energy demand. Furthermore, electricity and heat demands for industry and buildings (households and services/commercial sectors) are estimated in the holistic accounting framework LENS, complemented by the transport demand data described above in Section 2.1. As a result, we generate national energy balances for 33 countries for each scenario that are aggregated into annual final energy demand inputs to REMix model nodes as specified in Figure B.7. Integrating European energy demands, imports to Germany and exports from Germany is highly relevant as transmission expansion is among the cheapest flexibility options in electricity systems with high shares of intermittent RES [11].

The REF scenario does not achieve GHG neutrality in 2050, but follows an 80% reduction of energy-related emissions in relation to 1990 emission levels. For EU-countries aside Germany, the national pathways for the REF scenario are based on the EU Reference Scenario 2018, which was adjusted in terms of target achievement, i.e. made more ambitious. The scenarios DEL, HYD and SYN achieve GHG neutrality

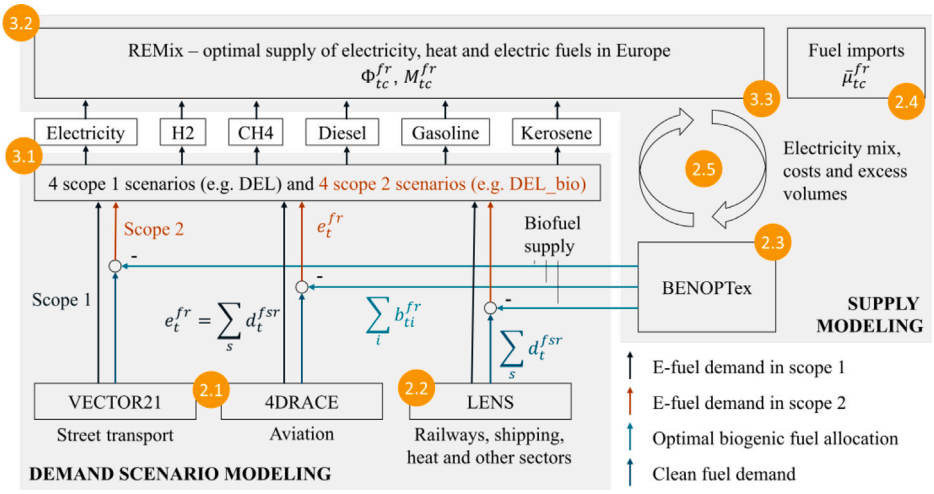


Fig. 1. Overview of the models used, the two modeling scopes and the model coupling logic. The other models shown contribute to the provision of solid scenario data for future transport sector demand (Section 2).

Table 1
Transport sector final energy demands in the four scenarios split into electricity, renewable gases and liquid renewable fuels. Liquid fuels contain jet fuel (e-kerosene), e-gasoline fuel and e-diesel fuel. All values given in TWh/a and rounded to 1 TWh/a.

			Target scenarios		
	2020	REF 2045	DEL 2045	HYD 2045	SYN 2045
Electricity	12	101	181	146	161
H_2 and methane (CH_4)	0	34	35	103	21
Liquid fuels	0	186	184	174	254

in 2045 by excessive expansion of renewable energy, electrification of end-use applications and through the complementary use of hydrogen and synthetic fuels. They are based on the EU long-term vision "A Clean Planet for All" [41] and the scenarios Electrification, Hydrogen (H_2) and Power-to-X (Power-to-X (PtX)) complemented by the 1.5TECH scenario for EU28.

In contrast to the European approach, the demand scenarios for Germany are based on the most recent German long-term scenarios developed for the German Federal Ministry for Economic Affairs and Climate Action [28], in order to better connect our work to the current discussions on the national energy transition. For both studies, we harmonized the scenario storylines on the demand side as far as possible and used system modeling to create new energy balances that are largely consistent between Germany and non-German countries. The resulting overarching demands for Germany are summarized in Table 1.

2.3. Biogenic resource potential and cost assumptions

In BENOPTex [42], ten energy crops and 13 groups of residues are modeled based on data provided in the "DE biomass monitor" [43]. The choice to cultivate various energy crops is an endogenous decision in the model based on the demand for fuel, heat, or electricity and respective costs. In Germany, wheat is considered the most common crop; hence, the final price of other energy crops is calculated such that their profit margins become on par with the wheat profit margin as the benchmark [44]. The production cost of energy crops consists of direct, labor, fuel, machine (fixed and variable), and service costs, which increase at a 4% rate until 2050. We incorporate energy consumption by agricultural and land machinery associated with biomass production for bioenergy, which includes consumed diesel (measured in liters per hectare) for various energy crop types [44,45]. The available land for planting energy crops is assumed to be 2.4 Mha in 2020, which will be reduced slightly in 2050 to 2.2 Mha in 2050 due to land competition among different sectors. Further information on biogenic feedstocks is given in Appendix B.3.

2.4. Fuel import cost-potential assumptions

Costs and maximum volumes of imports of renewable hydrogen and RFNBO are based on a global fuel market scenario analysis carried out in the MENA-Fuels project [46]. Global technical potentials for solar thermal, photovoltaic and wind power plants, taking into account exclusion areas, technical and economic assumptions for the production of hydrogen and synthetic crude oil, as well as assumptions on CO_2 supply costs from industry and Direct Air Capture (DAC), transport costs and import duties, represent the basis for bids on the global market [47].

These bids are combined into dynamic energy carrier-specific cost potential curves in 50 EUR/MWh-increments. In addition, further processing steps in the exporting countries are assumed, in order to estimate potentials for hydrogen, methane, synthetic gasoline, diesel and kerosene. In REMix, fossil fuel imports are only possible for gaseous CH_4. The transport sector is modeled as an increasing demand sector for electricity, clean gaseous and liquid fuels. More information is given in Appendix B.2.4.

2.5. Model coupling

The REMix-framework minimizes the costs of energy supply by varying the energy infrastructure capacities and their dispatch in high spatial and temporal detail. In this study, we employ a model with a 4h-resolution, 9 nodes in Germany and 13 European nodes outside of Germany (see Figure B.7). Each scenario is comprised of 4 base years — 2020, 2030, 2040 and 2045 that are myopically optimized. More technical details and assumptions can be found in Appendix B.2. The model was first introduced for the European electricity system modeling [48] and expanded to the heat sector [49], electric vehicles [50] and gas infrastructure [51].

The demand models VECTOR21, 4DRACE and LENS provide fuel demands d_t^{fsr} for fuel f in sector s and year t in region r. These demands are then added over all sectors per fuel to arrive at the fuel demand across sectors d_t^{fr}. In scope 1, these demands for renewable fuel are directly implemented as binding constraints in REMix' Linear Programming (LP) formulation as shown in Eq. (1). Here, biofuels are not assumed to supply the transportation sector, implying competition between domestic electricity-based fuel production and respective imports. In scope 2, the demands are reduced by the supply of biogenic

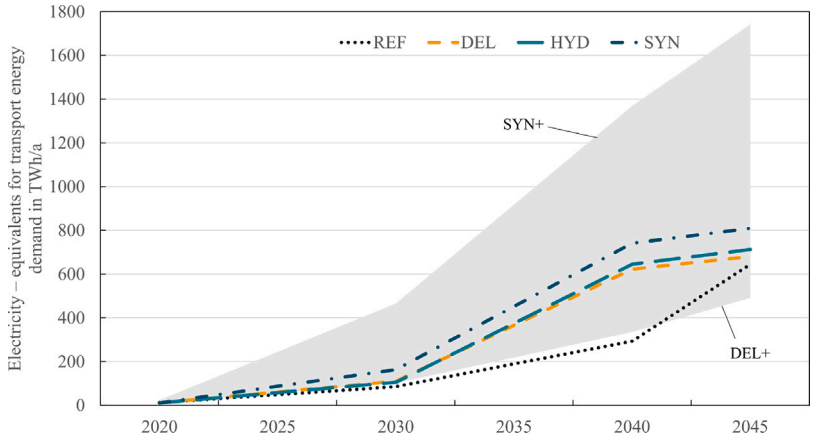


Fig. 2. Electricity equivalents of final energy demand in the transport sector in the four scenarios and two extremes of final energy use. All renewable energy demands are calculated to electricity equivalents to make them comparable. The REF scenario's GHG reduction ambition is lower especially in the years 2030 and 2040. Own depiction.

fuels b_{ti}^{fr} according to Eq. (2). for all mapped fuel supply technologies i.

$$\text{Scope 1: } e_t^{fr} = \sum_s d_t^{fsr} \tag{1}$$

$$\text{Scope 2: } e_t^{fr} = \sum_s d_t^{fsr} - \sum_i b_{ti}^{fr} \qquad ,\forall t \tag{2}$$

BENOPTex allocates the cheapest primary energy source – biofuel, synthetic fuel or fossil fuel – to the respective final energy demand harmonized with scope 1. The allocation builds on a broad set of 77 biomass residue streams, assumptions on agricultural land as well as efficiencies of conversion processes. For one transformation pathway, BENOPTex runs once relating to four REMix runs as BENOPTex includes interannual optimization along a pathway. The RFNBO demand (e_t^{fr}) comprises only electricity-based fuels and can be supplied by production facilities in Germany (Φ_{ti}^{fr}) or imported (M_{tc}^{fr}) drawing from discretized cost categories c (cf. Section 2.4) as described in Eq. (3).

$$\sum_i \Phi_{ti}^{fr} + \sum_c M_{tc}^{fr} = e_t^{fr} \qquad ,\forall t, f, r \tag{3}$$

Further formal description of REMix is given in Appendix B.7.

3. Results and discussion

We start by describing the differences of the transport sector's energy demands in different scenarios in Section 3.1. Then, we analyze the necessary energy system infrastructure build-up in Section 3.2. In Section 3.3, we show the effect of biofuel availability on energy supply infrastructure before we relate our results to earlier studies in Section 3.4.

3.1. The influence of conversion depth on transport sector energy demand

Fig. 2 shows transport sector final energy demand across the four scenarios . Results are shown against the background of two theoretical extreme cases: An almost complete switch to electricity as final energy (DEL+) and an almost complete switch to hydrocarbons (SYN+). While the impact of direct vs. indirect electrification is large in the thought experiment of lowest (DEL+) vs. highest (SYN+) conversion depth, scenarios incorporating sales preferences in road transport and technology shift details in aviation sectors show less divergence.

In 2045, transport sector final energy demands range from 680–810 TWh/a of electricity equivalents in the target scenarios (DEL, HYD and SYN) translating to an increase between 5%–25% compared to the reference case. All target scenarios exhibit stark gradients in the decade 2030–2040, mainly driven by a lack of drive-train shift in road transport, followed by a slower growth between 2040 and 2045, resulting in a S-shaped electricity demand.

The difference between DEL and HYD is small with 30 TWh/a difference in 2045, which can be explained by the fuel contributions shown in Figure C.16. In the HYD scenario, the road transport demand for both hydrocarbons and electricity is mainly replaced by hydrogen (see Figure C.16). While this implies less losses for the conversion step from H_2 to hydrocarbons, it implies more losses for the conversion from electricity to H_2. The aviation sector with its respective e-kerosene demand is the strongest driver of transport sector primary energy demand in 2045 across all three scenarios (between 39%–47% of electricity equivalents). All scenarios imply drastic changes in vehicle fleets, which are described and discussed in Appendix B.4.1. Transport sector contributions to overall transport energy demand for 2045 are depicted across the four scenarios in Figure C.14. Dynamic developments are shown in Figures C.13 and C.15.

The comparison of the two extreme cases with detailed subsector models for road and aviation demands show that incorporating technical detail and user preferences for vehicle purchases strongly reduces the uncertainty of future transport sector energy demand. This holds true when transport demand itself and modal choices remain similar to today's levels. The final energy demands we find are similar to the ones reported in Gnann et al. [27] with slightly higher electricity demands, slightly lower kerosene, more specific (i.e. narrower range) road sector demands and no CH_4 demands in transportation (see Appendix D.2 for a detailed comparison).

The most important limitation of our approach is that we did not explicitly model scenarios incorporating strong modal shifts and transport reduction policies as in Arnz et al. [52]. A combined approach of our detailed fleet modeling with their avoid and shift scenarios would provide an unprecedented transport sector modeling detail. Another limitation of our approach is that we do not consider spatially explicit fleet scenarios e.g. higher BEV developments in southern Germany from northern Germany. Incorporating navigation fuel demand scenarios similar to the ones for aviation is as well an interesting pursue for future research as demands for synthetic diesel and kerosene both imply demand for clean hydrogen.

3.2. The influence of conversion depth on energy supply infrastructure extension and usage

As shown in the previous paragraph, conversion depth influences the demand for renewable fuels and, consequently, implicit electricity demand. We now turn to the second-order implications of these variations on energy supply infrastructure. Our primary interest lies in the differences across the three target scenarios: DEL, HYD, and SYN, with the lower-ambition REF scenario serving as a reference. The analysis in

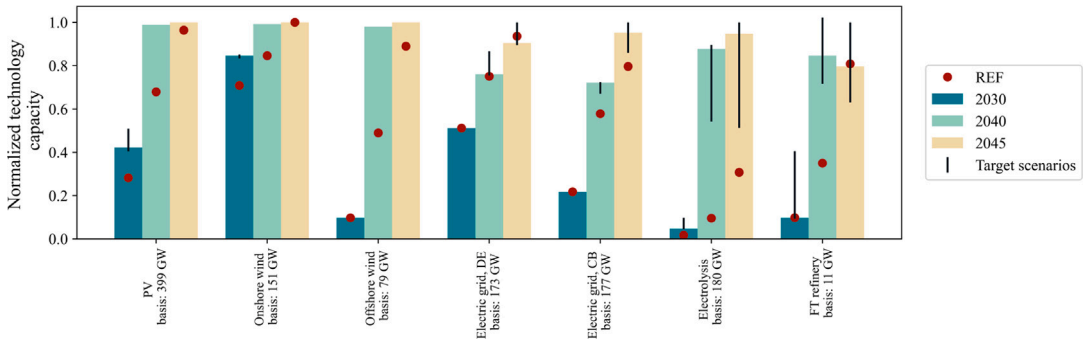


Fig. 3. Influence of conversion depth on cost-optimal technology capacity in Germany in 2030, 2040 and 2045. The red dots show the respective values from the reference scenario while the black lines show the variability of the respective technology capacity in the respective year for the three target scenarios. The bars show the middle value of the target scenarios. The normalization basis for all values in a group is the maximum value in 2045 across the scenarios. For intermittent RES – PV and wind power – the variability in the years 2040 and 2045 is negligible, thus no vertical lines exist.

this section is conducted within the scope of scope 1, meaning that no biofuel supply is available.

Fig. 3 illustrates the variability of cost-optimal technology expansion across the modeled scenarios and years. The power plant expansion depicted in the first three groups differs between the REF and target scenarios; however, it shows significant variability only for PV and onshore wind extensions in 2030. From 2040 onward, the variability between the target scenarios remains below 1% of the normalization basis. This supports previous findings that the expansion of intermittent RES is a no-regret option for GHG neutral energy supply systems. Under cost-optimal conditions, onshore wind capacity expands the earliest, continuing until 2030, accompanied by significant expansions of PV. In the decade from 2030 to 2040, all intermittent RES options are rapidly expanded, reaching their exogenously defined maximum potential.

Wind and solar power curtailment occurs only in 2030, ranging between 15–20 TWh/a, with the lowest value found in the SYN scenario. Due to early diesel and gasoline demands in 2030, demand-driven electrolysis capacities are expanded, which can help balance intermittent RES feed-in to some extent, thereby reducing curtailment compared to the DEL and HYD scenarios.

The following groups illustrate the expansion of inner-German power lines and cross-border interconnectors within the electricity grid. The inner-German electric grid expansion shows some variability beyond 2030 across all scenarios, including REF. The variabilities in 2040 and 2045 are attributed to increased inner-German Direct Current (DC) grid expansions (approximately 10 GW more in 2040) in the DEL scenario compared to HYD and SYN. The inner-German Alternating Current (AC) grid is expanded in all scenarios by 43–60 GW by 2040, with further expansions of 23–32 GW in the years leading up to 2045. The results indicate that inner-German grid expansion is cost-optimal, regardless of the degree of GHG reduction ambition. Achieving primarily direct electrification necessitates increased inner-German grid expansion.

Increased CO_2 reduction ambition requires higher cross-border grid capacities between Germany and its neighbors. Increasing conversion depth affects DC grid expansion in 2040 (15, 25 and 26 GW) and AC grid expansion in 2045 (35, 40 and 50 GW). In total capacities, around 100 GW is the minimal cross-border capacity in REF with 120–130 GW in the target scenarios in 2040. In 2045, capacities are expanded to 150–180 GW for the target scenarios. For comparison, the German grid development plan foresees aggregated interconnector capacities of around 40 GW with Germany's electrical neighbors. This fourfold increase transfers findings by Sensfußet al. calling for increased inner-German transmission grid expansion compared to the grid development plan to crossborder interconnectors [35].

H_2 production capacity is affected the strongest by conversion depth. It strongly varies across DEL, HYD and SYN. Conversion depth influences both, electrolysis capacity and H_2 production very similarly. In 2030, DEL and HYD require 7–8 GW while SYN requires more than twice the capacity mainly driven by increased e-diesel and e-gasoline demands from private vehicles. While the 20 TWh/a of H_2 produced in DEL and HYD mainly supply industry and early stage kerosene and diesel demands, the H_2 production of 50 TWh/a in SYN supplies significant domestic synfuel production of over 40 TWh/a of synthetic fuels.

In the following decade, H_2 production is vastly expanded in the three target scenarios, however with around 75 GW in DEL only half of the 150 and 145 GW in HYD and SYN respectively. Strongly increased e-kerosene demands and stable e-diesel demands between 2040 and 2045 are compensated by imports of RFNBO.

In 2040, all target scenarios reach above 300 TWh/a of domestic H_2 production with slightly below 400 TWh/a in DEL at the lower limit and slightly above 630–650 TWh/a in HYD and SYN, respectively. The split between DEL on the one hand and HYD and SYN intensifies in 2045 where H_2 production is around 350 TWh/a in the former and ranges from 700–750 TWh/a for the latter two, complemented by additional H_2 imports of 50, 190 and 340 TWh/a in DEL, HYD and SYN, respectively. This strong dynamic is not only driven by transport sector defossilization but even stronger by drastically increased H_2 and synthetic CH_4 usage in Combined Heat and Power (CHP) power plants in HYD and SYN. From 2040 onwards, more H_2 is used for methanation (160–300 TWh/a) for heat provision than for Fischer–Tropsch refineries (around 100 TWh/a) for transport final energy demands in all scenarios. Of the 175–250 TWh/a final energy demand for liquid hydro-carbons between 52%–57% are produced in Germany while the rest is imported.

Looking at the spatial distribution of H_2 production within Germany, deeper pathways increase the variability of H_2 production volumes across nodes as shown in the turquoise bars of Fig. 4. While they lie between 20–60 TWh/a for most nodes with the northern node Bremen, Lower-Saxony (BLS) at 120 TWh/a in DEL, this range increases to 10–100 TWh/a with BLS at 190 TWh/a in HYD and SYN.

Calculatory electrolysis full load hours increase from below 3000 in 2030 to around 4000 in 2040 and 3900–4200 in 2045 increasing with conversion depth. This demonstrates the challenge of profitable electrolysis operation especially in the medium term where H_2 demands are still comparably low. We identify this as a field of further research.

Turning to liquid hydrocarbons, domestic synthetic diesel, gasoline and kerosene supply shows some variation, especially in the short term, and interesting dynamics due to changing import shares. While road sector fuel demands peak in 2040 before declining until 2045, the demand for electric kerosene and diesel in aviation and shipping increases steadily. Fischer Tropsch fuel production facility (FT) refineries are expanded to around 10 GW of H_2 input with no further additions in 2045 due to increasing import volumes at low prices and limited intermittent RES production potential. Fuel production itself peaks in

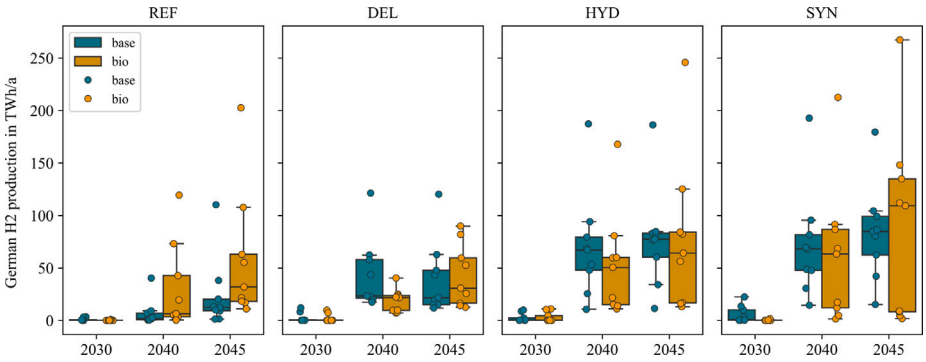


Fig. 4. Absolute H_2 production distribution across the nine German nodes in the four scenarios for scope 1 (base) and 2 (bio).

2040 with 60–90 TWh/a and is reduced towards 2045 to 30–70 TWh/a.

Refineries' production ratio of the three products is fixed, whereas final energy demand shares of the respective fuels develop dynamically towards dominant diesel shares in 2040 and balanced diesel and kerosene shares in 2045. This effect can be illustrated using the example of the model node Saarland, Rhineland-Palatinate, Hesse (SRH), where Germany's airport with the highest kerosene demand (Frankfurt am Main) is located. Across the target scenarios, below 5 TWh/a gasoline, 5–10 TWh/a diesel and 45–50 TWh/a kerosene are demanded in 2045, showing the discrepancy to the balanced production output. This discrepancy is compensated by imports, as can be seen in Figure C.23. Future research should give (potentially fixed but various) output shares for refineries to account for chemical plant heterogeneity.

Increased conversion depth leads to higher final energy demands for renewable fuels. This can be exemplified in the cases of gasoline and diesel demand. While domestic gasoline production shows no strong dependence on conversion depth, higher final energy demand in 2040 is compensated mostly by imports. In 2045, the SYN scenario shows an increase of domestic production to around 50% of final demand (27 TWh/a vs. 6 TWh/a in DEL). This dynamic is also observed for diesel and kerosene demand from 2040 onwards with decreasing or stable domestic production shares and growing imports supplying increasing kerosene and diesel final demand in 2045. For a discussion of our methods as well as a comparison of our scenario results with previous studies see Appendix D.3.

Our energy system modeling is limited since we do not explicitly model European fuel imports and exports between countries (only transmission grids). Gaseous and liquid fuel transport infrastructure modeling can yield interesting insights into European energy sovereignty and how it can be affected by European biofuel policies.

To our knowledge, we here for the first time combine results of a detailed modeling of transport subsector fuel demands with a fully sector-coupled energy system modeling in both high detail and transformation dynamic. Because our intermittent RES expansion potential assumptions are comparably low, we may overestimate power and fuel imports. However, we found very little H_2 imports only under GHG neutrality (in 2045) and resulting imports of diesel, gasoline and kerosene seem in line with or even below today's volumes.

3.3. The effect of biofuels on electricity supply infrastructure expansion

Biofuel availability may reduce the demand for electricity-based fuels as illustrated for the scenarios SYN and SYN_bio in Fig. 5. Various biomass streams lead to the reduction of e-fuels demands shown in Fig. 5. In all scenarios, there is a discernible decline in the consumption of rapeseed and sugar beet, which are traditionally used for biodiesel and bioethanol production. This decrease can be attributed to the assumed phased-out policies on conventional biofuels by policymakers under the EU regulation REDII. On the other hand, the combined consumption of maize silage and poplar exhibits an upward trajectory, indicating an increasing utilization of these feedstocks in the future. Poplar is mostly allocated to biomass-to-liquid processes to produce biodiesel and Sustainable Aviation Fuel (SAF) for road and aviation sectors. Also, paludiculture usage grows in all scenarios.

In the following, we assess how decreased e-fuels demands affect energy supply infrastructure expansion and usage. Liquid synthetic fuels are required at a level of 260 TWh/a in SYN vs. 110 TWh/a in SYNbio in 2045. As shown in Fig. 5, the difference mainly stems from a substitution of both, e-diesel and e-kerosene demand by biodiesel and biokerosene. Road sector synthetic fuel demand plays a larger role only in 2040. However, due to technical differences between Otto and Diesel engines, e-gasoline can only substitute up to 10%, thus only in early years when significant fossil gasoline is used. This is shown in Fig. 5 where gasoline substitution in 2030 is significant, because still large fossil gasoline demand exists, but this potential is diminished with reduced fossil gasoline demand in the consecutive years.

Fig. 6 shows the fuel origins in the SYN and SYN_bio scenarios for e-diesel, e-gasoline and e-kerosene. Biofuel availability drastically reduced efuel demand, especially for kerosene and Diesel, also reducing absolute domestic efuel production in 2045 and limiting necessary imports. Domestic efuel production is especially high in 2040 when still some emissions from heating and power are allowed for and strongly reduced in 2045.

Intermittent RES expansion is only slightly affected in 2030 and not from 2040 onwards, due to large electricity demands from other sectors. The reduced demand for electricity-based liquid hydrocarbons has strong implications on H_2 and refinery production capacities. This is especially true for the year 2040 as can be seen in Fig. 4 showing lower and less variable H_2 production across the nine German nodes in all three target scenarios DEL with biofuel availability (DEL_bio), HYD with biofuel availability (HYD_bio) and SYN_bio. See Figure C.21 for a direct comparison of the German electrolysis capacity in all 8 scenarios.

We now look at the effect of an optimal biofuel supply for transport on the necessary expansion of energy supply infrastructure in the two synthetic fuel scenarios SYN and SYN_bio. This is done for the technologies with the highest gradients shown in Table C.12.

In the SYN scenario, biofuels can reduce necessary intermittent RES capacity expansions in 2030. Needed PV power plant capacity could be reduced from over 200 GW in 2030 by more than 40 GW to 160 GW. Onshore wind power plant capacity expansion could be reduced by 13 GW from 129 to 116 GW. Germany-internal grids can be slightly reduced, while cross-border capacities can be significantly reduced from 2040 onwards from 130 and 180 to 120 and 160 GW in 2040 and 2045 respectively. In the DEL scenario, this effect cannot be observed. Here, a decrease in expanded offshore wind power capacity from 80 to 70 GW can be observed. Germany-internal grid extension is higher by 15 and 29 GW while cross-border capacities are slightly lower by around 12 and 18 GW in 2040 and 2045 respectively.

Electricity imports are high in the four high conversion depth scenarios HYD, SYN, HYD_bio and SYN_bio with biofuel availability

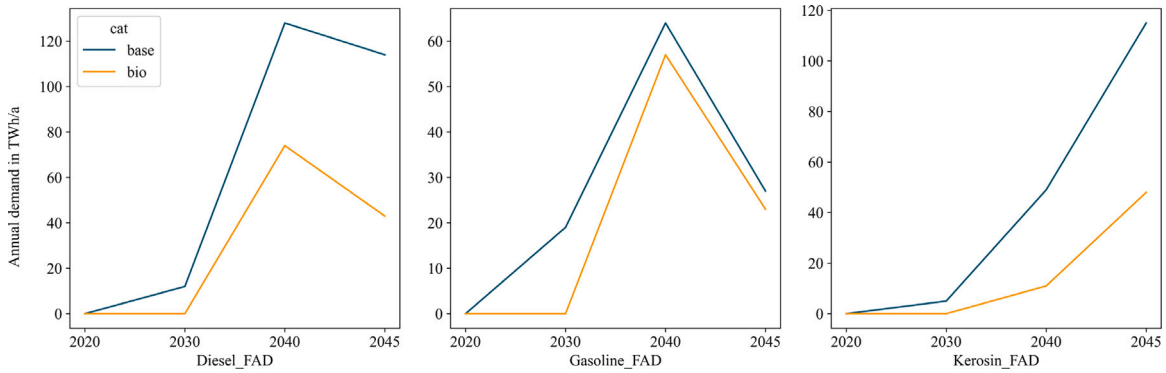


Fig. 5. Influence of biofuel supply availability on transport sector final energy demand exemplified for Diesel, Gasoline and Kerosene for the scenarios SYN (turquoise) and SYNbio (orange). See C.22 for all fuels and scenarios.

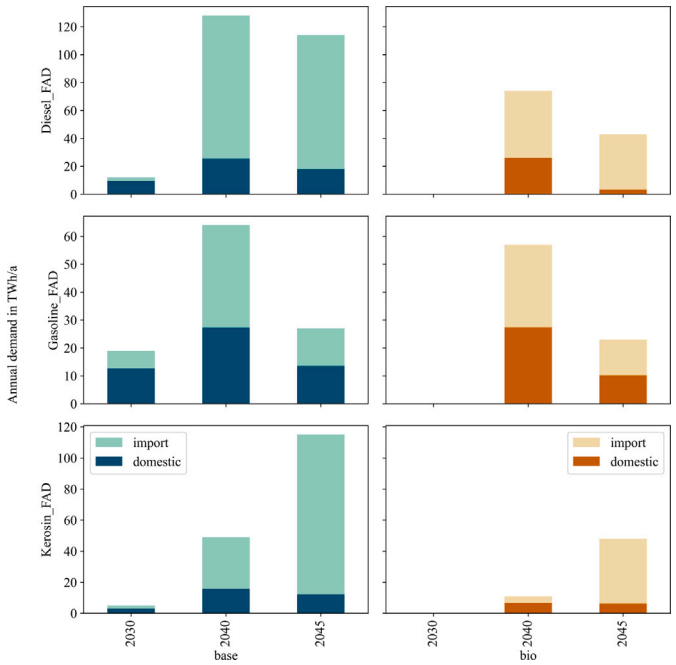


Fig. 6. Demand for electricity based fuels in scenarios SYN and SYN_bio differentiated in imported and domestic supply. Imports from non-EU countries. Domestic: Fuel production in Germany by Fischer Tropsch and refinement with fixed production ratio of products.

slightly reducing imports in 2040. However, in DEL_bio electricity imports can be kept to today's levels in 2040, halved compared to DEL and significantly reduced by a factor of 4 compared to the above mentioned scenarios. This shows, that biofuel availability may reduce electricity import dependence.

The two models are bilaterally soft-coupled, i.e. results of REMix are fed into BENOPTex and vice-versa until convergence is reached [30]. However, this approach implies that the competition between biofuels and RFNBO imports is not assessed in high spatial detail. This might be an interesting pursue for future research.

To our knowledge, the impact of biofuel availability on energy system transformation scenarios has never been assessed in the presented detail for Germany. The only study that assesses the implication of a biofuel shortage is [53]. However, their focus is on all three demand sectors: Heat, industry and transport with a coarser detail in transport and specifically road and aviation subsector demand modeling. Their central finding – that the transport sector is only slightly affected from a biofuel shortage – only holds true when clean fuels contribute little to the energy system demand. See Appendix D.4 for a more detailed discussion.

3.4. Overarching discussion

Here, we discuss the main results on the background of previous findings. For a more comprehensive description of limitations, see Appendix D.1.

Penny-switching effects occur in linear optimization models such as the one used here. The starkest example of this is the offshore wind expansion as can be observed in Figure C.17. In 2030, offshore wind is still more expensive than PV and onshore wind combined with remaining gas power plants for periods of low wind and solar feed-in. This contradicts current policy targets of 30 GW installed capacity of offshore wind in 2030. The near-optimal feasible solution space may vary despite only small differences in objective function [54]. Thus, the precise supply capacity mix before 2040 should be interpreted carefully. Beyond 2040, this effect does not occur, since solar and wind power capacity is expanded to its maximum potential.

H_2 production in Germany in 2045 is found to be very high between 400–650 TWh/a. This is in line with H_2 demands of 360–690 TWh/a reported in [28]. While they assume a European H_2 grid and find H_2 imports of 180–420 TWh/a, we assume transmission only in Germany.

This results in higher shares of domestic H_2 production in our scenarios of 70%–90%. Thus, our scenarios can be read as scenarios where European electricity markets are integrated but H_2 and clean fuel supply are managed nationally.

Biofuels have been controversially discussed due to competition with agriculture, and, in the future, bio-based chemical industries [55]. Biofuel policies have also been shown to increase land-use change effects in a US policy analysis [56]. However, we considered biomass only from waste biomass (see Table B.9) or sustainable agricultural potential by assuming the available land for conventional energy crops to decrease compared to the status quo and by limiting the use of conventional biofuels according to RED II (see [30], Table 1).

Within the scope of our model setup, investment and import decisions are taken from a central European planner perspective which is a significant simplification. Especially the trade of clean fuels depends on a multitude of external individual, social, environmental, technical and economic factors and path-dependencies.

Furthermore, the modeling is based on exemplary demand scenarios from a holistic projection of future economic activities and demand drivers as well as different narratives of the technological development of the demand sectors, which cannot be evaluated here in terms of robustness and evidence. Optimistic assumptions are usually made regarding the development of efficiency in all sectors; in reality, however, long-term energy demand and its spatial distribution may develop significantly differently. Since both, very progressive road sector policies, ambitious CO_2 pricing regimes as well as efficiency gains are assumed, fuel demands may be higher than reported here. Under the given constraint of GHG neutrality in 2045, this implies higher clean-fuel imports, higher electricity imports from neighboring countries or structural changes to transport demands e.g. through fundamental behavioral changes in travel patterns [52].

Our findings from answering research question 1 for Germany can be translated to other regions and countries to some extent. They hold true only if ambitious transport sector CO_2 emission reduction policies are implemented and no significant lifestyle changes occur. Incorporating purchase preferences into vehicle demand modeling narrows down demand uncertainty. Our quantification can act as a first-guess for other regions with similar sub-sectoral composition as Germany. While the answer to research questions 2 and 3 are highly specific to the German energy system with its specific resource availability, demand characteristic, positioning in the European grid etc. some qualitative insights may be transferred. Increased demand for clean fuels (higher conversion depth) leads to higher electricity imports, lower internal transmission needs, larger hydrogen infrastructure, and higher H_2 imports in the long-term compared to a largely electrified scenario. Biofuels may reduce high gradients of H_2 production and crossborder interconnection capacity in the medium term, reduce transport sector import-dependence and act as a bridge to infrastructure-heavy electricity-based energy systems.

4. Conclusion

This paper sheds light on the implications of different transport sector defossilization pathways on cost-optimal energy system infrastructure build-up. We focus on two factors that are especially unknown, the impact of conversion depth and biofuel availability on energy supply infrastructure transformation.

We propose a methodology that introduces three important innovations to the field of research: First, a combination of transport demand modeling in the key transport demand sectors of aviation and road transport with energy system optimization at high temporal and spatial resolution. Secondly, the integration of detailed potentials and costs for the import of green energy carriers to Germany. And thirdly, the optimization of fuel allocation to meet demand in the transport sector, taking into account a wide range of biogenic feedstocks. To account for the most important policy uncertainties, we consider four demand-scenarios each without and with biofuel availability.

We find that considering user behavior and technical specifics of airplane fleet planning strongly limits the realistic range of assumptions on transport final energy demand development. All scenarios show the strongest increase in final energy demands for renewable fuel between 2030 and 2040. Road sector contribution to final energy demand peaks in 2040 and decreases beyond that while synthetic kerosene demand for aviation and synthetic diesel demand for shipping gain increasing importance. German transport energy demand in electricity equivalents of a synthetic fuel oriented scenario is more than 100 TWh/a higher than in lower conversion-depth scenarios.

Our results for the target scenarios support German intermittent RES expansions as no-regret option in all scenarios and underpin their outstanding importance for transport sector defossilization. Conversion depth affects cost-optimal energy transmission networks. Electricity grids in Germany are expanded slightly more in a low conversion-depth scenario while cross border grid expansion capacity increases with higher conversion depth, especially in later years. This supports previous findings that the current grid extensions planned in the German grid development plan are insufficient and extends them to interconnectors between Germany and its neighboring countries.

Hydrogen production capacity is strongly expanded in all scenarios between 2030 and 2040 under the assumption of domestic hydrogen supply strategies. Fischer–Tropsch refinery capacity is only slightly expanded in 2030 except for the high conversion depth scenario where 5 GW are needed. This capacity is approximately doubled in the following decade up to 2040 in all scenarios but not further expanded afterwards. From thereon, increasing final energy demands are supplied by imports due to limited intermittent RES and increased low-price volumes.

Lastly, we show that biofuel substitution in transport sector demands can have an influence on energy supply infrastructure dynamic, especially in high fuel demand scenarios. Cross-border electric grid expansion can be reduced by around 10 GW and 15–20 GW in the years 2040 and 2045 through biofuel availability. Under direct electrification, biofuel availability leads to electricity import reductions to 50% (around 100 TWh/a). Electrolysis capacity expansion before 2040 can be reduced and shifted to consecutive periods by biofuel availability. Import dependence of clean Diesel is around 70-80 % and kerosene beyond 80% with biofuel availability mainly reducing 2030 and 2040 import dependence. Biofuel availability may thus reduce import dependence of fuels and electricity in the medium term.

Further research questions remain. We assume a fair-share for Germany accessing clean fuel imports corresponding to the German share of global population. Relaxing this constraint and incorporating trade-mechanisms similar to how we incorporated biofuel demands is an interesting pursue. Integrating liquid fuel transport between model nodes and gaseous fuel infrastructure expansion across Europe may yield further insights. The model instances were solved using a time resolution of 4 h. Increasing this resolution may further increase the need especially for short-term flexibility but is not expected to drastically change the effects described here. In order to scrutinize the results, multiple weather years for the electricity demand and intermittent RES feed-in should be used for calculation.

CRediT authorship contribution statement

Niklas Wulff: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Danial Esmaeili Aliabadi:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization. **Samuel Hasselwander:** Software, Data curation, Writing – original draft. **Thomas Pregger:** Data curation, Writing – original draft, Writing – review & editing. **Hans Christian Gils:** Resources, Writing – review & editing, Supervision. **Stefan Kronshage:** Data curation. **Wolfgang Grimme:** Software, Data curation, Writing – original draft. **Juri Horst:** Writing – original draft. **Carsten Hoyer-Klick:** Resources, Project administration. **Patrick Jochem:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work has been supported by the German Federal Ministry for Economic Affairs and Climate Protection under grant numbers 03EIV116A, 03EIV116F, through the research project "Begleitforschung Energiewende im Verkehr — BEniVer". Eugenio Salvador Arellano Ruiz provided invaluable software engineering support and Özcan Deniz provided valuable data. We thank the BEniVer project steering team for fruitful discussions, specifically Andrea Amri-Henkel, Markus Millinger, Matthias Jordan, Juliane Prause, Ralph-Uwe Dietrich, Moritz Raab, Sofia Haas, Nathanael Heimann, Patrick Matschoss, Eva Hauser, Simon Pichlmaier, Sandra Richter and Manfred Aigner. We thank Andreas Meurer for fruitful discussions on the results.

All authors have read and agreed to the published version of the manuscript.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.esr.2024.101606.

Data availability

All result data used for creating the Figures of this document is available in a Zenodo repository https://doi.org/10.5281/zenodo.14203522. Raw model output data is made available upon request.

References

[1] F. Creutzig, P. Jochem, O.Y. Edelenbosch, L. Mattauch, D.P.v. Vuuren, D. McCollum, J. Minx, Transport: A roadblock to climate change mitigation? Science 350 (6263) (2015) 911–912.

[2] A. Schwab, A. Thomas, J. Bennett, E. Robertson, S. Cary, Electrification of Aircraft: Challenges, Barriers, and Potential Impacts, Tech. Rep., National Renewable Energy Lab.(NREL, Golden, CO (United States, 2021.

[3] V. Ram, S.R. Salkuti, An overview of major synthetic fuels, Energies 16 (6) (2023) 2834.

[4] Eurostat, Energy statistics—an overview, 2021, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview. (Accessed 04 2023).

[5] I.E.A. IEA, World Energy Outlook 2021, OECD Publishing, Paris, 2021, http://dx.doi.org/10.1787/14fcb638-en, available at https://www.iea.org/reports/world-energy-outlook-2021.

[6] O. Ruhnau, S. Bannik, S. Otten, A. Praktiknjo, M. Robinius, Direct or indirect electrification? a review of heat generation and road transport decarbonisation scenarios for germany 2050, Energy 166 (2019) 989–999, http://dx.doi.org/10.1016/j.energy.2018.10.114.

[7] K.S. Rogge, P. Johnstone, Exploring the role of phase-out policies for low-carbon energy transitions: The case of the German Energiewende, Energy Res. Soc. Sci. 33 (2017) 128–137.

[8] S. Rausch, Assessing nuclear phase-out, Nature Clim. Change 12 (4) (2022) 314–315.

[9] C. Brunner, G. Deac, S. Braun, C. Zöphel, The future need for flexibility and the impact of fluctuating renewable power generation, Renew. Energy 149 (2020) 1314–1324.

[10] O. Omoyele, M. Hoffmann, M. Koivisto, M. Larrañeta, J.M. Weinand, J. Linßen, D. Stolten, Increasing the resolution of solar and wind time series for energy system modeling: A review, Renew. Sustain. Energy Rev. 189 (2024) 113792, http://dx.doi.org/10.1016/j.rser.2023.113792.

[11] D.P. Schlachtberger, T. Brown, S. Schramm, M. Greiner, The benefits of cooperation in a highly renewable European electricity network, Energy 134 (2017) 469–481, http://dx.doi.org/10.1016/j.energy.2017.06.004.

[12] European Parliament, European Council, regulation (EU) 2019/942 of the European Parliament and of the Council of 5 June 2019 establishing a European Union Agency for the Cooperation of Energy Regulators (recast) (text with EEA relevance.): Document 32019r0942, 2019, available online: http://data.europa.eu/eli/reg/2019/942/oj. (Accessed 04 2023).

[13] M. Robinius, A. Otto, K. Syranidis, D.S. Ryberg, P. Heuser, L. Welder, T. Grube, P. Markewitz, V. Tietze, D. Stolten, Linking the power and transport sectors—part 2: Modelling a sector coupling scenario for germany, Energies 10 (7) (2017) 957, http://dx.doi.org/10.3390/en10070957.

[14] K. Hansen, B.V. Mathiesen, I.R. Skov, Full energy system transition towards 100% renewable energy in germany in 2050, Renew. Sustain. Energy Rev. 102 (2019) 1–13.

[15] N. Erkul, Turkey halts ethanol-mixed fuel for more disinfectants, 2020, URL: https://www.aa.com.tr/en/energy/refining-petro-chemistry/turkey-halts-ethanol-mixed-fuel-for-more-disinfectants/28639. (Accessed 21 2024).

[16] F. Musonda, M. Millinger, D. Thrän, Modelling assessment of resource competition for renewable basic chemicals and the effect of recycling, GCB Bioenergy 16 (4) (2024) e13133.

[17] P. Stegmann, M. Londo, M. Junginger, The circular bioeconomy: Its elements and role in european bioeconomy clusters, Resour. Conserv. Recycl.: X 6 (2020) 100029.

[18] S.A. Ikonnikova, B.R. Scanlon, S.A. Berdysheva, A global energy system perspective on hydrogen trade: A framework for the market color and the size analysis, Appl. Energy 330 (2023) 120267, http://dx.doi.org/10.1016/j.apenergy.2022.120267.

[19] P. Runge, C. Sölch, J. Albert, P. Wasserscheid, G. Zöttl, V. Grimm, Economic comparison of electric fuels for heavy duty mobility produced at excellent global sites - a 2035 scenario, Appl. Energy 347 (2023) 121379, http://dx.doi.org/10.1016/j.apenergy.2023.121379.

[20] E. Commission, REPowerEU: A plan to rapidly reduce dependence on Russian fossil fuels and fast forward the green transition, Off. J. Eur. Union (2022).

[21] C. Kuzemko, M. Blondeel, C. Dupont, M.C. Brisbois, Russia's war on Ukraine, European energy policy responses & implications for sustainable transformations, Energy Res. Soc. Sci. 93 (2022) 102842.

[22] L.E.V. de Souza, E.M.G.R.L. Bosco, A.G. Cavalcante, L. da Costa Ferreira, Postcolonial theories meet energy studies:institutional orientalism as a barrier for renewable electricity trade in the Mediterranean region, Energy Res. Soc. Sci. 40 (2018) 91–100, http://dx.doi.org/10.1016/j.erss.2017.12.001.

[23] C. Bu, X. Cui, R. Li, J. Li, Y. Zhang, C. Wang, W. Cai, Achieving net-zero emissions in china's passenger transport sector through regionally tailored mitigation strategies, Appl. Energy 284 (2021) 116265, http://dx.doi.org/10.1016/j.apenergy.2020.116265.

[24] X. Yang, J. Pang, F. Teng, R. Gong, C. Springer, The environmental co-benefit and economic impact of china's low-carbon pathways: Evidence from linking bottom-up and top-down models, Renew. Sustain. Energy Rev. 136 (2021) 110438, http://dx.doi.org/10.1016/j.rser.2020.110438.

[25] N.V. Emodi, C. Okereke, F.I. Abam, O.E. Diemuodeke, K. Owebor, U.A. Nnamani, Transport sector decarbonisation in the global south: A systematic literature review, Energy Strategy Rev. 43 (2022) 100925, http://dx.doi.org/10.1016/j.esr.2022.100925.

[26] F. Wiese, J. Thema, L. Cordroch, Strategies for climate neutrality, lessons from a meta-analysis of german energy scenarios, Renew. Sustain. Energy Transit. 2 (2022) 100015, http://dx.doi.org/10.1016/j.rset.2021.100015.

[27] T. Gnann, D. Speth, M. Krail, M. Wietschel, S. Oberle, Pathways to carbon-free transport in germany until 2050, Energies 13 (2022) 136, http://dx.doi.org/10.3390/wevj13080136.

[28] F. Sensfuß, C. Maurer, M. Krail, D. Speht, T. Gnann, M. Wietschel, P. Mellwig, J. Müller-Kirchenbauer, Langfristszenarien für die transformation des energiesystems in deutschland: Treibhausgasneutrale hauptszenarien - modul verkehr, 2022, URL: https://www.langfristszenarien.de/enertile-explorer-wAssets/docs/LFS3_Langbericht_Verkehr_final.pdf.

[29] S. Teske, T. Pregger, S. Simon, T. Naegler, J. Pagenkopf, Ö. Deniz, B. Van den Adel, K. Dooley, M. Meinshausen, It is still possible to achieve the paris climate agreement: Regional, sectoral, and land-use pathways, Energies 14 (2021) 2103, http://dx.doi.org/10.3390/en14082103.

[30] D. Esmaeili Aliabadi, K. Chan, N. Wulff, K. Meisel, M. Jordan, I. Österle, T. Pregger, D. Thrän, Future renewable energy targets in the EU: Impacts on the German transport, Transp. Res. D 124 (2023) 103963, http://dx.doi.org/10.1016/j.trd.2023.103963.

[31] D. Esmaeili Aliabadi, M. Jordan, A. Meurer, N. Wulff, Power-To-X in Regional Energy Systems: Planning, Operation, Control, and Market Perspectives, Exploring the Interplay of Power-to-X and Bioenergy, CRC Press, 2024, (Ch. Defossilization Dynamics).

[32] K. Löffler, T. Burandt, K. Hainsch, P.-Y. Oei, F. Seehaus, F. Wejda, Chances and barriers for germany's low carbon transition-quantifying uncertainties in key influential factors, Energy 239 (2022) 121901.

[33] R. Edwards, D. Mulligan, L. Marelli, et al., Indirect Land Use Change from Increased Biofuels Demand-Comparison of Models and Results for Marginal Biofuels Production from Different Feedstocks, Tech. rep., Publications Office of the European Union, 2010, http://dx.doi.org/10.2788/54137.

[34] S. Løkke, E. Aramendia, J. Malskær, A review of public opinion on liquid biofuels in the EU: Current knowledge and future challenges, Biomass Bioenergy 150 (2021) 106094.

[35] F. Sensfuß, C. Maurer, M. Krail, D. Speht, T. Gnann, M. Wietschel, P. Mellwig, J. Müller-Kirchenbauer, Long-term scenarios 3. scientific analyses on the decarbonization of germany. tn scenarios on behalf of the german federal ministry for economic affairs and climate action, 2022, URL: https://langfristszenarien.de/enertile-explorer-de/.

[36] C.C. Gong, F. Ueckerdt, R. Pietzcker, A. Odenweller, W.-P. Schill, M. Kittel, G. Luderer, Bidirectional coupling of the long-term integrated assessment model REgional Model of INvestments and Development (REMIND) v3.0.0 with the hourly power sector model Dispatch and Investment Evaluation Tool with Endogenous Renewables (DIETER) v1.0.2, Geosci. Model Dev. 16 (17) (2023) 4977–5033, http://dx.doi.org/10.5194/gmd-16-4977-2023.

[37] C. Dieckhoff, A. Leuschner, Die Energiewende Und Ihre Modelle: Was Uns Energieszenarien Sagen KÖnnen - Und was Nicht, transcript Verlag, Bielefeld, 2016, http://dx.doi.org/10.14361/9783839431719-fm.

[38] D. Esmaeili Aliabadi, N. Wulff, M. Jordan, K.-F. Cyffka, M. Millinger, Soft-coupling energy and power system models to analyze pathways toward a de-fossilized German transport sector, in: Operations Research Proceedings 2022, Springer, 2022, pp. 313–320, http://dx.doi.org/10.1007/978-3-031-24907-5_38.

[39] S. Hasselwander, I. Österle, Ö. Deniz, The future role of synthetic fuels in german road transport - estimation of potential fuel demand using technology-based scenario analyses, 2023, URL: https://elib.dlr.de/196101/.

[40] E. Commission, Regulation (eu) 2023/2405 of the european parliament and of the council of 18 october 2023 on ensuring a level playing field for sustainable air transport (refueleu aviation), 2023, available at https://eur-lex.europa.eu/eli/reg/2023/2405.

[41] European Commission (Ed.), In-depth analysis in support on the COM(2018) 773: A Clean Planet for all - a European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy, 2018.

[42] M. Millinger, P. Tafarte, M. Jordan, F. Musonda, K. Chan, K. Meisel, D. Aliabadi Esmaeili, A model for cost- and greenhouse gas optimal material and energy allocation of biomass and hydrogen, SoftwareX 20 (2022) 101264, http://dx.doi.org/10.1016/j.softx.2022.101264.

[43] DBFZ, DBFZ ressourcendatenbank, 2023, URL: . (Access 14 January 2023).

[44] M. Millinger, D. Thrän, Biomass price developments inhibit biofuel investments and research in germany: The crucial future role of high yields, J. Clean. Prod. 172 (2018) 1654–1663, http://dx.doi.org/10.1016/j.jclepro.2016.11.175.

[45] T. Belau, für Technik und Bauwesen in der Landwirtschaft, K, Daten für die Planung des Energiepflanzenanbaus, KTBL, Energiepflanzen, 2012.

[46] P. Viebahn, J. Kern, J. Horst, A. Rosenstiel, J. Terrapon-Pfaff, L. Dore, C. Krüger, O. Zelt, T. Pregger, J. Braun, U. Klann, Synthese und handlungsoptionen – ergebnisbericht des projekts mena-fuels. teilbericht 14 des wuppertal instituts, des deutschen zentrums für luft- und raumfahrt (dlr) und des instituts für zukunftsenergie- und stoffstromsysteme (izes) an das bundesministerium für wirtschaft und klimaschutz (bmwk), 2022, URL: https://wupperinst.org/fileadmin/redaktion/downloads/projects/MENA-Fuels_Teilbericht_14_Synthesebericht_de_v3.pdf.

[47] J. Horst, U. Klann, Mena-fuels—analyse eines globalen marktes für wasserstoff und synthetische energieträger hinsichtlich künftiger handelsbeziehungen. mena-fuels: Teilbericht 12 des instituts für zukunftsenergie- und stoffstromsysteme (izes) an das bundesministerium für wirtschaft und klimaschutz (bmwk), 2022, URL: https://wupperinst.org/fa/redaktion/downloads/projects/MENA-Fuels_Teilbericht_12_Handelsmodell.pdf.

[48] H.C. Gils, Y. Scholz, T. Pregger, D. Luca de Tena, D. Heide, Integrated modelling of variable renewable energy-based power supply in europe, Energy 123 (2017) 173–188, http://dx.doi.org/10.1016/j.energy.2017.01.115.

[49] H.C. Gils, Balancing of Intermittent Renewable Power Generation by Demand Response and Thermal Energy Storage (Ph.D. thesis), University of Stuttgart, 2015, http://dx.doi.org/10.18419/opus-6888.

[50] D. Luca de Tena, T. Pregger, Impact of electric vehicles on a future renewable energy-based power system in europe with a focus on germany, Int. J. Energy Res. 42 (8) (2018) 2670–2685, http://dx.doi.org/10.1002/er.4056.

[51] H.C. Gils, H. Gardian, J. Schmugge, Interaction of hydrogen infrastructures with other sector coupling options towards a zero-emission energy system in Germany, Renew. Energy 180 (2021) 140–156, http://dx.doi.org/10.1016/j.renene.2021.08.016.

[52] M. Arnz, L. Goeke, J. Thema, F. Wiese, N. Wulff, M. Kendziorski, K. Hainsch, P. Blechinger, C. von Hirschhausen, Avoid, shift or improve passenger transport? impacts on the energy system, Energy Strategy Rev. 52 (2024) 101302, http://dx.doi.org/10.1016/j.esr.2024.101302.

[53] M. Jordan, K. Meisel, M. Dotzauer, J. Schröder, K.-F. Cyffka, N. Dögnitz, C. Schmid, V. Lenz, K. Naumann, J. Daniel-Gromke, G. Costa de Paiva, H. Schindler, D. Esmaeili Aliabadi, N. Szarka, D. Thrän, The controversial role of energy crops in the future German energy system: The trade offs of a phase-out and allocation priorities of the remaining biomass residues, Energy Rep. 10 (2023) 3848–3858, http://dx.doi.org/10.1016/j.egyr.2023.10.055.

[54] F. Neumann, T. Brown, The near-optimal feasible space of a renewable power system model, Electr. Power Syst. Res. 190 (2021) 106690, http://dx.doi.org/10.1016/j.epsr.2020.106690.

[55] R. Rodrigues, R. Pietzcker, P. Fragkos, J. Price, W. McDowall, P. Siskos, T. Fotiou, G. Luderer, P. Capros, Narrative-driven alternative roads to achieve mid-century co2 net neutrality in europe, Energy 239 (2022) 121908, http://dx.doi.org/10.1016/j.energy.2021.121908.

[56] K.G. Austin, J. Jones, C.M. Clark, A review of domestic land use change attributable to u.s. biofuel policy, Renew. Sustain. Energy Rev. 159 (2022) 112181, http://dx.doi.org/10.1016/j.rser.2022.112181.