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Model coupling and comparison on optimal load shifting of battery electric vehicles and heat pumps focusing on generation adequacy

S. Misconel [a,b,*], F. Zimmermann [c], J. Mikurda [d], D. Möst [b], R. Kunze [e], T. Gnann [f], M. Kühnbach [f], D. Speth [f], S. Pelka [f], S. Yu [f]

[a] EURAC Research, Institute for Renewable Energy, I-39100, Bolzano, Italy
[b] Technische Universität Dresden, Faculty of Business and Economics, Chair of Energy Economics, 01062, Dresden, Germany
[c] Karlsruhe Institute of Technology, Institute for Industrial Production, Chair of Energy Economics, 76187, Karlsruhe, Germany
[d] University Duisburg-Essen, Faculty of Business and Economics, Chair of Energy Economics, 45141, Essen, Germany
[e] Energy Systems Analysis Associates – ESA^2 GmbH, 01187, Dresden, Germany
[f] Fraunhofer Institute for Systems and Innovation Research (ISI), 76139, Karlsruhe, Germany

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ABSTRACT

The energy transition fosters a dynamic landscape marked by renewable energy, electrification, and complex interactions among actors and technologies. Employing model experiments and comparisons shows promise for exploring these connections and enhancing model clarity and precision. This study adopts a multi-model approach, integrating a model comparison to probe how the electrification of demand-side sectors and strategic load shifts of battery electric vehicles and heat pumps might impact Germany's generation adequacy by 2030. Specific demand models from the transport and heating sectors and a future load structure projection model are interlinked with three electricity system models. The comparative analysis of the three electricity system models unveils discrepancies in dispatch decisions for power plants, flexibility options' load shifts, and their effects on generation adequacy, directly tied to model attributes.

The comparison underscores methodological variations (linear optimization versus agent-based simulation, myopic foresight versus perfect foresight) as pivotal, emphasizing the significance of considering load change and start-up costs for power plants. The results show that with optimized load shifting by electric vehicles and heat pumps, the adequacy of power generation is less strained despite increased electricity demand. Moreover, load shifts mitigate curtailment of renewables and consumers, reducing carbon emissions by lowering conventional power generation.

List of abbreviations

BEV	Battery electric vehicle
CAC	Continuously available capacities
CCGT	Combined cycle gas turbine
CCOT	Combined cycle oil turbine
CHP	Combined heat and power
CRC	Continuously reliable capacities
DWH	Data Warehouse
EENS	Expected energy not served
EMS	Energy models system
EV	Electric vehicle
FLH	Full load hours
HP	Heat pump
IAM	Integrated assessment models
LOLE	Loss of load expectation
LP	Linear programming
OCGT	Open cycle gas turbine
OCOT	Open cycle oil turbine
PID	Power import dependency
PSP	Pump storage plant
PtH	Power-to-Heat
PV	Photovoltaic
RES	Renewable energy sources
TES	Thermal energy storage
TYNDP	Ten-Year-Net-Development-Plan
VoLL	Value of lost load
vRES	Volatile renewable energy sources
WY	Weather year

* Corresponding author. EURAC Research, Institute for Renewable Energy, Viale Druso 1, I-39100, Bolzano, Italy.
E-mail address: steffi.misconel@eurac.edu (S. Misconel).

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1. Introduction

Model-based analyses have long been used to understand how political, socio-economic, and technological factors impact energy system development. Initially focused on a holistic view, the evolving energy landscape has sparked the creation of specialized partial models, each delving into specific aspects like decentralization, sector coupling, and new energy technologies [1]. This shift arose due to the complexity of new factors, making it impractical to cover all aspects comprehensively within a single model. As a result, model coupling became crucial in energy system analysis [2]. New sustainable energy system strategies can be developed by interlinking different models to a consistent energy models system (EMS). However, differences in data structures and approaches often lead to varied and incomparable results in model-based scenario analyses [3].

Limited research exists on model experiments including model coupling and model comparisons based on harmonized input data, to classify and discuss methodological approaches and their results transparently and thus interlink result deviations with models' properties. Moreover, model coupling between sectoral models that consider new electricity-consuming devices in the context of demand-side sector electrification to enable the integration of high shares of volatile renewable energy sources (vRES) and the decarbonization of the entire energy system is rare in the existing literature. Additionally, the research question arises whether these devices, with their additional electricity demand, jeopardize generation adequacy or provide sufficient flexibility to benefit the energy system.

To contribute to these methodological and contextual research gaps, this paper analyzes how the electrification of demand-side sectors by emerging electricity appliances with high energy demand, such as battery electric vehicles (BEVs) and heat pumps (HPs), will affect generation adequacy in Germany in 2030, especially during critical supply situations. Using a multi-model approach with an integrated model comparison, the study compares three electricity system models, identifying key model characteristics leading to differences in flexibility provision through optimal load shifting of BEVs and HPs from a system perspective. Harmonized input parameters and simplified scenario analyses isolate model result deviations and link them to specific model properties.

Seven models are coupled to a consistent EMS to address cross-sectoral interdependencies between the demand-side and electricity sector.[1] Specific demand-side models from the transport (ALADIN), building stock and heating (FORECAST) sector as well as an hourly electricity demand projection model (eLOAD) are interlinked with three electricity system models (IDILES-JMM, PowerACE and ELTRAMOD). The demand-side models simulate future energy demand, market penetration of BEVs (passenger cars) and HPs, and their uncontrolled load profiles. The electricity system models focus on optimal load shifting of BEVs and HPs and its implication on generation adequacy in Germany in 2030, considering an average (2016) and an extreme (2012) weather year (WY). The results of the electricity system models are directly compared regarding their dispatch decisions for power plants, load shifting of demand flexibility and their ability to smooth the residual load. This transparent comparison of electricity system models enhances understanding of methodologies and demonstrates how model properties influence results when input parameters are harmonized.

The remainder of this paper continues with a review of existing model comparisons in Section 2. Followed by descriptions of the scenario framework, applied models, model coupling, and data exchange in Section 3. Section 4 presents and compares results regarding optimal BEV charging, HP operation, and residual load smoothing by electricity system models. Based on this, Section 5 indicates the influence of increased demand electrification on future generation adequacy. Consequently, Section 6 summarizes the insights and outlines conclusions.

2. State of research

In scientific literature, methodological model comparisons have been comprehensively discussed for decades. Literature can be classified into (I) conceptual model comparisons based on comprehensive literature reviews and theoretical model characteristics and (II) applied model comparisons based on model results and harmonized input parameters. Table 1 classifies chosen scientific contributions into these categories, also noting considerations like sector coupling, flexibility provision by electric vehicles (EVs) and power-to-heat (PtH), and soft-linked model coupling in the model comparisons.

The first theoretical model comparisons (I) have been carried out by Sweeney [4], emphasizing the benefits: spotting errors, resolving disagreements, and aiding in model selection. In contrast, van Beeck [5] established classification schemes for energy system models, identifying purposes, model approaches, system boundaries (geographical, sectoral, temporal resolution), assumptions, and data needs. Presently, many qualitative model comparisons follow these structures. In Ventosa et al. [7], an overview of relevant publications examines electricity market modeling and compares 36 electricity system models, highlighting differences in mathematical structures (optimization, equilibrium, or simulation models), market representations, computational aspects, and model purposes. Furthermore [7], classifies models based on market structures (perfect competition, oligopoly, monopoly), time scopes, uncertainties, interperiod links, and network transmission considerations. Fattahi et al. [2] outline key criteria and challenges by comparing 19 energy model systems, including the rising need for flexibility via electrification, emerging technologies, efficiency enhancements, decentralization, and macroeconomic interplays. These challenges drive necessary modeling capabilities: high temporal resolution, technological learning, flexibility options, actors' behavior analysis, cross-border trade considerations, and integration with macroeconomic models. However, studies exploring model comparisons considering EVs [23], PtH [27], or sector coupling [68] remain limited.

Applied model comparisons (II) involve comparing model results derived from harmonized input parameters. Numerous model comparisons occur between integrated assessment models (IAM) evaluating carbon mitigation scenarios across diverse global regions. Thereby the role of advanced low-carbon technologies and carbon constraints are analyzed [56]. Several applied model comparisons focus on electricity systems with high shares of vRES [28]. These studies delve into novel operation and investment strategies related to flexibility options, emphasizing how temporal representation and techno-economic details significantly impact modeling outcomes [50]. Further multi-model comparisons identify drivers that lead to deviations in model outputs by simultaneously using harmonized input assumptions. For instance, Mai et al. [52] point out that modeling complementary technologies, such as energy storages and transmission network, capacity decommissioning, ancillary services and costs, and model coupling, significantly influence results deviations. Inter- and intra-model comparisons[2] with five electricity system models for European decarbonization pathways until 2050 are conducted in Siala et al. [69]. The author estimates the impact of model approaches (optimization vs. simulation), planning horizon (intertemporal vs. myopic), temporal and spatial

[1] The research results of this paper have been developed within the MODEX-EnSAVes project, which is funded by the German Federal Ministry for Economic Affairs and Climate Protection (BMWK). In the project eleven models are involved. In this paper the focus is only on seven models, which were responsible for the data exchange within the model coupling.

[2] An intra-model comparison can be conducted by performing sensitivities across possible combinations of input parameters in the same model to assess results deviations. A more robust framework is presented by inter-model comparisons, where both varying input assumptions and different model structures are compared with each other [52].

Table 1
Overview of selected literature in the context of energy system model comparisons.

No.	Author	Year	Sector coupling	EV	PtH	Model coupling	No° of models	Source
(I) **Conceptual model comparisons** based on literature reviews or theoretical aspects								
1	Sweeney	1983	–	–	–	–	7	[4]
2	van Beeck	1999	–	–	–	–	10	[5]
3	Worrell et al.	2004	–	–	–	–	15	[6]
4	Ventosa et al.	2005	–	–	–	–	36	[7]
5	Jebaraj et al.	2006	–	–	–	–	252 publications	[8]
6	Hiremath et al.	2007	–	–	–	–	70 publications	[9]
7	Sensfuβ et al.	2007	–	–	–	–	72 publications	[10]
8	Bhattacharyya et al.	2009	–	–	–	–	10	[11]
9	Connolly et al.	2010	–	–	–	–	37[c] (68)	[12]
10	Foley et al.	2010	–	–	–	–	7	[13]
11	Möst and Keles	2010	–	–	–	–	20	[14]
12	Mundaca et al.	2010	–	–	–	–	12	[15]
13	Bazmi and Zahedi	2011	–	–	–	–	277 publications	[16]
14	DeCarolis et al.	2012	–	–	–	–	12	[17]
15	Herbst et al.	2012	–	–	–	–	71 publications	[18]
16	Keirstead et al.	2012	–	–	–	–	219 publications	[19]
17	Després et al.	2015	–	–	–	–	5	[20]
18	Pfenninger et al.	2014	–	–	–	–	130 publications	[21]
19	Hall et al.	2016	–	–	–	–	22[c] (110)	[22]
20	Mahmud et al.	2016	–	x	–	–	67[c] (125)	[23]
21	Lund et al.	2017	–	–	–	–	81 publications	[24]
22	Gacitua et al.	2018	–	–	–	–	21	[25]
23	Lopion et al.	2018	–	–	–	–	24	[26]
24	Lyden et al.	2018	x	x	x	–	13[c] (51)	[27]
25	Ringkjøb et al.	2018	–	–	–	–	75	[28]
26	Dagoumas et al.	2019	–	–	–	–	122 publications	[29]
27	Maruf	2019	x	–	–	–	16	[30]
28	Savvidis et al.	2019	–	–	–	–	40	[31]
29	Fattahi et al.	2020	x	x	x	x	19	[2]
30	Prina et al.	2020	x	–	–	–	22	[32]
31	Ridha et al.	2020	–	–	–	–	145	[33]
32	Klemm and Vennemann	2021	–	–	–	–	13[c] (145)	[34]
33	Yoro et al.	2021	–	–	–	–	14	[35]
34	Berendes et al.	2022	–	–	–	–	5	[36]
35	Prina et al.	2022	–	–	–	–	~100 publications	[37]
(II) **Applied model comparisons** based on model results and harmonized input parameters								
36	Weyant et al.	2006	–	–	–	–	19 (IAM)	[38]
37	Lund et al.	2007	x[b]	–	–	–	2	[39]
38	Clarke et al.	2009	–	–	–	–	10 (IAM)	[40]
39	Edenhofer et al.	2010	–	–	–	–	5	[41]
40	Krey and Clarke	2011	–	–	–	–	15 (IAM)	[42]
41	Koelbl et al.	2014	–	–	–	–	12 (IAM)	[43]
42	Kriegler et al.	2014	–	–	–	–	18 (IAM)	[44]
43	Luderer et al.	2014	–	–	–	–	17 (IAM)	[45]
44	Ommen et al.	2014	–	–	–	–	3	[46]
45	Neves et al.	2015	–	–	–	–	3	[47]
46	Riahi et al.	2015	–	–	–	–	9 (IAM)	[48]
47	Wilkerson et al.	2015	–	–	–	–	3 (IAM)	[49]
48	Poncelet et al.	2016	–	–	–	x	3	[50]
49	Cebulla et al.	2017	–	–	–	–	2	[51]
50	Mai et al.[a]	2018	–	–	–	–	3	[52]
51	Gils et al.	2019	x	x	x	–	4	[53]
52	Pavičević et al.	2019	–	–	–	–	4	[54]
53	Priesmann et al.	2019	–	–	–	–	160[d]	[55]
54	Sugiyama et al.	2019	–	–	–	–	6 (IAM)	[56]
55	Siala et al.	2022	–	–	–	–	5	[57]
56	Gils et al.	2022a	x	x	x	–	9	[3]
57	Misconel et al.	2022	–	–	–	–	4	[58]
58	Hobbie et al.	2022	–	–	–	–	8	[59]
59	Gnann et al.	2022	–	x	–	–	3	[60]
60	Gils et al.	2022b	x	x	x	–	8	[61]
61	Bucksteeg et al.	2022	–	–	x	–	5	[62]
62	Ruhnau et al.	2022	–	–	–	–	5	[63]
63	Syranidou et al.	2022	–	–	–	–	8	[64]
64	van Ouwerkerk et al.	2022	–	–	–	–	6	[65]
65	Raventós et al.	2022	–	–	–	–	8	[66]
66	Candas et al.	2022	x	–	–	–	5	[67]
67	*Approach of this paper*	2024	x	x	x	x	3[c] (6)	

[a] Scenarios with and without harmonized input parameters.
[b] Consideration of electrolysis.
[c] Models compared in detail (all models).
[d] Model configurations; IAM – Integrated Assessment Models.

resolution. Results show that the approach fundamentally influences capacity expansion, while the planning horizon has a minor impact on scenarios with high CO_2 allowance prices. Moreover, lower temporal and spatial resolution lead to significant vRES integration through higher utilization of storage and neglecting transmission boundaries. A model comparison with harmonized input parameters of three electricity system models considering sector coupling for a mostly renewable German power sector in 2050 is presented in Gils et al. [53]. Result differences occur in power generation structure, utilization of storage, and other flexibility options, which can be traced back to diverse modeling of technological and temporal details. Gils et al. [3] systematically compare nine electricity system models with sector coupling, employing harmonized input parameters. Structural disparities emerge notably in the optimization approach and technology modeling, specifically regarding power plant ramping, BEVs, reservoirs, and demand response. Misconel et al. [58] conduct a scenario analysis using three electricity system models for the German electricity sector until 2030, focusing on investment, dispatch, and generation adequacy. Minor result discrepancies stem primarily from variances in model approaches, myopic foresight perspective, deviations in temporal resolution, and technological modeling detail levels.

As shown in Table 1, there is only limited research on model experiments, including soft-linked model coupling with an integrated model comparison focusing on sector coupling and the flexibility provision of BEVs and HPs. Therefore, this paper contributes threefold to previous research by providing an applied and systematic model comparison (I) of three electricity system models focusing on sector coupling (II) by implementing optimal dispatch strategies for BEVs and HPs from a system perspective, which is realized through a soft-linked model coupling (III) of a transport (ALADIN), a heat demand (FORECAST), and an electricity projection model (eLOAD) with three electricity system models (IDILES-JMM, PowerACE, ELTRAMOD). This transparent comparison deepens understanding of modeling approaches, indicating how model properties influence results with harmonized inputs. Additionally, this model experiment enhances model credibility, adding transparency to policy discourse based on model-based analyses.

3. Material and methods

The section begins by describing the three demand-side models (ALADIN, FORECAST, eLOAD) and the three electricity system models (IDILES-JMM, PowerACE, ELTRAMOD) in subsection 3.1. Subsection 3.2 outlines the scenario framework. Subsection 3.3 details the model coupling and data exchange processes, including specific information about the exchanged data for battery electric vehicles, heat pumps, and electricity demand. Lastly, subsection 3.4 explains the methodological approach for load shifting of BEVs and HPs within the electricity system models.

3.1. Model descriptions

The models involved span three sectors: transport, heating/building stock, and the electricity sector (cf., Table 2). This model experiment couples seven models to an EMS to explore development pathways for flexibility options, specifically BEVs and HPs with thermal energy storage (TES), to analyze their impact on critical supply situations in Germany. Subsequently, it compares the optimal dispatch of these flexibility options and their impact on generation adequacy among three electricity system models utilizing different approaches.

ALADIN simulates the development of technology components in the German vehicle fleet (road traffic), especially regarding to the share of new driving technologies, such as BEVs. The basis of the agent-based model is several thousand vehicle driving profiles of at least one week observation period [97,98]. These technical potentials result in the individual utility determination for several drivetrains based on their total cost of ownership, their charging infrastructure cost, and the willingness to pay more for a BEV. ALADIN also models user behavior concerning alternative fuel vehicles [99], leading to stock calculations and simulations of energy demand, especially for passenger BEVs.

FORECAST simulates the future energy demand in the building sector by considering building stock development and thermal equipment. In this study, FORECAST is used to model the diffusion and electricity consumption of HPs in the residential sector [77]. Input data includes (1) building data (e.g., stock, number of dwellings, floor area, U-values, etc.); (2) technology data (e.g., stock, efficiency, investment and operation cost, lifetime); (3) energy carriers and prices, (4) policy scenario parameters.

eLOAD simulates the future national electricity system load with an hourly resolution. The model uses a process-specific load profile database to decompose the system load. Subsequently, relevant processes and applications are projected into future years and re-aggregated to build the future system load. By applying this partial decomposition approach, socio-technical transformations are considered that are leading to structural changes in the system load. In this study, the analysis focuses on the projection of the system and the process loads of BEVs and HPs.

The electricity system models – **IDILES-JMM**, **PowerACE,** and **ELTRAMOD** – determine the development of electricity generation dispatch, and load shifting by optimizing BEV charging and HP operation from an energy system perspective to achieve cost efficiency in the electricity market. Each model offers a different model approach and diverse set of skills, enriching the comprehension and decision-making process within the energy sector.

IDILES-JMM is a combined model. IDILES is a model framework based on the dispatch model JMM for co-optimizing long-term (dis)investment decisions. Using a Bender's decomposition approach, power system components are iteratively adjusted to satisfy equilibrium conditions, considering market prices and system costs. The higher-order problem is to minimize long-run costs, considering investments, operating, and fixed costs. In the complementary lower-level problem, operating costs are minimized using JMM, which is a dispatch model with hourly resolution that focuses on the detailed representation of the power and heat market. JMM uses rolling scheduling to reduce the size of the linear optimization problem. The model is running in a rolling 12-h scheduling structure for this purpose, alternating 36- and 24-h optimization periods representing day-ahead and intraday markets.

PowerACE is an agent-based simulation model analyzing electricity spot markets with an hourly resolution, including annual investment planning for dispatchable power plants. Agents represent utilities and segments such as power plants, vRES, demand or demand-side management (DSM). Bids for dispatchable power plants consider variable costs, depending on fuel and CO_2 prices, and start-up costs. Each bid includes a price and a volume. The market clearing process is a linear optimization to maximize welfare, accounting for limited trading capacity to neighboring market areas.

ELTRAMOD is a deterministic linear optimization model that analyzes electricity markets, focusing on investment and dispatch decisions under the assumption of full competition and perfect foresight. It minimizes total system costs while ensuring energy balance for each time step. The energy balance ensures that electricity generation is equal to the residual load, including e.g., hourly electricity exchange flows across market areas, additional electricity demand for charging storage units, and sector coupling technologies, such as BEVs and HPs. Further technical restrictions limit the generation of power plants to the installed capacity and the technology-specific availability.

3.2. Scenario framework

To ensure consistent model coupling and comparison, fundamental scenario framework parameters were predefined. The analysis horizon is set at 2030. Weather and weekly load structure data reference 2016 for average weather conditions and 2012 for extreme weather conditions to

Table 2
Overview of applied models and approaches of the EMS.

Sector	Specific area	Model approach	Model name	Selected references	Model output
Transport sector	Development pathways for vehicle technologies	Agent-based simulation	**ALADIN**	[70–73]	Development pathways for transport demand regarding the share of different (new) transport modes and vehicle technologies
Heating sector	Development pathways for thermal equipment	Bottom-up cohort simulation	**FORECAST**	[74–77]	Development pathways for thermal equipment and energy requirements for buildings
Electricity sector	Hourly electricity demand	Simulation, partial optimization	**eLOAD**	[78–81]	Hourly system load and load profiles for individual power applications
	Power plant investments	Optimization (LP) Bender's Decomposition	**IDILES**	[82,83]	Development pathways of fuel-specific power generation dispatch and advantageous load shifts on the demand side (optimized charging of BEVs and optimized operation of HPs with TES) from an energy system perspective
	Dynamic dispatch planning	Optimization (LP)	**JMM**	[84–87]	
	Power plant investments and dispatch	Agent-based simulation	**PowerACE**	[88–91]	
	Power plant investments and dispatch	Optimization (LP)	**ELTRAMOD**	[83,92–96]	

assess their impact on generation adequacy. Load data resolution is hourly throughout the year. The modeling is limited to Germany at a national level.

Data harmonization significantly affects the quality of results in model comparisons since database deviations can distort results and cause misinterpretations. To obtain an overview of the required input data and resulting outputs of the model comparison, data were systematically recorded in an input-output table in a shared database according to eight main categories [100].

- **Macroeconomic and statistical data** (e.g., GDP, population, employees, buildings, policy goals)
- **Environmental data** (e.g., weather, fuel types, emission factors)
- **Demand data** (e.g., energy demands, hourly profiles for electricity, heat)
- **Techno-economic data** (e.g., efficiencies, specific investments, lifetimes, availabilities)
- **Installed infrastructure data** (e.g., power plants, storage, electricity grids, vehicle fleets, EV charging points)
- **Deployment/utilization data for infrastructures** (e.g., profiles of power/heat generation, electricity grid utilization)
- **Prices and costs** (e.g., fuel, electricity, heat, CO_2 allowances)
- **Stakeholder behavior and acceptance** (e.g., self-consumption maximization, driving profiles)

Certain datasets serve as input parameters for models and simultaneously appear as output generated by other models (e.g., energy demand used as input for supply-side models and produced as output from sector-specific demand simulation models). Vital framework data, essential as model drivers, encompass.

- Installed power generation capacity
- Fuel and CO_2 allowance prices
- Fuel-specific CO_2 emission factors
- Electricity load profiles
- Annual electricity and heating demand
- Cross-border flows with neighboring countries
- Vehicle stock types and consumption factors
- Residential building stock size and energy demands
- Techno-economic power plant data

This harmonized data, stored in the ESA[2] Data Warehouse (DWH), serves as a centralized resource for all models. Comprehensive metadata on applied datasets and their sources are accessible at [101].

3.3. Model coupling and data exchange

To model BEV and HP load-shifting potential in electricity system models, extensive input parameters provided by the demand-side models via the DWH are required. Fig. 1 illustrates the coupling between demand-side and generation-side models within a unified EMS, showcasing limited essential data exchange among model groups.

ALADIN passes BEV data – total numbers, charging availability profiles, load capacity, and storage volume per BEV – to eLOAD and the electricity system models. FORECAST contributes residential HP data –installed capacity, performance coefficients, and thermal energy storage volumes. eLOAD calculates hourly system and process loads of BEVs and HPs, feeding this information to the electricity system models. This model coupling addresses flexible DSM utilization (i.e., BEVs and HPs) and evaluates power sector generation adequacy. Results from the EMS runs concerning BEV and HP market ramp-up are integrated into electricity system models. The electricity system models then recalibrate power plant dispatch alongside optimal BEV and HP load shifting, excluding power plant investments to isolate technology-specific load shift differences. The comparative evaluation relies on power plant dispatch, DSM technologies, and generation adequacy indicators. ELTRAMOD and IDILES-JMM base dispatch decisions on minimizing system costs, while PowerACE follows an agent-based approach to maximize total welfare. After an EMS loop, wholesale electricity prices from ELTRAMOD feed back into transport and heating models, allowing recalculation into retail electricity prices for households, tertiary, and industry sectors, factoring in taxes and levies.

3.3.1. Battery electric vehicles

ALADIN provides process-relevant BEV data, which are required to model electro-mobility demand shifts. The number of BEVs[3] (private/commercial passenger cars), average charging, and storage capacities per BEV (cf., Table 3) are transferred annually. Furthermore, hourly driving and charging availability profiles (parked with/without grid connection) are passed to the electricity system models (cf., Fig. 2 a-b). No bidirectional charging is considered in the electricity system models. Moreover, commercial fleet and private BEVs are differentiated in driving and parking profiles.

[3] The total number of BEVs is expected to reach 7.5 million by 2030, with commercial fleet and private vehicles contributing almost equally to the total. Due to the beginning of the MODEX project in 2019, the current German government's target of approximately 15 million BEVs (30 % of the total passenger vehicle fleet) by 2030 could not be taken into account. However, a greater emphasis is placed on the methodology and comparison of the models, rather than on a perfect forecast.

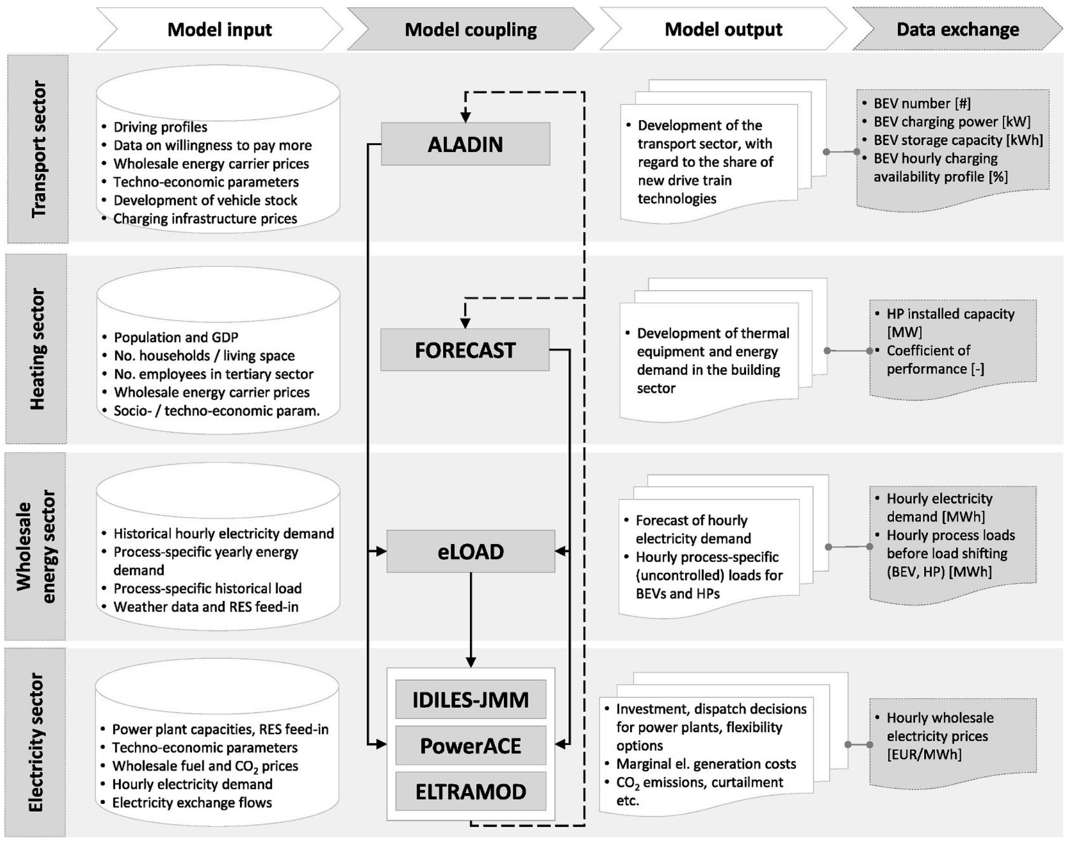

Fig. 1. Model coupling and data exchange of the EMS to investigate the impact of the flexible utilization through BEVs and HPs on future generation adequacy.

Uncontrolled BEV process loads and charging availability profiles exhibit daily and weekly structures (cf., Fig. 2 a-b), notably differing between weekdays and weekends. BEV charging sees a peak between 8 and 10 a.m. as users charge vehicles at work. After a slight valley around noon, charging increases when BEV users reach home. Evening peaks occur daily, notably larger on weekdays. A load reduction occurs from Friday onwards, with lower uncontrolled BEV process loads mainly on weekends.

Charging availability displays an almost sinusoidal pattern (cf., Fig. 2 b). BEVs remain connected to the grid predominantly at night, but with a decreasing availability towards the weekend. Fleet vehicles show higher charging availability peaks but lower availability around midday on weekdays. Private vehicles display less connectivity during weekends, hinting at more leisure trips, maintaining an average availability above 40 %. This highlights theoretical storage potential, considering bi-directional charging or vehicle-to-grid concepts. Aggregated BEV loads remain stable seasonally.

3.3.2. *Heat pumps with thermal energy storage*

FORECAST models HP diffusion, passing annual installed HP capacity to eLOAD and the electricity system models. eLOAD uses the FORECAST output to determine the hourly process load, exchanging parameters like maximum shift duration of heat demand and the yearly-averaged coefficient of performance (COP).[4] HP capacity is ~8 GW, requiring ~14 TW h annual electricity demand. Each HP is combined with a TES to provide flexibility to the system. When coupling a TES with an HP, the TES acts as a buffer to store excess heat generated by the HP during off-peak hours. TES can be discharged directly to provide space heating and water heating when needed, helping to improve energy efficiency and reduce overall energy costs. The TES is typically charged during off-peak hours when electricity rates are lower or when excess renewable energy is available. It is discharged during peak hours when electricity demand is high, helping to reduce strain on the grid and save costs. The total assumed storage volume is about ~8 GWh_{th}.

Table 3
Total BEV number, average charging, and storage capacities per BEV for Germany in 2030.

	BEVs (passenger cars)			Average charging capacity	Average storage capacity
	Commercial	Private	Total BEVs		
	[Mio.]	[Mio.]	[Mio.]	[kW_{el}/BEV]	[kWh_{el}/BEV]
2030	3.97	3.60	7.57	6.13	19.37

Unlike BEVs, HPs show no weekly variation but have seasonal differences aligned with temperature. The HP process load, constant throughout the day with minor morning/evening increases, follows a seasonal pattern shown in Fig. 3 due to weather-dependent space heating demand. In summer there exists almost no demand for space heating, regardless of the weather year. WY 2012 stands out with a peak demand of nearly 90 % of installed HP capacity at the year's start.

3.3.3. *Hourly electricity demand*

eLOAD computes hourly electricity demand and process loads for BEVs and HPs. TYNDP's annual electricity demand guides eLOAD's system load projection [102]. ALADIN and FORECAST provide BEV and HP load profiles. For calculating an aggregated HP profile with hourly resolution, a temperature-dependent load profile [103] and hourly

[4] The consideration of a yearly-averaged COP was chosen to reduce complexity, as several iterations with a soft-linked data exchange had to be calculated as part of the model coupling. To take into account the degradation of the efficiency and capacity of HPs, e.g. in cold weather, it would be more accurate to implement an hourly temperature-dependent COP.

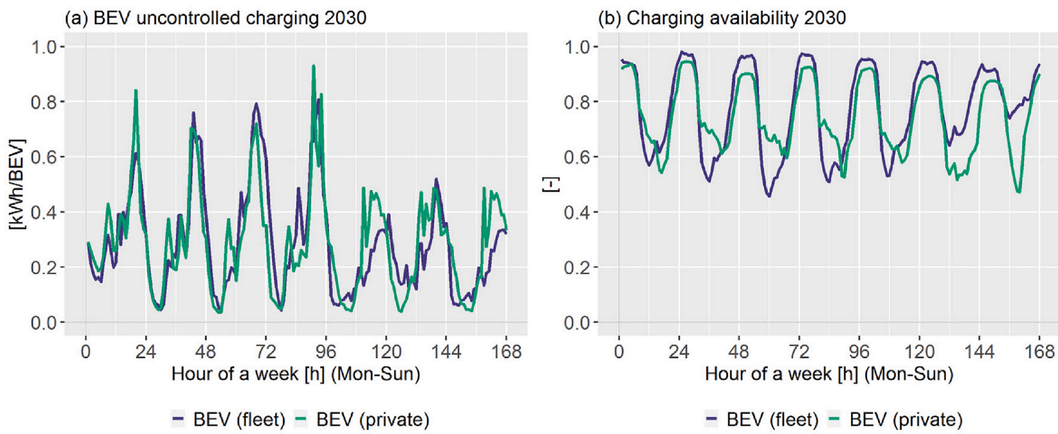

Fig. 2. Average weekly process load per BEV (based on total BEVs number) (a) and charging availability for parked BEVs with grid access (b) for Germany in 2030 (WY2016/2012).

temperature data [104] are used.[5] Fig. 4 illustrates the average hourly electricity demand and process loads for BEVs and HPs in Germany during winter and summer weeks in 2030 for WYs 2016/2012. Load peaks, occurring in winter evenings, result from BEV charging coinciding with high HP loads.[6]

In electricity system models, exogenous input parameters like hourly system load and vRES feed-in influence optimal BEV and HP dispatch as the models aim to smooth the residual load. Fig. 5 presents monthly residual loads and annual load duration curves for WYs 2016/2012. As shown in Fig. 5 (b), the steeper curve in WY 2012 indicates a higher capacity deficit (86 GW_{max}) and more hours of low or negative residual load (−42 GW_{min}), suggesting greater vRES surpluses than WY 2016. February in WY 2012 shows significant capacity deficits, potentially leading to critical supply situations (cf., Fig. 5 a).

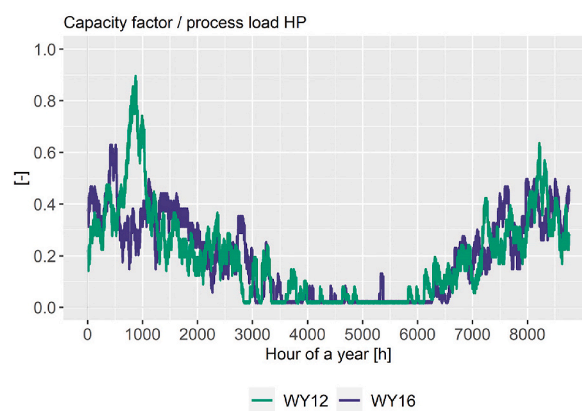

Fig. 3. Average capacity factors of residential HPs for space and water heating in Germany for an average (WY 2016) and an extreme weather year (WY 2012).

3.4. Methodical approach for load shifting in electricity system models

This section outlines the methodology for load shifting in BEVs through controlled charging and the optimized dispatch of HPs (with TES) within the electricity system models, IDILES-JMM, PowerACE, and ELTRAMOD.

Load shifting of BEVs and HPs in electricity system models involves the optimization of when these devices charge and consume electricity to reduce peak demand on the grid and maximize the utilization of RES. For BEVs, load shifting involves charging the vehicles during off-peak hours when electricity is cheaper and demand on the grid is lower. This helps to reduce the overall electricity costs for both consumers and grid operators, as well as reducing the strain on the grid during peak demand periods. Additionally, by integrating smart charging capabilities, BEVs can be scheduled to charge at times when there is an abundance of RES available, further reducing the environmental impact of transportation. Heat pumps work similarly, with load-shifting strategies designed to optimize their operation to coincide with periods of low electricity demand and high RES production. This can include pre-heating or pre-cooling buildings during off-peak hours and storing thermal energy for later use. By shifting the load of heat pumps to times when electricity is cheaper and cleaner, overall energy costs can be reduced and the RES integration into the grid can be maximized.

In PowerACE, an agent calculates daily load shifting for BEVs and HPs, aiming to smooth the residual load over 24 h. Hourly deployment is constrained by the installed capacity of HPs or BEVs connected to the grid. The hourly electricity demand for the following day, derived from heat demand, BEV driving profiles, and charging states, must be met within the observation horizon. This electricity demand can be shifted within the maximum shift duration. The agent demands the resulting daily use of these technologies on the spot market by creating and submitting bids to the market operator.

The optimization models IDILES-JMM and ELTRAMOD use storage modeling for demand shifting of BEVs and HPs to minimize total system cost while smoothing the residual load. HPs have specified heat demand, met by direct heat generation or withdrawal from the coupled TES. The storage fill level, along with technology capacities, influences possible load shifting.

For BEVs, JMM models the electricity demand related to charging considering arrival and departure rates, along with fixed battery levels upon arrival and departure from the parking location with grid access, impacting load shifting. These two battery levels remain constant in JMM, resulting in a time-varying electricity demand trajectory, differing from PowerACE and ELTRAMOD. Like HPs, the BEVs' storage level,

[5] The FORECAST model incorporates various input data to model the diffusion and electricity consumption of HPs in the residential sector. This includes building stock data (e.g., age classes, number of dwellings, floor area, U-values), technology data (e.g., stock, efficiency, investment and operation costs, lifetime), energy carriers and prices, and policy scenario parameters.

[6] According to FORECAST, HPs will have a market share of 19 % in single-family homes and 18 % in multi-family homes in Germany by 2030. A large proportion of heat will continue to come from natural gas, district heating, and biomass. FORECAST results show that 2.7 million HPs will be installed in Germany by 2030, with increasing use in single-family homes and efficient new buildings. However, rising electricity prices are influencing investment decisions in HPs. The FORECAST model favors investments in district heating and biomass due to lower costs for end energy consumers (cf. Table A1 in the appendix).

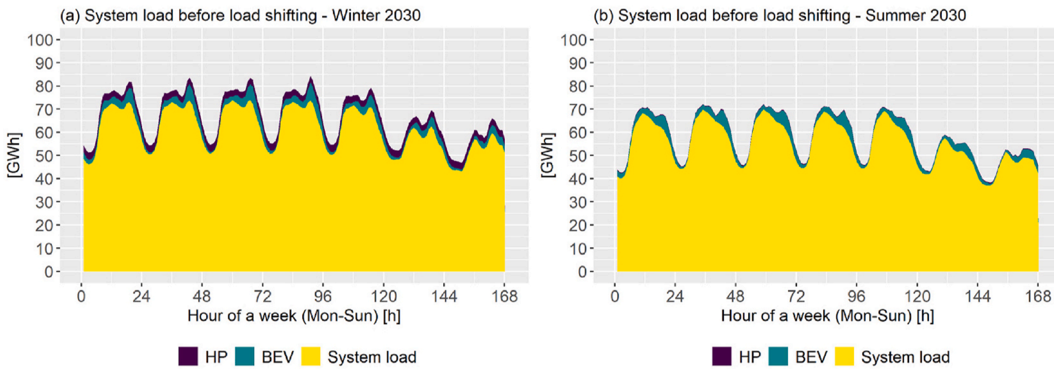

Fig. 4. Average hourly load profiles for total system load and uncontrolled process loads of BEVs and HPs in Germany for a stylized winter (a) and summer (b) week in 2030 (WY 2016).

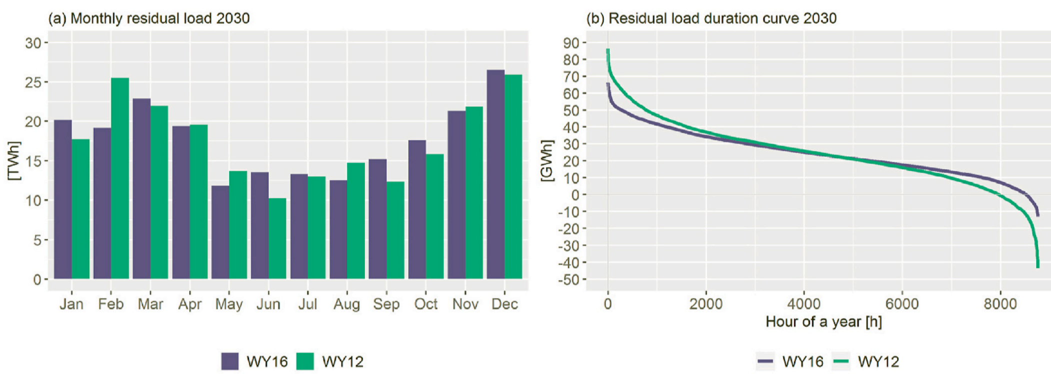

Fig. 5. Monthly residual load (a) and duration residual load curve (b) for an average (WY2016) and extreme (WY2012) weather year for Germany in 2030.

along with capacities, constrains load shifting.

In ELTRAMOD, private and commercial fleet BEVs' driving profiles (process load) must be met hourly. In this context, BEVs are modeled similarly to storage facilities. The total available storage level is the sum of all vehicles' storage capacity plus the charging amount, minus driving BEVs' electricity consumption. The upper storage level is constrained by the total capacity of all vehicles. In the first and last hour of the year, the storage facilities are filled to 50 %. Another constraint limits BEVs' maximum charging capacity, determined by all vehicles' charging capacity and the availability profile. The maximum charging quantity is the total storage capacity minus the previous hour's storage level. Hourly charging amounts (i.e., BEVs' electricity consumption) contribute to the optimization problem's energy balance. BEVs and HPs are modeled with assumed activation costs of 0 EUR/MWh, implying a regulatory obligation to activate DSM measures supporting system stability.

4. Impact of flexibility options on residual load

In the following section, the results for the different WYs are presented concerning the load shifting of BEVs and HPs in the three electricity system models – IDILES-JMM, PowerACE, and ELTRAMOD. Furthermore, the residual load after dispatch of the considered flexibility options and the resulting impacts on generation adequacy are described. All results were derived with a fixed power plant fleet, which is identical in all models (cf., Table A2).

4.1. Load-shifting potential of battery electric vehicles

Fig. 6 shows the mean hourly process load of BEVs (uncontrolled charging) and compares the optimized charging profile of BEVs for work and weekend days of the winter and summer season in an average (2016) and an extreme (2012) WY for the electricity system models IDILES-JMM, PowerACE, and ELTRAMOD.

The models shift the BEVs' electricity demand for charging within predefined parameters (i.e., maximum charging power, storage capacity, charging availability profile). Notably, all models exhibit a demand shift from evening to early afternoon and morning, aligning with lower general electricity demand periods. On weekends, a noticeable shift occurs, resulting in higher peak demand than weekdays, especially with increased BEV charging during times of lower total electricity demand and higher PV generation, evident in summer with up to 12 GW (maximum BEVs' electricity demand) in ELTRAMOD and IDILES-JMM. The average weekly pattern of optimized BEV charging is similar between the optimization models IDILES-JMM and ELTRAMOD, with minor time differences attributed to their slightly different mathematical approaches. IDILES-JMM integrates BEVs' load shift within a rolling 24-36-h planning, whereas ELTRAMOD simulates BEVs' load shift with perfect foresight over a year. Gils et al. [3] demonstrate similar findings, showing less discrepancy between power system models for the dispatch of peak load power plants, controlled charging of BEVs, and optimized HP operation. The authors highlight more significant result differences for long-term storage operation, vehicle-to-grid, and demand response. While IDILES-JMM and ELTRAMOD minimize total costs, PowerACE, an agent-based model, prioritizes smoothing residual load from the agents' perspective. The results in the agent-based model PowerACE differ from the optimization models, as it only allows day-ahead load shifting within 24 h, leading to abrupt transitions between weekday and weekend load patterns (high load in night hours vs. low load in early morning hours). Moreover, PowerACE shifts load peaks from noon to night hours, which is observed consistently across all WYs and seasons. In total cost-optimizing models like IDILES-JMM and ELTRAMOD, a portion of weekday load is shifted to midday hours on weekends, particularly noticeable in summer due to high PV feed-in and lower overall

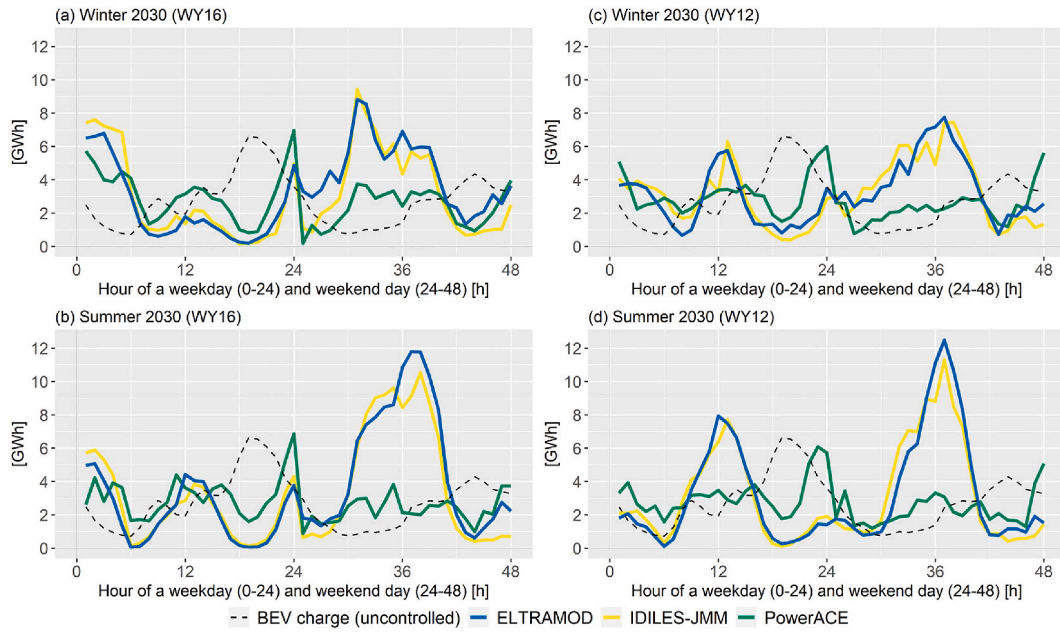

Fig. 6. Comparison of mean hourly BEV process load (uncontrolled charging) and optimized controlled BEV charging profiles for an average weekday (0–24 h) and weekend day (24–48 h) for the winter (top) and summer (bottom) season in an average (2016 – left) and extreme (2012 – right) WY for Germany in 2030 between the electricity system models IDILES-JMM, PowerACE, and ELTRAMOD.

electricity demand.

Result deviations and methodological disparities indicate that total cost-optimizing models achieve more significant electricity demand shifts than the agent-based model PowerACE, suggesting untapped potential in the latter. However, uncertainties remain about agents accessing all information to optimally utilize shifting potentials in the electricity market.[7] Additionally, Gils et al. [61] state that different technology modeling approaches for BEVs lead to significant variations in the flexibility provided. Specifically, imposing costs for deviating from a predefined charging profile greatly reduces the use of BEV flexibility. Conversely, neglecting a minimum battery level results in increased utilization of this flexibility.

4.2. Load-shifting potential of heat pumps

Fig. 7 compares the average process load profile of HPs (without TES) with the optimized utilization profile of HPs, incorporating TES for space and water heating in residential buildings. Integrated TES enhances HPs' flexibility, allowing them to respond more dynamically to residual load smoothing across all models. Load peaks mainly occur in the early morning (04:00–06:00), midday (12:00–13:00), and evening (20:00–24:00), aligning with increased RES feed-in during these periods (e.g., PV at noon, wind at night). This indicates a high HP utilization, and a decreasing variation of the residual load during periods of high RES feed-in (i.e., times with low electricity prices – also shown in Ref. [62]). Load valleys emerge between these times, with minimal variation in the optimized HPs' dispatch between week and weekend days. In summer, residential heat demand decreases significantly due to the absence of space heating needs, focusing on hot water preparation. IDILES-JMM and ELTRAMOD exhibit similar responses in HP load shifting, while PowerACE differs slightly by operating within a 24-h rhythm without shifting loads to the next day. Evaluating TES over a shorter time horizon of 24–36 h in IDILES-JMM produces similar results to ELTRAMOD with perfect foresight. This is because the objective function of IDILES-JMM includes remuneration for the storage filling level at the end of each optimization period (same applies to BEVs – also shown in Ref. [3]).

Interaction with BEV load smoothing is also noted; for instance, ELTRAMOD shows higher BEV charging on weekends at midday (13:00) compared to increased HP utilization in IDILES-JMM. Moreover, CHP ramping (as considered in IDILES-JMM) has a substantial impact on the interaction of CHP, HPs, and TES. Strong fluctuations in the residual load are preferably compensated by adjusting the HP operation in case of additional CHP ramping restrictions, which favors a more intense usage of TES (also shown in Refs. [3,62]). All three electricity system models consider a constant yearly-averaged COP. However, the authors in Gils et al. [53,61] discovered that higher utilization of TES in building heat pumps is observed when considering a time-variable COP. This approach favors partially adjusting the heat pump operation based on the heat source temperature.

4.3. Smoothed residual load through optimal dispatch of flexibility options

Fig. 8 (a–d) illustrates the impact of load shifting from BEV charging and HP dispatch on residual load smoothing across the three electricity system models for winter (top) and summer (bottom) weekdays and weekends for an average (2016 – left) and an extreme (2012 – right) weather year. In general, the residual load on winter days (top) is higher and has fewer valleys compared to summer days (bottom) due to lower PV feed-in. When comparing different weather years, the extreme weather year (2012 – right) exhibited more extreme residual load valleys on weekdays in both summer and winter, indicating a greater potential for smoothing the residual load. Since BEVs and HPs are electricity-consuming technologies (power-to-X), their dispatch results in load increases. The primary goal of the electricity system models is to smooth residual load valleys (i.e., low to negative residual load), especially during midday on weekdays and weekends with high PV feed-in, particularly in the summer season (Fig. 8 b, d). The models avoid appliance use during residual load peaks, especially in summer, to prevent exacerbating extreme situations with capacity deficits. In general, the residual load smoothing effect is more pronounced in the

[7] For all models, the annual sum of the shifted load of controlled BEVs charging is identical with the sum of the process load for uncontrolled charging.

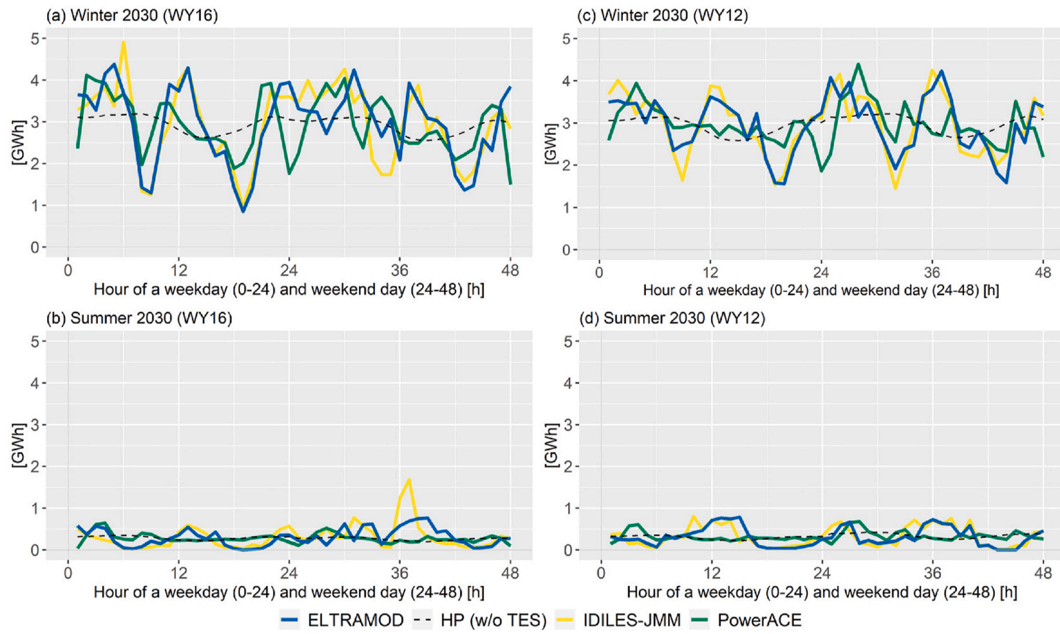

Fig. 7. Comparison of mean hourly HP process load (w/o TES) and optimized HP dispatch with TES for an average weekday (0–24 h) and weekend day (24–48 h) for the winter (top) and summer (bottom) season in an average (2016 – left) and extreme (2012 – right) WY for Germany in 2030 between the electricity system models IDILES-JMM, PowerACE, and ELTRAMOD.

optimization models than in the agent-based model PowerACE, as explained before. Additionally, the similarity in the smoothing effect between the optimization models IDILES-JMM and ELTRAMOD is notable. Hence, the difference between the myopic perspective (12-h rolling planning) and the perfect foresight perspective has a minor impact on the load-shifting effect of BEVs and HPs.

In the appendix, Figure A1 presents the mean hourly residual load smoothing effect of all considered flexibility options, including BEVs and HPs with TES, pumped storage plants (PSP), renewable curtailment, and load shedding. The peak load shaving due to PSP in the early morning (06:00–09:00) and evening (18:00–20:00) is striking. Residual load valleys are additionally smoothed by charging of PSP, especially on weekends. Due to the different utilization of PSP, explained more in detail in Ref. [58], the power system models differ slightly in the overall smoothing effect. The highest residual load smoothing is observed in ELTRAMOD, the perfect planner (perfect foresight for one year), closely followed by IDILES-JMM with the rolling planning algorithm in a 24-36-h rhythm, which only slightly affects the PSP dispatch. The agent-based model PowerACE shows the least smoothing effect due to the load shift within 24 h.

Comparisons between WYs show minor differences in residual load smoothing among electricity system models. For a detailed analysis of dispatch decisions of the individual generation technologies and flexibility options in the three electricity system models, the hourly energy

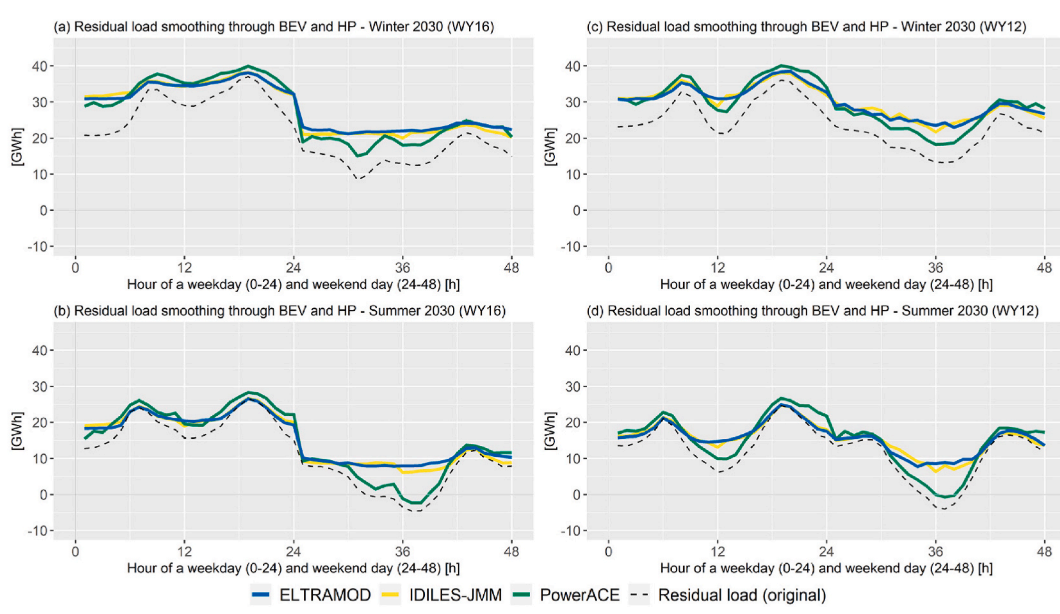

Fig. 8. Comparison of mean hourly (non-optimized) residual load and smoothed (optimized) residual load through load shifting of BEVs and HPs for week (0–24 h) and weekend day (24–48 h) for the winter (top) and summer (bottom) season in an average (2016 – left) and extreme (2012 – right) WY for Germany in 2030 between the electricity system models IDILES-JMM, PowerACE, and ELTRAMOD.

balance during the week with the highest residual load (WY 2016/2012) is examined in Fig. 9. The WY 2012 is characterized by a more fluctuating residual load, simultaneously resulting in a more volatile utilization of load-shifting technologies that are supposed to contribute to the residual load smoothing. In general, annual PSP dispatch, vRES curtailment, and load shedding are higher in the WY 2012 compared to the WY 2016 in all models (cf., Table 5). Higher vRES curtailment occurs if flexible sector coupling and storage are not operated optimally due to a lack of temporal foresight (PowerACE – also shown in Ref. [61]). Additionally, inflexibilities such as technical restrictions on conventional generation units (e.g., minimum operation times, minimum downtimes, ramping constraints, or CHP must-run requirements) can amplify vRES curtailment (see also [62]). Load shedding varies among models (cf., Fig. 9 *d*-f), with IDILES-JMM experiencing more due to the provision of reserve power, limiting flexibility in peak capacity and storage (i.e., oil-fired plants and PSP). PowerACE and ELTRAMOD utilize residual load valleys to charge PSP, especially during RES surpluses. IDILES-JMM has virtually no PSP charging in the week with the highest residual load, which is likely due to the need to provide reserve power, which limits the amount of electricity that can be generated. While in IDILES-JMM and PowerACE also the conventional power plant fleet reacts more flexibly to the fluctuating demand, in ELTRAMOD the demand is smoothed more by the load shifting of BEVs, HPs and PSP (cf., Fig. 9 e-f). The reason for this is the considered load-changing costs for ramping up and down conventional generators in ELTRAMOD, which makes a very short-term shutdown of power plants uneconomical compared to cost-neutral load shifting. In contrast, in IDILES-JMM and PowerACE only start-up costs for conventional power plants are considered (cf., Table A4 [58]). Gils et al. [3] demonstrate that additional ramping constraints and costs can reduce electricity supply by up to 5 %, leading to increased curtailment, load shedding, and system costs. Moreover, while IDILES-JMM and PowerACE react to the positive residual load extremum (capacity deficit) in WY 2012 with load shedding,[8] ELTRAMOD activates PSP for load smoothing. Using a perfect foresight approach over one year (ELTRAMOD), the lower availability of flexible conventional power plants or sector coupling options can be partially offset by the more intensive use of PSP (see also [61]). Additionally, reduced storage possibilities due to limited time foresight result in higher utilization of thermal power plants (IDILES-JMM, PowerACE – also shown in Ref. [61]).

5. Impact of flexibility options on generation adequacy

Since renewable electricity generation is heavily dependent on weather conditions, and electricity demand increases through the electrification of the demand-side sectors (e.g., due to BEVs and HPs), the question arises what impact load shifting may have on generation adequacy in the power system, especially during critical supply situations (i.e., periods of high electricity demand and very low RES feed-in). To assess generation adequacy, IDILES-JMM, PowerACE, and ELTRAMOD model results are compared using specific indicators, focusing on the year 2030 (WY 2016/2012). The continuously reliable capacity (CRC) is utilized to evaluate generation adequacy. In this paper, CRC is defined as non-weather-dependent electricity generation capacity excluding PSP and considering existing reserve power plant capacities not participating in the market, along with technology-specific availability (based on [58, 105]). To better compare the load-shifting effects of BEVs and HPs between the electricity system models, all models apply the same CRC (58.7 GW), since the power plant fleet and its reserve capacity are fixed, i.e., no model-endogenous capacity expansion (cf., Table A5). To assess the generation adequacy, an analysis of the coverage of the hourly residual load by the CRC, without considering the hourly net electricity exchange flows between Germany and its neighbors, is performed. The following four generation adequacy indicators are determined and compared between the models.

- **Loss of Load Expectation (LOLE)** refers to the number of hours in a year when the CRC fails to cover the residual load.
- **Power Import Dependency (PID)** is defined as the difference between residual load and CRC. The PID is zero if the CRC is greater than or equal to the hourly residual load. Positive PID indicates insufficient CRC, requiring electricity imports or other flexibility options.
- **Maximum Power Import Dependency (PIDmax)** can be calculated for specific stress situations[9] or for an entire year, denoting time intervals where PID remains positive for several hours.
- **Expected Energy Not Served (EENS)** represents the amount of energy not delivered over a period, based on consecutive hours with positive PID.

Figs. 10 and 11 depict generation adequacy indicators before and after activation of BEV and HP load shifting. The x-axis represents the duration of individual stress situations, while the y-axis shows EENS values. Color gradients indicate the maximum PID during a stress situation. Fig. 10 (a) reveals stress situations occurring in the average WY (2016) without additional BEV and HP electricity demand. With the added process load from BEVs and HPs (cf., Fig. 10 b), stress situations increase in frequency, along with the number of consecutive hours, EENS, and PIDmax. The situation is more critical in an extreme WY (2012), with more frequent and prolonged stress situations featuring higher EENS and PIDmax. Activating load shifting in the electricity system models, involving controlled BEV charging and optimized HP utilization with TES, minimizes stress situations threatening generation adequacy in both WYs (cf., Fig. 11). PowerACE, as agent-based model, exhibits a slightly higher frequency of critical security of supply situations for the average WY (2016) compared to IDILES-JMM and ELTRAMOD optimization models. This discrepancy arises because the integrated agent slightly underestimates the load-shifting potential due to its limitation to shifting within a 24-h timeframe. IDILES-JMM exhibits the highest indicators for critical situations during the extreme WY (2012). The modeling of reserve power and heat provision by CHP in IDILES-JMM contributes to more stress situations, as the available capacity is constrained by reserves for balancing power or is prioritized for heat provision in CHP. Consequently, this leads to lower electricity provision by lignite power plants in IDILES-JMM compared to other models (cf., Table A3). ELTRAMOD simplifies by excluding reserve power and CHP must-run conditions in this model experiment, showing fewer stress situations, and making it a “perfect planner” (perfect foresight for one year).[10] ELTRAMOD exhibits the highest residual load smoothing, followed by IDILES-JMM using the rolling planning algorithm in a 24–36 h rhythm, minimally impacting PSP dispatch. Due to the load shift within 24 h, PowerACE shows the least residual load smoothing effect by BEVs and HPs, which also affects critical supply situations. Table 6 summarizes the annual security of supply indicators of all models for the WY 2016 and 2012.

In the extreme WY (2012), characterized by heightened residual load fluctuations[11] and low winter temperatures, the additional electricity

[8] Load shedding is penalized with the value of lost load (VOLL), which is assumed to be 800 EUR/MWh_{el} in all models [58].

[9] Most commonly, stress situations occur when high electricity demands meet low feed-in from weather-dependent renewable energy sources.

[10] The visual representation may suggest increased stress situations in ELTRAMOD after load shifting, but Table 6, detailing annual generation adequacy indicators, contradicts this. ELTRAMOD, functioning as the “perfect planner,” experiences the least stress situations, with variations primarily in their durations, leading to fewer overlaps in graphical points.

[11] Namely, electricity demand becomes more volatile, marked by fluctuating feed-in and load peaks from wind and PV sources.

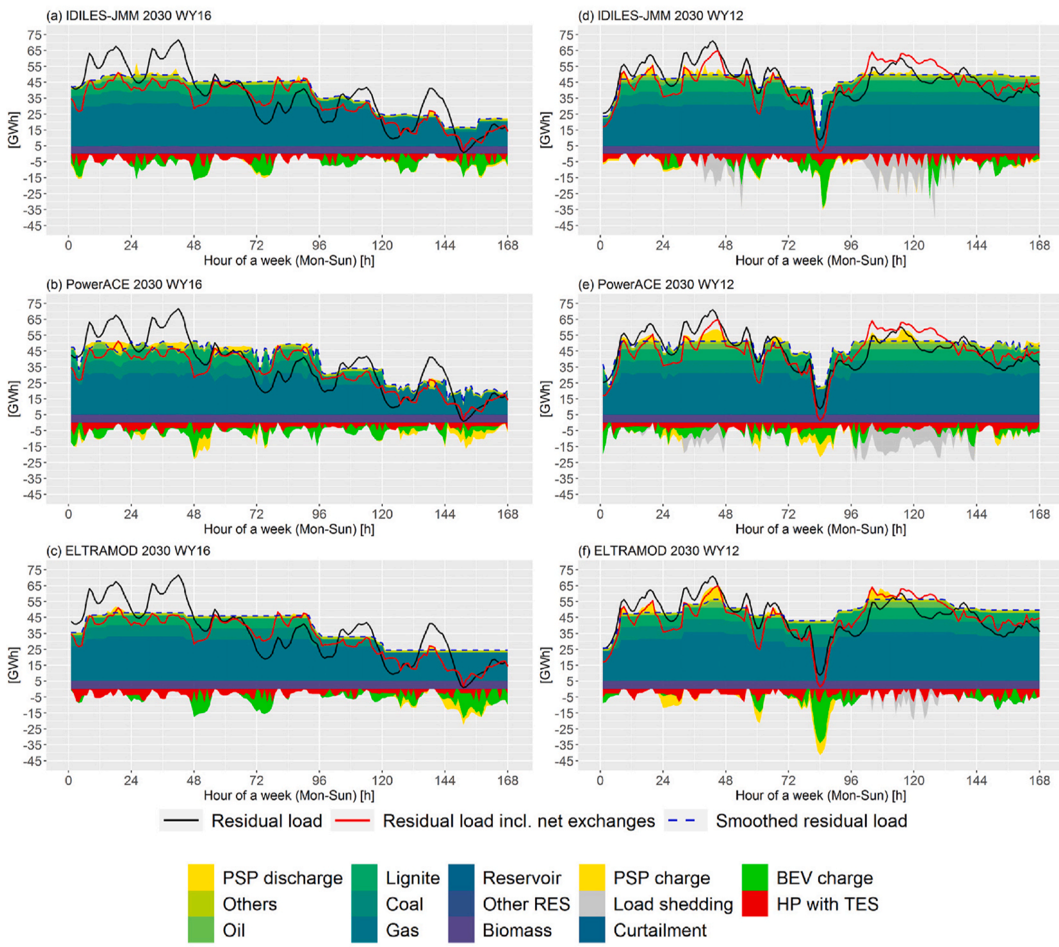

Fig. 9. Comparison of the hourly energy balance for the week with the highest residual load for an average (2016 – left) [t8137-t8304] and extreme (2012 – right) [t529-t696] WY for Germany in 2030 between the electricity system models IDILES-JMM, PowerACE, and ELTRAMOD.

Table 4
Weather year independent annual electricity consumption for general electricity demand, BEVs charging and HP utilization in Germany in 2030.

	2030	
	[TWh_{el}]	[%]
System load	507.3	92.8
BEV process load	25.4	4.6
HP process load	14.1	2.6
Total	**546.8**	**100**

demand from BEVs and HPs (without load shifting) leads to more frequent stress situations compared to the average WY 2016. (cf., Fig. 10). Despite activated load shifting in power system models, complete avoidance of critical supply situations is not achieved. On average, the frequency of stress situations can be reduced by 95 % in an average (2016) and by 68 % in an extreme (2012) WY through load shifting of BEVs and HPs.

In an average WY (2016), the average PIDmax is approximately 16.6 GW, implying a maximum power import capacity of around 9 GW (subtracting the full available PSP capacity of 7.6 GW, in the absence of other flexibility options) (cf., Table 6). In an extreme WY (2012), the average PIDmax is about 46.6 GW, necessitating around 39 GW of required import capacities or additional flexibility from batteries, power-to-gas-to-power, or demand-side management processes, after considering PSP.

All models show that as stress situation duration increases, both EENS and maximum PID values also rise. Future reliance on electricity imports from neighboring countries, especially during winter with potentially prolonged stress conditions, is expected for Germany to maintain high generation adequacy. Investments in grid expansion and flexible options in Germany and neighboring countries are crucial to

Table 5
Comparison of yearly vRES curtailment, load shedding, conventional electricity generation and PSP operation for an average (2016) and extreme (2012) WY between the electricity system models after load shifting of BEVs and HPs for Germany in 2030.

	WY 2016			WY 2012		
[TWh/yr]	**IDILES-JMM**	**PowerACE**	**ELTRAMOD**	**IDILES-JMM**	**PowerACE**	**ELTRAMOD**
vRES curtailment	0.1	0.8	0	4.4	7.5	3.1
Load shedding	0.05	0.04	0	5.0	4.3	1.2
Conv. generation	174.0	172.7	170.3	176.0	174.4	172.9
PSP charging	4.5	13.5	7.0	5.8	14.8	13.9
PSP discharging	4.4	10.1	5.3	5.5	11.2	10.3

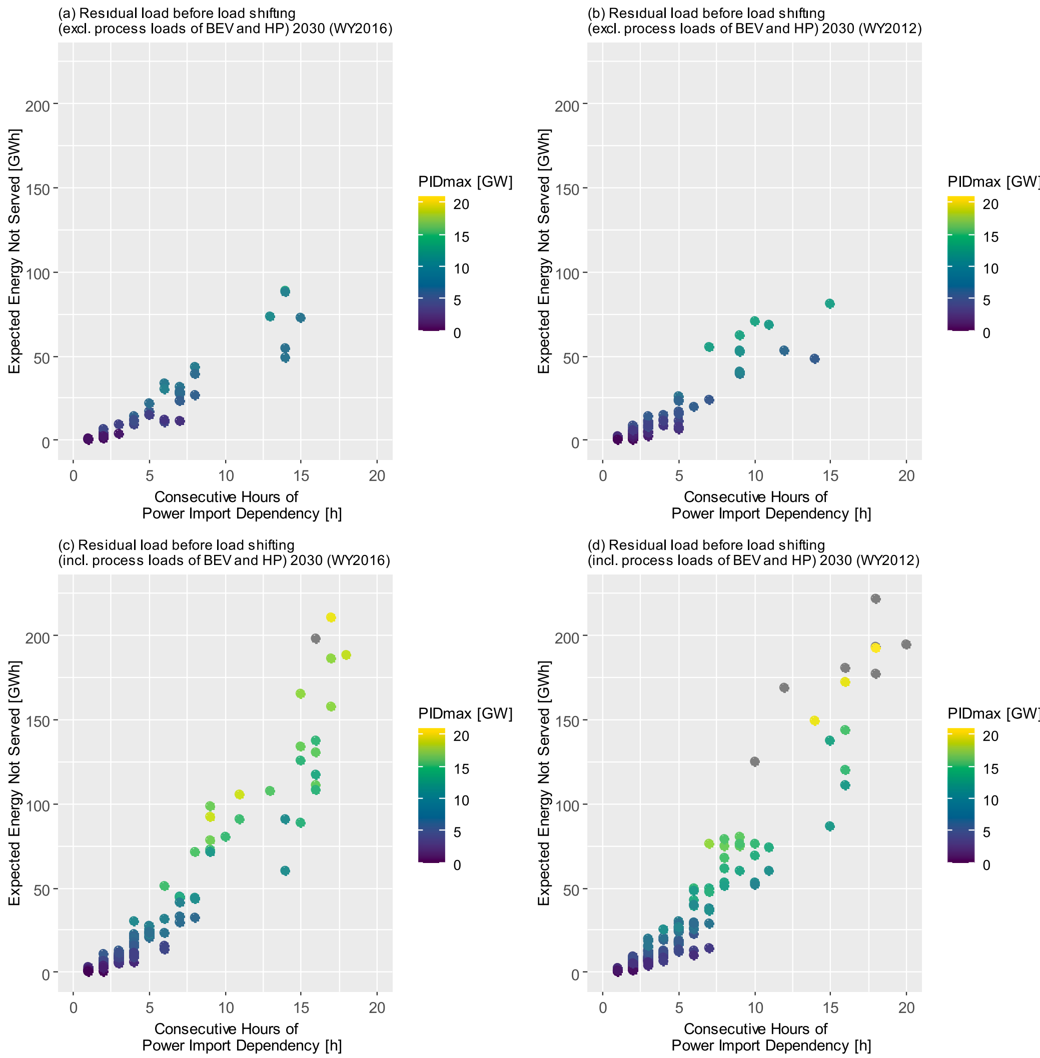

Fig. 10. Critical supply situations (a–b) without additional electricity demand from BEVs and HPs and (c–d) with additional electricity demand from BEVs and HPs before load shifting for Germany in 2030, taking into account an average (2016 – left) and extreme (2012 – right) WY.

mitigate residual load peaks and avert critical supply situations.

6. Conclusion

Research on model experiments, especially those involving soft-linked model coupling and integrated model comparison focusing on sector coupling and the flexibility provision of BEVs and HPs, is limited. This paper makes a threefold contribution to existing research by: (I) systematically comparing three electricity system models; (II) focusing on sector coupling by implementing optimal dispatch strategies for BEVs and HPs from a system perspective; and (III) utilizing a soft-linked model coupling.

The novelty of this paper lies in the multi-model approach, which integrates a comparison of electricity system models to analyze the impact of electrification and optimal load shifting of BEVs and HPs. Additionally, the paper examines how electrification and optimal load shifting of BEVs and HPs affect generation adequacy in Germany in 2030, especially during critical supply situations, considering both average (2016) and extreme (2012) weather years. Therefore, specific demand-side models from the transport sector (ALADIN), heating sector (FORECAST), and an electricity projection model (eLOAD) are coupled with three electricity system models (IDILES-JMM, PowerACE, ELTRAMOD).

The comparison between IDILES-JMM, PowerACE, and ELTRAMOD highlights key model characteristics that lead to differences in flexibility provision through optimal load shifting of BEVs and HPs. Harmonized input parameters and simplified scenario analyses isolate deviations in model results and attribute them to specific model properties.

Results reveal that variations stem primarily from different model approaches and optimization logic. IDILES-JMM employs a 12-h rolling planning algorithm, alternating between 24- and 36-h loops for optimal dispatch decisions. ELTRAMOD utilizes a closed-loop linear optimization on an hourly basis throughout the year to determine optimal dispatch and load-shifting decisions. In PowerACE, agents submit hourly bids that are auctioned to maximize welfare for all market participants. Comparing load-shifting effects of BEVs and HPs, PowerACE's agent-based approach,[12] transforming load-shifting potential into day-ahead

[12] Agent-based models allow for more realistic simulations of complex systems, incorporating the behaviors and interactions of individual agents. Accounting for the diverse behavior of agents involves several key steps e.g., incorporating agent heterogeneity, behavioral rules, learning and adaptation mechanisms, and interaction networks among agents, etc. Agent-based models can be highly complex and require a significant amount of computational resources. They need a large amount of data to accurately represent the behavior of agents, which can be time-consuming and costly.

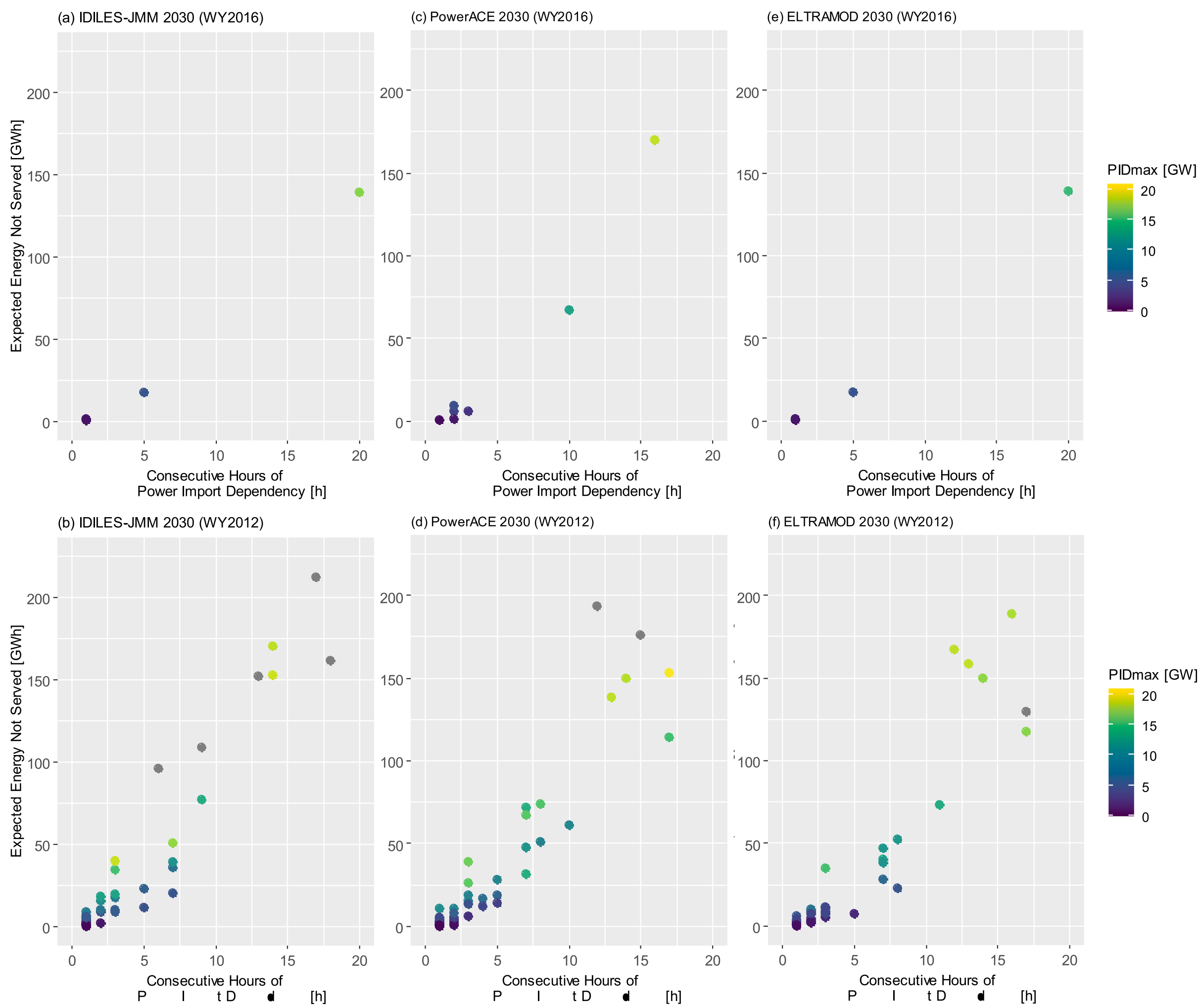

Fig. 11. Comparison of critical supply situations between the power system models (a–b) IDILES-JMM, (c–d) PowerACE, (e–f) ELTRAMOD after optimal load shifting (residual load minimizing) of BEVs (controlled charging) and HPs (with TES) for Germany in 2030 under consideration of an average (2016 – top) and extreme (2012 – bottom) WY.

bids, creates an information deficit. Its demand response optimization limits load shifting to one calendar day (24 h). In contrast, total cost optimizers like IDILES-JMM (with rolling planning horizon) and ELTRAMOD (with perfect foresight[13]), excel in determining residual load smoothing and minimizing system costs as they have complete information, akin to a central planner. Deviations in load-shifting activities depend also on varying considerations of load change and start-up costs for power plants.[14] Since load shifting can directly affect critical supply situations, PowerACE exhibits higher generation adequacy indicators in the average WY (2016) due to minimal residual load smoothing through BEVs and HPs compared to IDILES-JMM and ELTRAMOD. In contrast, reserve power and CHP heat provision modeling can have an impact on generation adequacy, notably shown in IDILES-JMM for the extreme WY (2012), where available capacity is reduced by reserves for balancing power and increased use for heat provision. Result deviations in load shifting of BEVs and HPs between agent-based and optimization models underscore the need to focus on actor perspectives when modeling flexibility options, anticipating less centralized and more decentralized organization of flexibility by small-scale actors in the future. Despite increased electricity demand, activating load shifting in BEVs and HPs reduces stress situations, enhancing generation adequacy. Across all electricity system models, load shifting indicates a reduction in curtailment of renewables and consumers, conventional power generation, and thus reduced CO_2 emissions. Generation adequacy indicators reveal conventional generation's inability to meet the hourly residual load consistently. In 2030, weather-dependent findings suggest an average[15] maximum requirement for additional flexibility of 9 GW in an average WY and 39 GW in an extreme WY for the German electricity market (assuming full availability of PSP). Load shifting from BEVs and HPs can significantly mitigate critical supply situations in an average WY compared to the scenario without

[13] Linear optimization models often incorporate perfect foresight over a year because it allows for a comprehensive evaluation of long-term planning and decision-making within the energy sector. By assuming perfect foresight, these models can optimize resource allocation, investment decisions, and operational strategies with a high level of detail and accuracy. Perfect foresight assumptions may not capture all uncertainties and risks inherent in the energy system, so sensitivity analyses or scenario planning is necessary to account for these factors.

[14] Considering load change costs for power plants can result in higher load-shifting activities since load shifting is assumed to be cost-neutral in this study, and thus more cost-effective in the short-term than ramping up and down conventional generation (e.g., for ELTRAMOD).

[15] The average PIDmax is determined across all considered electricity system models (IDILES-JMM, PowerACE, ELTRAMOD).

Table 6
Comparison of generation adequacy indicators after load shifting of BEVs and HPs between electricity system models for an average (2016) and an extreme (2012) WY for the future power system in Germany in 2030.

2030	Frequency of stress situations [−]		Loss of load expectation (LOLE) [h]		Expected energy not served (EENS) [GWh]		Max. Power import dependency (PIDmax) [GW]	
	WY16	**WY12**	**WY16**	**WY12**	**WY16**	**WY12**	**WY16**	**WY12**
IDILES-JMM	5	57	28	338	160	4150	17	71
PowerACE	8	54	37	370	261	4146	19	33
ELTRAMOD	6	44	29	325	160	3460	14	36

load shifting.

The study does not account for time-variable COP, leading to potential underestimation of required generation capacity during cold winter hours. Time-variant COP values are lower in winter due to colder temperatures, coinciding with high heating demand. Additionally, HP operation tends to concentrate during hours with a higher COP, increasing TES usage. Moreover, the study does not include vehicle-to-grid, which could offer additional flexibility by allowing BEV to discharge energy back to the grid during peak demand periods, aiding in grid balance and avoiding critical supply situations.

In an extreme WY, supply bottlenecks persist, necessitating a diverse flexibility portfolio. This includes electricity imports, battery storage, additional generation capacities (e.g., flexible low-carbon power plants, storage discharge), and demand-side flexibility (e.g., vehicle-to-grid, electrolyzers). Anticipating future trends, low-carbon backup capacities, like green H_2-fired power plants, are deemed crucial. Escalating fuel (mainly gas) and CO_2 prices drive this development, boosting contribution margins for low or zero-emission power plants (e.g., green H_2-fired plants, reservoirs, PSP). Furthermore, extreme WYs may witness increased load shedding and renewable energy curtailment, emphasizing the importance of additional flexibility options.

Activating BEVs' and HPs' flexibility mandates regulatory adaptations for demand response and prosumer involvement in the wholesale electricity market. This entails encouraging private consumers to employ HPs flexibly with battery and thermal storage, alongside controlled bi-directional BEV charging in their households. Compensation for consumer flexibility is crucial, achieved through dynamic pricing structures, real-time wholesale electricity prices, and additional revenues for DSM or flexible network fees. Automation via smart meters and appliances is necessary for demand response, allowing communication between distributed vRES and smart appliances like BEVs and HPs. Utilities and aggregators must devise innovative, appealing business models to motivate end users to offer flexibility and accept load balancing, even if not always aligned with their preferences.

CRediT authorship contribution statement

S. Misconel: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation. **F. Zimmermann:** Writing – review & editing, Validation, Software, Resources, Methodology, Investigation, Formal analysis. **J. Mikurda:** Writing – review & editing, Validation, Software, Resources, Methodology, Investigation, Formal analysis. **D. Möst:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **R. Kunze:** Writing – review & editing, Resources, Funding acquisition, Data curation, Conceptualization. **T. Gnann:** Writing – review & editing, Software, Funding acquisition. **M. Kühnbach:** Writing – review & editing, Funding acquisition. **D. Speth:** Software. **S. Pelka:** Software. **S. Yu:** Software.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT 3.5 to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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.

Data availability

Data will be made available on request.

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Appendix

Table A.1
Development of final energy demand, market shares, and prices for heating energy carriers according to the FORECAST model results.

	2020	2025	2030
End energy demand [PJ]			
Biomass	110.5	135.5	150.1
Coal	6.6	6.4	5.6
District heat	239.9	269.0	295.6
Electricity	56.6	54.7	47.9

(*continued on next page*)

Table A.1 (*continued*)

	2020	2025	2030
Electricity heat pumps	25.6	41.9	52.2
Environmental heat	56.2	92.1	114.9
Fuel oil	403.6	389.0	342.2
Natural gas	698.6	588.9	541.3
Solar	3.1	4.4	4.5
Market share in single-family homes [%]			
Biomass	0.10	0.10	0.12
District heat	0.21	0.20	0.26
Heat pump	0.16	0.16	0.19
Fuel oil	0.27	0.23	0.00
Natural gas	0.26	0.31	0.43
Market share in multi-family homes [%]			
Biomass	0.94	0.93	0.11
District heat	0.22	0.21	0.28
Heat pump	0.15	0.15	0.18
Fuel oil	0.27	0.24	0.00
Natural gas	0.27	0.31	0.43
Price for end energy consumers [ct/kWh]			
Pellets	5.27	5.42	5.62
District heat	9.38	10.03	10.77
Heat pump	22.65	23.6	25.79
Fuel oil	7.06	9.52	10.82
Natural gas	7.97	8.86	9.46

Table A.2
Installed capacity of the conventional power plant fleet and renewable energy sources in Germany for 2030. Data based on [102,104,106].

[GW]	Installed capacity
Oil	4.3
Gas	35.5
Coal	9.8
Lignite	8.4
Mine Gas	0.2
Sewage Gas	0.1
Waste	2.1
Reservoir	0.3
Pumped storage	7.6
Wind onshore	58.5
Wind offshore	15.0
PV	66.3
Run-of-river	4.3
Biomass	7.6
Other RES	0.2
Total	**220.2**

Table A.3
Power generation of the conventional power plant fleet and renewable energy sources in an average (2016) and in an extreme (2012) WY in Germany for 2030.

	WY 2016			WY 2012		
[TWh]	IDILES-JMM	PowerACE	ELTRAMOD	IDILES-JMM	PowerACE	ELTRAMOD
Oil	0.5	0.4	0.0	1.8	2.6	1.2
Gas	136.5	125.8	135.4	131.7	122.5	131.7
Coal	14.4	18.8	9.8	17.7	20.6	13.8
Lignite	9.5	14.1	11.3	12.2	16.0	13.1
Mine Gas	1.1	1.3	1.4	1.0	1.2	1.3
Sewage Gas	0.1	0.5	0.4	0.1	0.5	0.4
Waste	10.9	11.0	11.3	10.5	10.3	10.7
Reservoir	1.0	0.8	0.7	0.0	0.0	0.0
Wind onshore	98.6	98.6	98.6	96.1	96.1	96.1
Wind offshore	56.5	56.5	56.5	44.6	44.6	44.6
PV	57.8	57.8	57.8	73.3	73.3	73.3
Run-of-river	19.1	19.2	19.2	19.2	19.2	19.2
Biomass	40.7	43.4	43.4	39.1	43.4	43.4
Other RES	0.0	1.5	1.5	0.0	1.5	1.5
Total	**446.7**	**449.7**	**447.3**	**447.3**	**451.8**	**450.3**

Table A.4
Different consideration and range of start-up and load change costs between the electricity system models. Data based on [58].

	Start-up costs	Load change costs	
		Ramp-up costs (fuel-related)	Ramp-down costs (depreciation-related)
	*[EUR/MW_{el}] **[EUR/MWh_{el}]	[MWh_{th}/MW_{el}]	[EUR/MW_{el}]
IDILES-JMM	0/3.0–16.7 *	–	–
PowerACE	0/4.0–180.0 **	-1	–
ELTRAMOD	–	0/3.5–16.7	0/1.7–10.0

[1] In PowerACE, start-up costs consider additional fuel consumption.

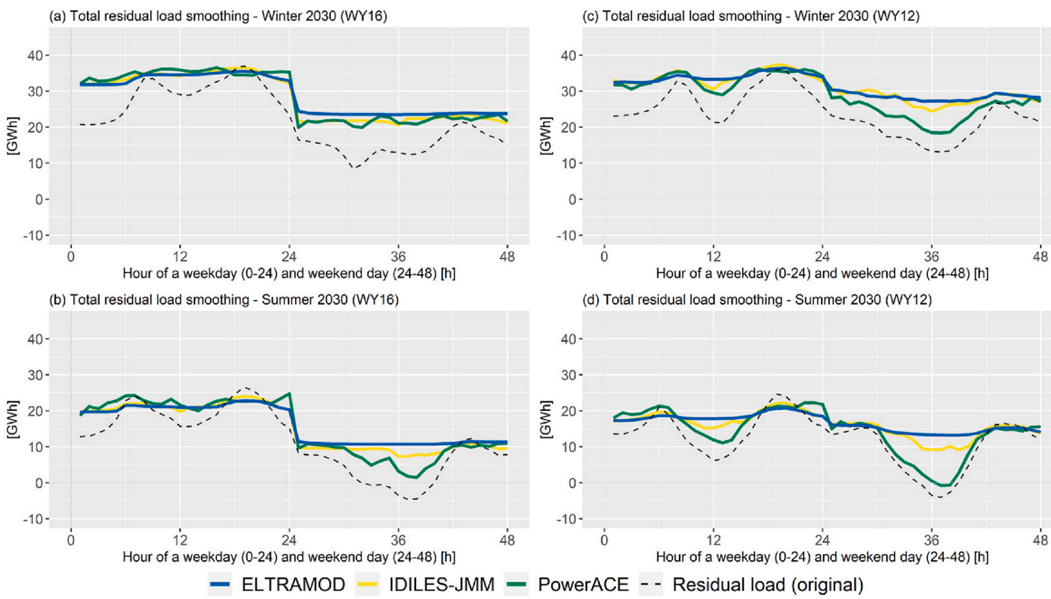

Fig. A.1. Comparison of mean hourly (non-optimized) residual load and smoothed (optimized) residual load through load shifting of BEVs, HPs, pumped storage and vRES curtailment for a week (0–24 h) and weekend day (24–48 h) for the winter (top) and summer (bottom) season in the average (2016 – right) and the extreme (2012 – left) WY for Germany in 2030 between the electricity system models IDILES-JMM, ELTRAMOD and PowerACE.

Table A.5
Continuously available capacity (CAC), mean availability factors and continuously reliable capacity (CRC) for Germany in 2030. Data according to Refs. [106, 107].

	Continuously available capacity (CAC)	Mean availability	Continuously reliable capacity (CRC)
	[MW]	[–]	[MW]
CCGT	24,133.5	0.86	20,754.8
CCOT	1017.9	0.84	855.0
Coal	9767.8	0.82	8009.6
GasSteam	6539.2	0.86	5623.7
Lignite	8351.8	0.85	7099.0
OCGT	4842.0	0.86	4164.2
OCOT	1588.7	0.84	1334.5
OilSteam	1731.1	0.84	1454.1
Reservoir	287.3	1.00	287.3
Mine Gas	221.7	0.70	155.2
Sewage Gas	136.8	0.70	95.8
Waste	1889.0	0.70	1322.3
Reserve control	–	–	7581.0
Total	**60,506.8**		**58,736.5**

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