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Meeting the Modeling Needs of Future Energy Systems.

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Meeting the modeling needs of future energy systems

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Abstract

Structural changes in the energy sector are creating considerable challenges for regulators, energy consumers and suppliers. Energy researchers rely on quantitative modeling approaches to address these challenges. We have therefore developed several models at the Chair of Energy Economics at KIT, for example, to analyze today's and future energy markets, to address the challenges for electricity networks caused by intermittent renewable and decentralized power and heat supply and to find solutions for integrating demand response. This paper presents a survey of these approaches and discusses further challenges. The developed models have proved to be suitable for answering different research question related to the structural changes. But as the energy sector remains in a constant state of flux, these models need to be further developed. On the one hand this means coupling different energy sectors and markets, and on the other improving their technical accuracy as well as their spatial and temporal resolution.

1. Introduction

According to the "Paris Agreement", which was negotiated at the 21st Conference of the Parties of the United Nations Framework Convention on Climate Change (UNFCCC), greenhouse gas emissions should be reduced in such a way that global warming will be limited to less than 2 degrees Celsius. This will only be achievable if the world economy is decarbonized drastically. As it seems to be relatively straightforward to decarbonize the power sector, it is expected that the contribution of this sector to such a decarbonization strategy will be significantly above average.

In Germany, a structural rearrangement of the power system has already been put in motion, given the national targets of a 80% share of renewable energy sources in gross electricity consumption and a cut of greenhouse gas emissions by up to 95% by 2050. This has led to an installed capacity of about 40 GW of photovoltaic (PV) and 45 GW of wind installation by 2015 (cf. BMWi, 2016). It seems very probable that the share of these two fluctuating renewable energy sources will further increase, not only in Germany, but in many countries worldwide. Due to the increasing fractions of decentralized generating plants, the interaction between different sectors (such as power to heat and power to gas or even with other economic sectors, e.g. the transport sector through the electrification of cars) and the more active role of the consumer, the overall complexity of the (future) energy system is likely to increase leading to a rising demand for decision support.

One possibility to support decision makers is to apply energy system analysis, which can assist stakeholders in the energy business with knowledge-based and systematic methods in order to reach decisions on a well-informed basis (cf. Möst, 2010, p. 12). In order to come to consistent strategies, the interdependencies between different alternatives (with regard to investment and production) have to be

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considered, which can be achieved by developing and using quantitative models. To support the transition process discussed above, rather complex models are needed, which are for example able to consider the high spatial and temporal resolutions required to adequately address renewable electricity generation.

Whilst models have become larger and more complex, there has been a parallel development in criticism against the lack of understanding, transparency, and replicability of these models. These more complex models and tools are thus only accessible to experts (i.e. developers) and can no longer be understood or employed by non-experts such as policymakers (cf. Allegrini et al., 2015)). On the other hand, trends are currently recognizable towards open-source models, which can be freely downloaded, modified and run, as developed in several current research projects. But making models open source does not (necessarily) improve their robustness, accuracy and/or certainty for the application in question. Hence why, as well as increasing modeling transparency, Strachan et al. (2016) identify three other key challenges for this interface, namely: better validating models in the context of a peer-review like process of iterative improvement; better communicating the purposes, methods, restrictions and implications of models and their results, especially to non-experts, e.g. policy stakeholder audience; and better dealing with and communicating with uncertainties related to modeling exercises. One further challenge facing energy system modelers is accounting for the heterogeneity of human behavior. Whilst there is a wide consensus about the ways in which socioeconomic characteristics shape energy demand, until now there has only been quite modest progress in including this in energy system models. So-called agent-based modeling approaches are especially promising in this regard (cf. section 2 and Rai & Henry, 2016).

Despite the progress achieved with regard to advanced methods, energy system modelers should always be aware that the main objective of energy system analysis is to derive robust trends, e.g. by analyzing different scenarios (Voß, 1982, p. 116). The more the real-world complexity has to be reduced in order to develop a model that can be solved within reasonable computation time, the more it has to be considered that the main purpose of modeling activities should be to model for insights, not for numbers (see Huntington et al., 1982, Bloomfield & Updegrove, 1981 and Sterman, 1991).

Hence, the objective of this paper is to give insights in modeling energy systems and illustrating the needs for new quantitative approaches as well as the challenges of future system models. With modeling examples from literature and own model work developed at KIT, we give a survey of possible methodological solutions for most of the areas of energy system analysis and aim to give insights how to address challenges we face especially in the electricity system since the large-scale introduction of renewable energies.

Beside introducing existing approaches in the literature, in the following chapters we mainly provide an overview of methodological approaches developed at the Chair of Energy Economics at KIT in order to consider most of the challenges of RES integration into the energy system, i.e.:

- the rise of fluctuating renewable energy generation increases concerns that the predominant market design in Europe, the so-called energy-only markets, will not provide adequate incentives for market participants to invest in new generation units (Cramton and Ockenfels, 2011) (see section 2),
- electricity has to be transported from remote areas, where wind power plants will be installed, to the load centers, posing significant challenges to transmission and distribution systems (see section 3),

- decentralized renewable energy system models require detailed data on renewable potentials, and should consider sector coupling as well as socioeconomic diversity on the demand side (see section 4), and
- as electricity generation becomes more fluctuating new flexibility potentials, like flexible loads on the demand side (see section 5), have to be tapped in order to permanently balance supply and demand.

2. Modeling future energy systems and markets

Energy markets, especially electricity markets, are increasingly dominated by decentralized and volatile electricity generation from renewable energy resources (RES). This development has not only an impact at the level of end energy consumers, but also strongly influences wholesale energy markets that still mainly operate on a marginal-cost based pricing approach (cf. Sensfuss et al., 2008). To analyze these impacts and the development of the energy markets in the future different modeling approaches have been developed.

Optimizing energy or electricity system models apply a cost minimizing or welfare maximizing approaches and a central planner perspective considering technical, economic and regulatory constraints, such as the carbon emission cap of the EU ETS. Constraints include capacity boundaries of power plants or priority feed-in of RES electricity into the energy system (cf. Ventosa et al., 2005 or Möst and Keles, 2010). They typically incorporate a bottom-up structure into the models, which means a detailed representation of energy technologies. In contrast to the central planner perspective of optimizing models, agent-based simulation (ABS) models focus on agent behavior and individual decisions of different market players, such as generation companies, energy consumers, regulators and transmission system operators (cf. Tesfatsion, 2002, Rai & Henry, 2016). Beside ABS models, game theoretic approaches focus also on the strategic bid behaviour of different market participants. They simulate agent strategies and try to find long-term equilibriums on electricity market based on a Cournot-Nash framework (cf. Hobbs, 2001 or Lise et al., 2006). This kind of models is preferably used to test different market design options in general or to design auctions (cf. Gebhardt and Wambach, 2008) for renewable energies as wells as reserve power markets (cf. Ocker and Ehrhart, 2017).

Other quantitative approaches, such as econometric, time-series or financial models follow a macro-economic approach and try to explain the development of a macro-economic variable based on the development of other parameters (cf. Smyth and Narayan, 2015). Some econometric time-series models based on ARMA or GARCH processes (Garcia et al., 2005), focus on deterministic patterns and autocorrelation in price series or other electricity market data (e.g. load) and incorporate explanatory variables, such as demand, renewable energy production, temperature, etc. to find fundamental drivers of main market parameters (cf. Barmack et al., 2008).

In the following, a brief overview of modeling approaches which have been developed at KIT to analyze energy markets under different framework conditions is given.

2.1. Modeling of wholesale electricity markets and systems

Two main model families are developed and applied at the chair of energy economics at KIT to simulate wholesale energy markets and systems: the optimization model PERSEUS and the agent-based simulation model PowerACE.

The fundamental model PERSEUS is based on a mixed-integer programming approach. The target function consists of all expenses relevant to the decision-making process and it is minimized under consideration of important technical, economic and environmental constraints. The main driver (constraint) for the power plant expansion and unit commitment problem is the electricity demand.

There are several versions of the PERSEUS model (cf. Heinrichs et al., 2014, Hartel et al., 2014), each of which is applied to specific research questions. The PERSEUS-EU model comprises the EU-28 countries (except Malta and Cyprus) as well as Norway and Switzerland. The countries are connected by net transfer capacities (NTC). Inside of each country, transmission capacities are not modeled and therefore intrazonal congestion does not exist ("copper plate" assumption). The existing power plant portfolios of the respective countries are characterized by power plant technologies and energy supply options taking into account technical, economic and environmental parameters (e.g. efficiency factors, investments, variable and fix costs). The model contains a multitude of investment options for future production capacities. On the basis of emission factors for greenhouse gases, the optimal resource allocation can be calculated considering given emission limits.

As it would be too complex to integrate the electricity demand for all 365 days of a year, typical days are analyzed, for which the load distribution is divided into representative time intervals. Every season of the year is represented by a typical weekday or weekend day of the respective season. The approach of typical days is also applied by other energy system models, e.g. TIMES (cf. Remme et al., 2001). The concrete time resolution and model horizon can be chosen by the analyst itself, e.g. until 2050, whereby the power plant expansion and the unit commitment are calculated in five year steps for most of the PERSEUS models. Figure 1 illustrates the main inputs and outputs as well as main components of the PERSEUS model. The aggregated time-solution is one of the shortcomings of the PERSEUS model. Another main weakness of the model is the perfect foresight assumption regarding main energy-related parameters, such as fuel prices and technology costs, which are highly uncertain for a time horizon of 20-30 years. However, the model is still useful, not for forecasting the developments for the next decades, but to analyze impacts of policy decisions on the energy system by comparing different scenarios and to develop cost-minimal energy paths for the energy transition from a normative perspective.

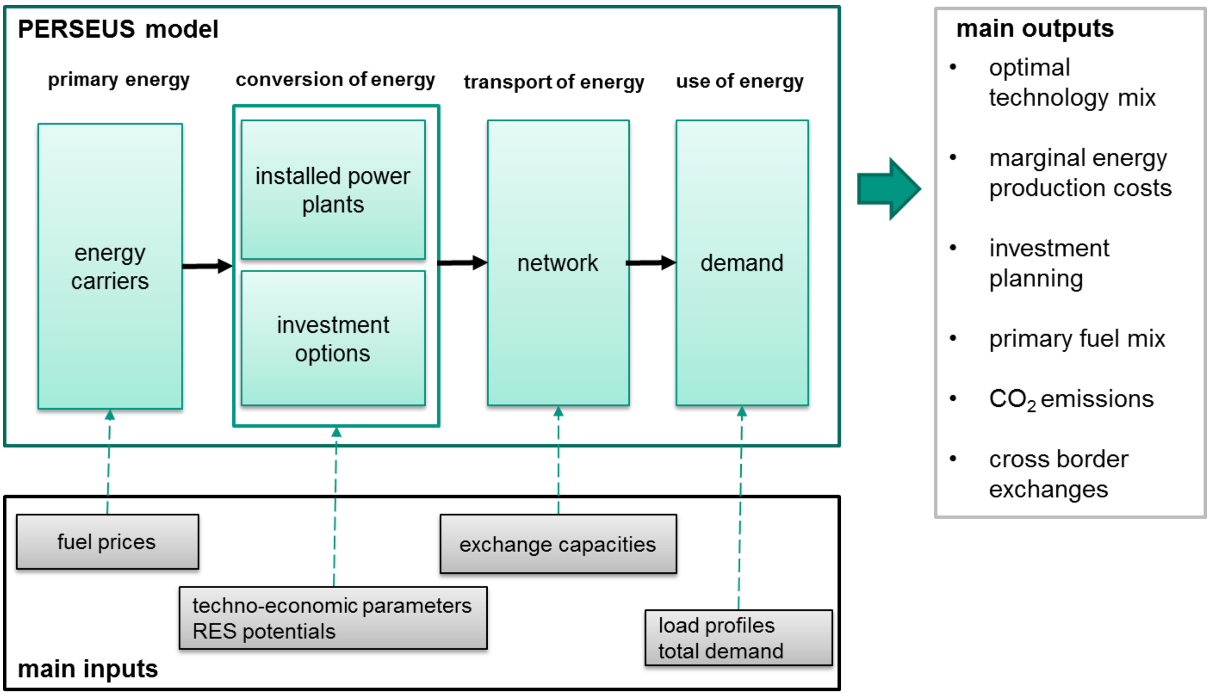

Figure 1: Schematic overview of the PERSEUS model architecture

Agent-based models, on the other hand, focus on the decisions of single market players and apply individual strategies within the market simulation. In this regard, the PowerACE model contains the major market players in the electricity market, such as generation companies or energy consumers. Their operations on the main markets, like the day-ahead, forward market or reserve power market, are simulated. Thereby, the agents consider technical restrictions (e.g. power plant capacities and other technology limitations) and economic characteristics and parameters of the energy market (cf. Sensfuß et al., 2008, Bublitz et al., 2014).

On the electricity supply side, power generators are represented by computer agents making decisions about the short and long term. They schedule the operation of power plants and make investment decisions on constructing new power plants or on the decommissioning of old and inefficient ones. The investment and decommissioning module is run once in each simulation year, whereas the supply agents, who are responsible for the investment planning, check their need for new capacity and the economic feasibility of new investments. Different technologies are handled as investment options. The agent carries out a net present value (NPV) calculation to determine the economic feasibility of each option. If there are investment options with a positive NPV, the agents successively invest in the technology with the highest NPV until they reach their capacity requirement to keep their market share; this is a simplifying assumption. As the supply agents carry out their investments, the investments of the previous agents are treated as known to the subsequent agents, so that the influence of these investments on future prices and thus on the successive investments are taken into account. Detailed information on the investment module of the market model PowerACE is provided by Genoese (2010) and Keles et al. (2016).

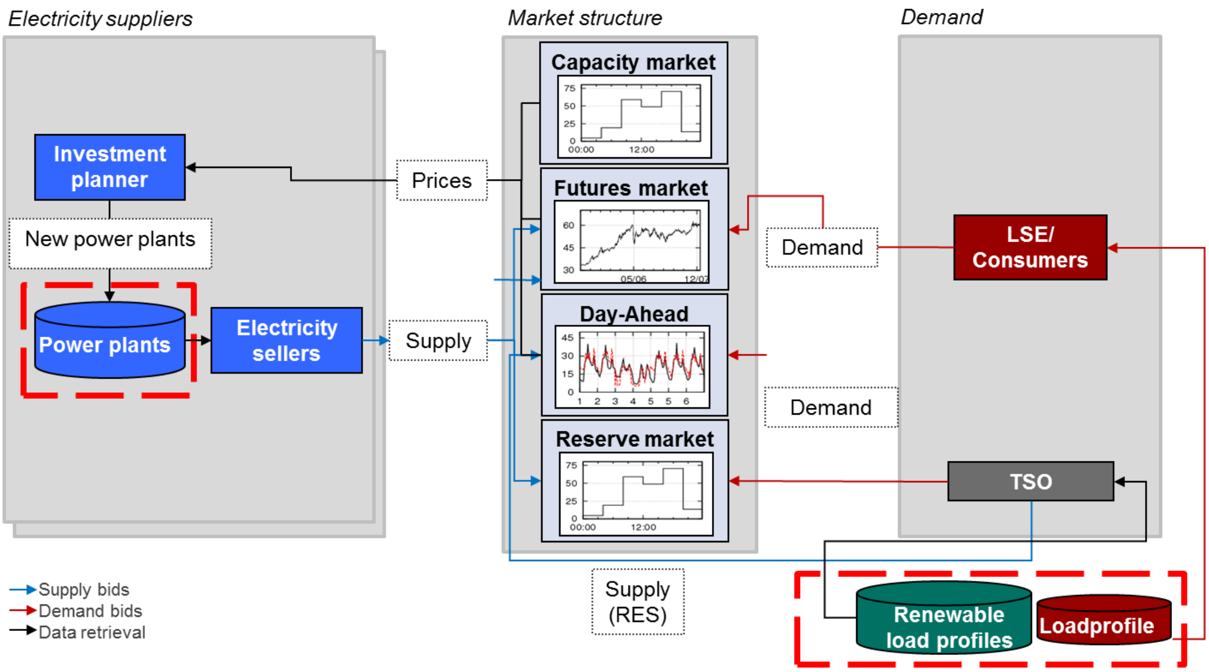

Figure 2: Schematic overview about the main elements of the PowerACE model and their interaction

On the demand side, an energy purchasing agent acts as a central buyer for all electricity consumers (cf. Figure 2). Furthermore, demand response (DR, cf. section 5) capacity is also traded by this agent. DR is separated to shiftable and interruptible loads. Both DR types are modeled as demand reducing bids that are offered if peak prices are expected. However, shiftable loads have to be consumed at another time, so that this capacity has to be repurchased at another point in time. Zimmermann et al. (2016) describe the simulation and discuss the impact of DR scenarios on the German electricity market in the future.

The data of the model is provided by different sources, e.g. the WEPP[2] database, the power plant list ("Kraftwerksliste") of the German federal agency for networks (Bundesnetzagentur, 2016), the European Energy Exchange (European Commission, 2013) and European Energy scenarios (EEX, 2016). In order to analyze rare effects and to adequately consider the fluctuations of RES electricity generation, the PowerACE model does not apply type days, but simulates the whole year with an hourly resolution. Figure 2 illustrates the main elements of the PowerACE model.

Contrarily to the PERSEUS model, the PowerACE model considers the imperfect foresight of market actors and at all the behavior of agents. However, the assumptions regarding their behavior are questionable and can be criticized, as hardly any data can be found to make these assumptions more reliable. For instance, there is no risk attitude included in the investment decisions of the investment agents. Nevertheless, the agent-based simulation, the model is based on, is one of the few approaches to capture market dynamics resulting from actions of single market participants.

2.2. Simulating different design options for electricity markets

As the share of RES electricity generation is growing, it is challenging the design of electricity markets, usually operating as EOMs based on marginal costs. Especially the long-term function of the EOM, which is providing sufficient price signals for new investments and thus guaranteeing the security of supply, is widely discussed in several European countries making new quantitative analyses necessary. Therefore, beside the energy only-market (EOM), the market design options modeled at the Chair of Energy Economics of the KIT cover the strategic reserve and the capacity market design. While the modeling of the EOM corresponds to the approach described in section 2.1, the modeling approaches of the latter are described in the following.

Within the study by Keles et al. (2016a), a strategic reserve is modeled to analyze its impact on generation adequacy. A single price auction for a strategic reserve is added to the PowerACE model mentioned avove. This auction is conducted each year by the transmission system operators (TSOs). The proposal for the German electricity market contains a volume of almost 5 GW of power plant capacities as a strategic reserve[3]. This volume is adopted in the model. The highest bid for the strategic reserve auctions in the model amounts to 55,700 €/MW[4]. Furthermore, only power plants that are technically able to deliver electricity within 10 hours are allowed to participate in the auction. To avoid disturbances of the spot market, operating agents of power plants in the strategic reserve are not allowed to send bids for these plants to the spot market. This is another requirement that can be found in real world applications of strategic reserves. The operator of the auction (the TSOs) receives the right to dispatch the contracted reserves in the spot market, if the market cannot be cleared due to scarcity of power plant capacities in the system. In this case, the reserve volume is offered in the spot market for the maximum price of 3000 €/MWh, equal to the system price threshold in the EPEX day-ahead market. The resulting market price in the hours, in which the strategic reserve is dispatched, corresponds to the maximum price.

As the power plants contracted for the strategic reserve are not allowed to participate in other wholesale markets, the price bids for the strategic reserve auction have to correspond to the value that is needed to cover all the fixed costs c_{fix} of the participating power plants. Furthermore, power plant operators can

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[2] The World Electric Power Plants (WEPP) database contains all major power plants in the world and is provided by the company Platts Ltd.

[3] In the German case, this new market is also called "capacity reserve" (in German "Kapazitätsreserve", cf. BMWi, 2015).

[4] The maximum price is determined by cost of new entry (CONE), e.g. the annuity of a gas turbine with specific investment of 400 €/kW, annual fixed cost of 9 €/kW, planning horizon of 15 years and interest rate of 8%.

also choose the strategy to stay in the energy markets, if their power plants still operate profitable on these markets. The agent-based simulation model PowerACE is also capable to simulate capacity markets operated by a central system operator. The approach follows the “forward capacity market”, which is currently applied in some North American markets, such as in the electricity market of the ISO in New England.

The model for the capacity market simulation contains an agent representing the central regulating instance who centrally purchases the capacity needed to cover peak load one year-ahead. Therefore, in the first step this agent determines the required amount of secured capacity that has to be delivered from dispatchable power plants. For simplicity reasons all suppliers are represented by a single agent who purchases the total required capacity in a central capacity auction. After determining the auction parameters, the purchasing agent asks for capacity and all electricity generators send their capacity bids to the market. All successful bids receive the resulting equilibrium price for the traded year. New power plants obtain the price for a guaranteed period of time, typically for the following five years. For a more detailed description of the models of capacity remuneration mechanisms (cf. Keles et al., 2016).

2.3. Price modeling and forecasting for energy markets

The models described above can also be used for simulation and forecasting electricity prices. However, they are more appropriate to analyze the long-term changes in the structure of the energy system and markets. Hence, they are well suited to simulate electricity prices for given energy scenarios that contain different policy implementations in the energy sector. For short and mid-term planning and price simulation time-series models, econometric models or financial models are also commonly used. In Keles et al. (2013) time-series and mean-reversion models are developed for electricity price simulation. The main steps of these models are the separation of historical series into deterministic ad stochastic components. The stochastic part is used to calibrate a stochastic time-series process, such as autoregressive moving-average (ARMA) models, or mean-reversion processes. The deterministic components are defined as the constant patterns that are repeated within the historical series. In the case of electricity prices a long-term trend, a daily and weekly cycle and an annual seasonality are determined. These components are removed from the historical series and added to simulated series of the stochastic part of the prices. For details of the approach, see Keles et al. (2013).

Dehler et al. (2016) also developed an econometric model to explain the price drivers of Swiss prices. The model is based on multiple regression considering the main independent variables gas, coal and carbon certificate prices as wells as electrical load and renewable power generation. Thereby, not only the values of these parameters for Switzerland are taken into account, but also for neighboring countries, e.g. electrical load in France or renewable power generation in Germany. Furthermore, as the influence of different parameters may change in the winter or in the summer, two versions of the model calibrated based on the related data. The influence of the drivers on prices may change also for different times of the day. That is why a different regression model is generated for each hour of the day.

Another modeling approach to forecast prices, especially electricity prices, are artificial neuronal networks (ANN). ANN models are data driven models, so that the selection of the appropriate data is essential for an ANN model. For the ANN electricity price model following data is used: series of the electrical load, calendar data (public holidays etc.), historical electricity price series themselves and also fuel prices, weather data and electricity feed-in from renewable energy sources. The historical series of this data is used to train (calibrate) the ANN model. However, as part of the historical series is required to validate the model, the whole time series is not used for calibration. Generally, the last year of the data is taken for validation purposes and the data for the previous years is applied as input for calibrating the model. This holds for the fundamental parameters that influence electricity prices as well as for the historical series of electricity prices themselves. Besides, the structure of electricity markets is permanently changing, so that the data must be up to date to model today's electricity prices. Hence, a compromise needs to be found between input data that is as new as possible and data series that are still long enough to explain the patterns and characteristics of current electricity prices. Other steps in preparing the ANN model include the determination of seasonality and autocorrelations, which helps to determine which parts of the historical electricity price series should be used as an input to the electricity model (cf. Figure 3). Finally, a normalization of all input data and training output data makes it possible to use data with different scales in the same model without distorting the influence between several input parameters and a single output parameter.

Having prepared the input data for training and simulation, which is one of the main challenges for modelers applying an ANN approach, the network of the model is configured. This includes the choice of the type of activation functions, learning rate and number of hidden layers. The decision for the final configuration of the network is made by information from the literature and by a "trial and error"-process, which means that different ANN configurations are implemented and simulation results are compared by applying validation indicators, such as the mean absolute error (MAE).

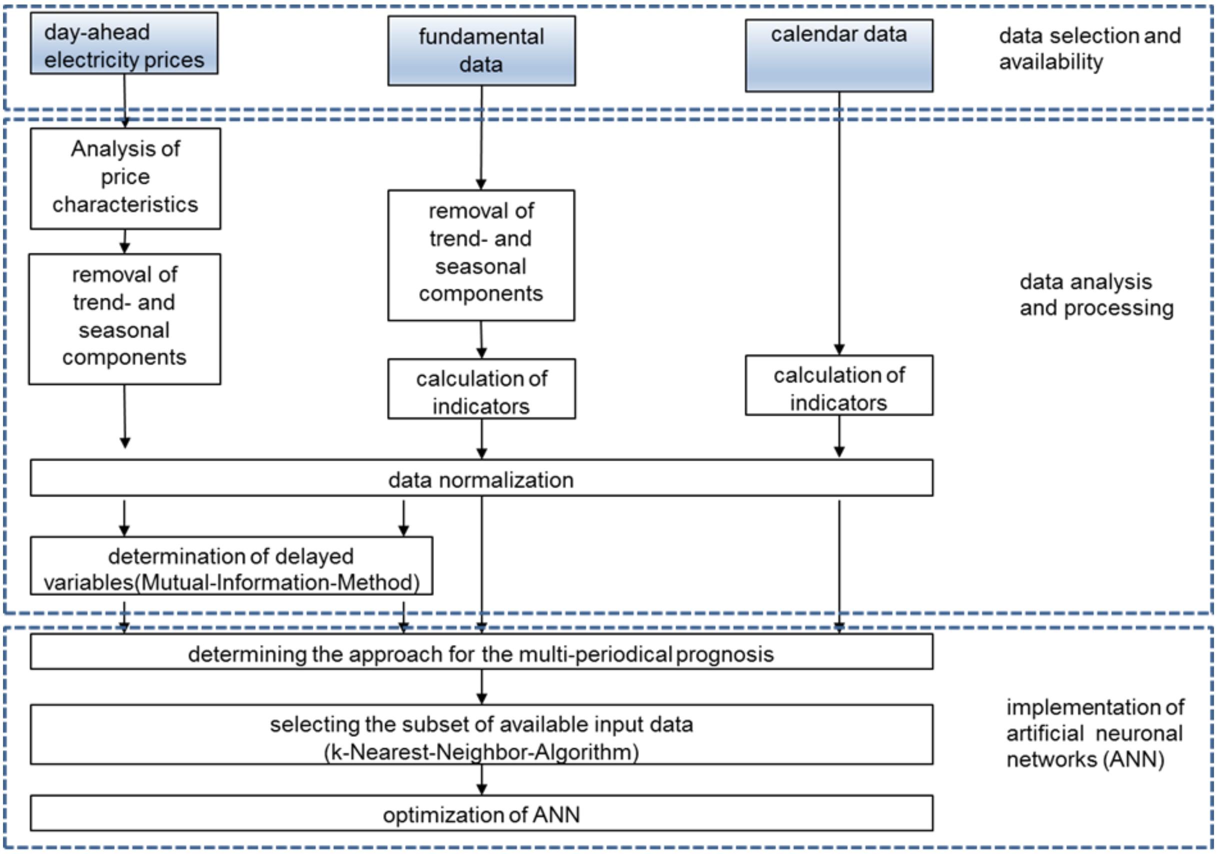

Figure 3: Overview of the modeling process with ANN (source: Keles et al., 2016b)

The time-series and ANN models are data-driven models using recent historical data as input for price simulation and forecasting. However, this data can be very fast outdated, as structural changes in the energy system, such as expansion of renewable energies, can break up historical relationships between input and output data. Fon instance, the influence of fuel prices on electricity prices diminishes more and more, as RES share within power generation increases. Therefore, these models have to be used with caution and only for a reasonable model time horizon.

2.4. Outlook over current and future challenges

The modeling approaches introduced above are very useful, if market and price dynamics as well as future developments are analyzed. However, fundamental changes in the energy system challenges their applicability to research questions the energy sector nowadays faces. Hence, they have to be permanently further developed to address, for example, challenges of fluctuating and decentralized production of electricity from RES or of different market designs applied in coupled markets. The market coupling among EU countries and algorithms applied to a wider market area has also lead to a strong growth of model scope and execution time. Therefore, the time and spatial resolution of the energy system and market models have to be increased. Such an increase in model resolution makes the development and application of new optimization and simulation algorithms or techniques necessary, as model execution times can be longer.

Furthermore, the energy market questions are more and more related to possible developments in the energy network. New regulations regarding the energy market influence the load on the electricity network (at the transmission and distribution levels) and can lead to essential challenges for the infrastructure. Therefore, system and market regulations should be evaluated with energy models that also take into account network restrictions before being implemented in reality (cf. section 3). There are already significant efforts at KIT to tackle the combined modeling of energy systems and the underlying network. However, most of these models are designed for national energy systems and have to be extended to larger energy systems, such as the European one. This is only one of the challenges of modeling electricity networks, as introduced in the following section.

3. Challenges of modeling electricity networks in energy system analysis

3.1. Challenges of the energy system transformation

The ongoing fundamental transformation of the energy system towards a low-carbon economy, and consequently the transformation of the electricity markets pose significant challenges to existing electrical transmission and distribution systems. The growing renewable energy capacity is often found in remote locations, far from consumption centers due to the varying spatial energy output and limited regional potential. Along with missing incentives from the existing European electricity markets to consider network constraints during investment decisions of thermal power plants and increasing volumes of cross-border exchange, this leads to increased distances between generation and consumption and subsequently to increasing congestion in the transmission and distribution networks. The measures applied by the transmission system operators to ensure network stability during congestion periods include ex-post modification of market results by redispatching power plants in order to eliminate temporary congestion. Furthermore, contracting reserve power plants, constructing new branches in the network and increasing capacity of existing branches with structural congestion by network expansion is applied. At the same time, network expansion projects are frequently subject to delays due to the lack of public acceptance, especially at a local level (Bertsch et al., 2016). The determination of an ideal-theoretic energy system requires a trade-off between network expansion and redispatch measures, as the optimal solution is defined by the minimum cost of utilizing both options (Kemfert et al., 2016). As far as future energy systems are concerned, it has to be assumed that the lack of public acceptance in network expansion shifts real solutions from networks with infrequent congestion towards congestion levels higher than the present one. As a consequence, cost of network operation can be expected to increase. Furthermore, interdependencies with the future development of the energy market are strengthened as the development of energy markets becomes a key factor for the future efficiency of network operation. Thus, it becomes increasingly relevant to integrate electricity networks in the modeling approach when investigating efficient future energy systems.

When applied to real-world cases, energy system modeling under incorporation of network constraints poses the challenge of high computational cost as it requires long-term modeling with high amounts of data while at the same time including computationally expensive power flow equations (Krishnan et al., 2016). Therefore, traditionally many approaches, which explicitly include the transmission network use a two-step approach of decoupling the market model and performing network simulations based on predetermined generation dispatch results obtained from a optimization or simulation approach (Hemmati et al., 2013a, Hemmati et al., 2013b). While significantly increasing computational performance, this procedure has disadvantages when modeling interactions between markets and networks. These interactions are either neglected in general or the interactions are included by using iterative approaches. Neglecting interactions between markets and networks circumvents any form of modeling influence of the network operation on the market side, while the latter raises new challenges for convergence and nullifies performance gains of the problem simplification. In both, existing and future energy markets, integrated approaches become more relevant as they allow incorporating the interdependence between markets and networks. In addition to that, flexibilities on the consumption (cf. section 5) and generation side, which are expected to play a larger role in systems with a high share of RES, can be incorporated.

In the following sections, selected models which deal with single or multiple of the main challenges of modeling electricity networks in energy systems with a focus on transmission networks are presented.

3.2. Regionalizing and aggregating consumption patterns and RES generation

The ongoing trend of decentralization in the electricity sector leads to an increasing amount of small-sized, intermittent generators from RES in general, and in particular from wind and solar, with strongly varying generation profiles in addition to a potential of spatially unequal distribution (cf. section **Fehler! Verweisquelle konnte nicht gefunden werden.**). Looking at the consumption-side, electricity demand and load profiles are strongly dependent on regional patterns of land occupancy and use. Furthermore, the availability of flexibilities on the consumption side correlates to types of sectoral energy demand dominating in regional electricity consumption. The modeling of these flexibilities typically includes additional temporally coupled variables and requires a high temporal resolution whereas existing energy models which cover real-world problem sizes lack this feature when focusing on long-term time horizons (Després et al. 2015, Pfenninger et al. 2014). The increasing amount of required combinations of feed-in and consumption, as well as an observed increase in ramping of residual load are also reflected in the trend of decreasing time intervals of market clearing. Consequential, improved methods for obtaining representative time slices and an increasing temporal resolution is required (Poncelet et al., 2016a). Moreover, network congestion patterns which are a major factor when determining the optimal energy system, become more and more individual and less structured. In order to obtain a solution which accounts for both, a cost-efficient generation expansion path and compliance with system security constraints, it is necessary to develop models which maximize the representativeness of consumption and feed-in patterns. This can be achieved by extending existing temporal clustering approaches, which usually follow rather simple heuristics towards multi-objective approaches with a flexible amount of time steps under an explicit consideration of network constraints (Slednev et al., 2016a) or by integrating a spatial component by means of multiple regions (Nahmmacher et al. 2016). Applying such advanced temporal clustering methods can increase the validity of previously discussed optimization models such as PERSEUS.

In order to achieve the required input data at an adequate spatial resolution, a flexible assignment of decentralized generation and consumption to the time-dependent network topology is required on a distribution network level, as it is integrated in (Slednev et al., 2016b).

3.3. Applying temporal decoupling of dispatch decisions

Another possibility for increasing the quality of results obtained by optimization models is the application of myopic approaches during generation expansion planning. Utilizing a myopic approach showed an increased performance, while achieving reliable results in comparison to the traditional perfect foresight approach (Babrowski et al., 2014a). Further approaches which allow for higher temporal granularity in dispatch are the combination of rolling horizon methods and the myopic approach (Heffels 2016) on the one hand, and the temporal decoupling of dispatch decisions using the abovementioned agent-based simulation model PowerACE (Ruppert et al., 2016) on the other hand. Increasing potentials of flexibility are becoming more and more relevant for incorporation into energy system models. These include additional flexibility from additional consumption and feed-in of electric vehicles and other devices with energy storage potential (cf. section 5) and increase the need for approaches which decrease computational complexity while at the same time maintaining the time-coupled effect of the individual element's dispatch (Babrowski et al., 2016). A drawback of myopic approaches is the delay of investment decisions in comparison to the global optimum (Keppo and Strubegger 2010) as well as difficulties in considering trends into the investment decision (Poncelet et al. 2016b). Another application of the application of computational reduction techniques is the integration of flexibilities such as Power-to-Gas (P2G) technology as an energy storage system in the optimization model PERSEUS-NET (Heffels 2016, Nolden et al. 2016) or demand side management (Steurer et al. 2015).

3.4. Modeling approaches for expanding and transforming network systems

Due to the new arising requirements on the transmission system in conjunction with the transformation of the energy system, fundamental changes on the topology are required in order to ensure efficiency and stability of the network. For long-term energy system modeling, a highly variable transmission network poses new challenges in terms of decentralized generation and consumption, which is not directly connected to the transmission level. In order to accurately portray existing challenges in an energy system model, approaches, which allow for an integrated long-term, regional operation, are needed.

Another aspect becoming more and more relevant due to the existing challenges of the present transmission network is the consideration of endogenous network expansion in energy system modeling. Since the development of RES, conventional generation expansion planning, and the required network for transmission and distribution are highly interlinked, an integrated modeling approach including both kinds of expansion problems is necessary and has been investigated with a large variety of approaches already (Lumbreras and Ramos, 2016). Existing approaches which handle real-world problem sizes, however, focus on generation expansion planning and dispatch solely (Nolden et al., 2013). In this context, multi-criteria approaches allow for an adequate interpretation of results obtained in a model including network expansion (Slednev et al., 2014). Endogenous network expansion requires the integration of an additional dimension of high complexity, which is also interacting with the underlying decentralized level of the distributed generation and consumption. This problem poses a further increase of computational challenges. Thus, it requires significant changes to traditional problem formulations as developed in the tool HiRESO, in order to allow obtaining solutions for real-world electricity systems within an acceptable runtime (Slednev et al., 2017). Table 1 gives an overview of the approaches developed at the Chair of Energy Economics at the KIT.

Table 1: Overview of modeling approaches including grid constraints at the Chair of Energy Economics

	High spatial resolution	High temporal resolution	Consideration of new flexibilities	Endogenous network expansion

Slednev et al. (2013)				x
Slednev et al. (2015)	x			
Babrowksi et al. (2016)			Storage, EV	
Heffels (2016)		x	P2G	
Nolden et al. (2016)	x		P2G	
Ruppert et al. (2016)	x	x		
Slednev et al (2017)	x			x

3.5. Outlook over current and future challenges

Key objectives of Europe's energy policy are the reduction of greenhouse gas emissions and the extensive expansion of RES in all countries. At the same time, modeling of single national power networks in energy system modeling under consideration of abovementioned challenges is already a challenge. This is due to the computational effort of the problem as well as the handling of the required input data with high spatial and temporal disaggregation over a long time period, which is required for expansion planning. However, the fact that a national electricity network in Europe is typically interlinked with its neighboring countries in a coupled, meshed network, poses the pressure to expand the scope of modeling to the entire interconnected network in order to represent for realistic power flows. In the case of energy system analysis including network constraints with focus on Germany, this implies an extension of the spatial scope to the European level. The importance of this impact is highlighted in ongoing research (Nolden et al., 2016), where model results – even for countries with big national electricity systems – prove to be highly sensible to changes regarding the hourly fluctuating cross-border exchange patterns.

In addition to network modeling in the context of electricity markets, the provision of regional network control on the distribution level becomes an important issue. Ignoring this fact within energy system models could significantly underestimate the cost of future energy systems and could favor RES or network expansion over other options. In terms of real-world application, the integration of the (n-1) security criterion into large-scale and long-term application is of a high importance as simplifications of the criterion pose the risk of underestimating congestion significantly (Capitanescu, 2016). The exponentially increasing model size, which goes along with an accurate implementation, makes this a challenging question.

In addition to the inter-modal coupling of electricity, heat, gas, and mobility sectors taking into account the interdependencies between them, the further consideration of networks for heat (e.g. for cities), as well as gas infrastructure will improve the robustness of energy system modeling approaches. Given the restrictions due to computational costs of unimodal approaches mentioned in this chapter, including multimodal aspects into the energy system models will be a challenging task for future research. A major element when modeling electricity networks in energy systems with increasing decentralized generation is including a high spatial resolution. The following section gives among others an overview over the approaches which allow the integration of highly disaggregated RES generation into energy system models.

4. Decentralized energy system modelling of Low Carbon Technologies (LCTs)

4.1. Introduction and overview

In a European context, buildings typically account for up to around 40% of final energy demand and CO_2 emissions. Of this, the vast majority of energy (around 80% in Germany) is employed to meet energy service demands for space heating and hot water. In addition, the vast majority of heat supply in Europe is object-based, which means the heat is generated in the same object (building) in which it is used. There are many approaches to modelling decentralized heat and electricity supply in buildings and cities, a review of which would go beyond the scope here (cf. Keirstead et al., 2012). Instead, the focus here is on the emerging trends in these modelling approaches and the related challenges for practitioners. One distinguishing characteristic of decentralized energy system models at the municipality or city scale is a high spatial and temporal resolution for both supply and demand systems, which in turn result in very large data requirements (i.e. for the same energy system compared to its representation as part of a national model). Some of this data relates to the (costs and) potentials for PV and wind within the energy system, as discussed in the subsequent subsection **Fehler! Verweisquelle konnte nicht gefunden werden.**.

Another common feature of these models is that they tend to be specific to one area of application, such as a specific city or region, and thus are not highly transferable to other areas. This is a substantial weakness of many energy system models, as well as being the main motivation behind the development of the RE³ASON (Renewable Energies and Energy Efficiency Analysis and System Optimization) model at KIT, which employs almost exclusively publicly-available data. The model is a long term expansion planning and dispatch optimization, which depicts the local energy system of a whole municipality/city and optimizes the energy supply and demand technologies into the future subject to constraints relating to e.g. energy, CO2 emissions and levels of energy autonomy (Mainzer et al., 2015). The RE³ASON model employs publicly available data from Open Street Map (OSM) and Bing maps, augmented by location-specific data from the user, if available. The model is schematically illustrated in Figure 4 below.

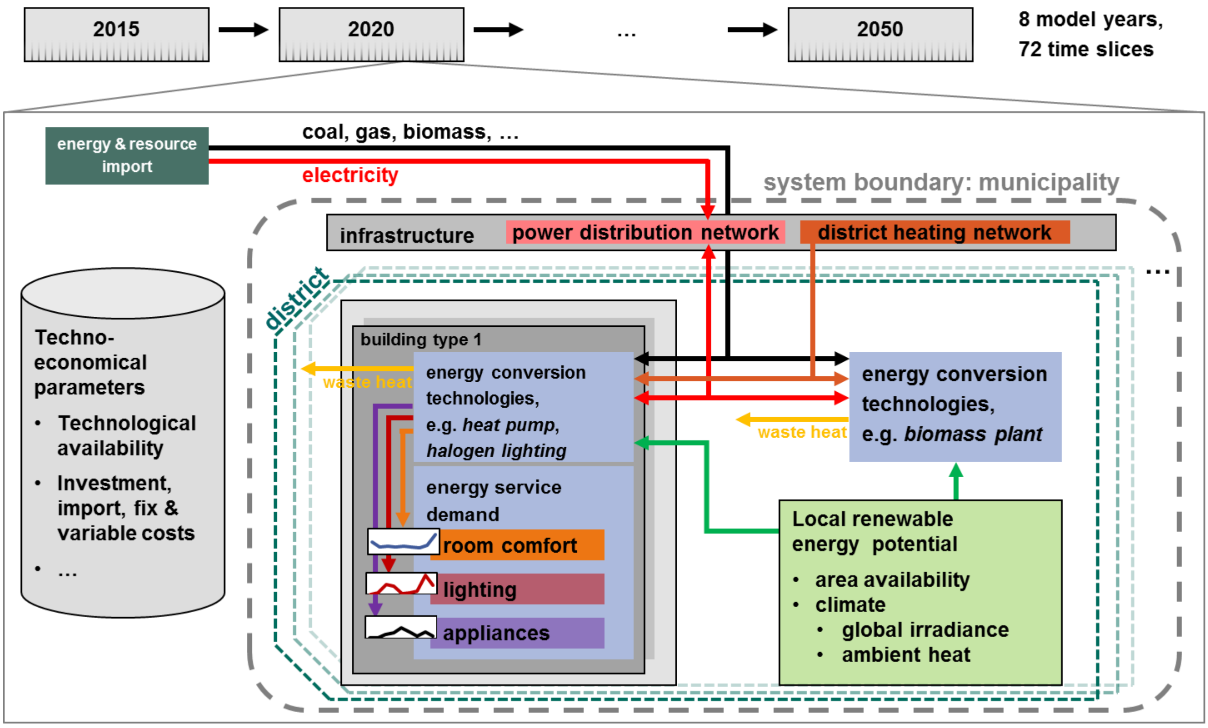

Figure 4: Schematic of the RE³ASON model (for details see text)

Another area in which decentralized energy system models are quite weak is in dealing with uncertainties. Many modelling approaches for decentralized energy systems employ deterministic data for e.g. load profiles in the short and long term. In reality, there are many stochastic influences on renewables energy supply and on residential energy demand that should be considered, including people's lifestyles, climate/weather, macroeconomic developments (markets) etc. As more renewables energies come into the energy system, the number and effect of these influences is likely to increase. Therefore, models need to better account for these aspects, whereby the main challenge is the adequate representation of the uncertain conditions. An additional problem is that the deterministic modelling of these energy systems already results in large-scale programs. Uncertainties are taken into account by the minority: the incorporation further increases the computing effort and makes their consideration difficult. In case of realistic energy systems, the problem ordinarily needs to be decomposed and distributively computed to keep the problem feasible. So, for example, Schwarz et al. (2016) optimize a residential quarter with uncertain PV supply and energy demand on high-performance computing systems. The uncertain parameters and their mutual dependencies are generated by a Markov process within a comprehensive model chain. They show that by decomposing and parallelizing the problem they can solve the stochastic program within an acceptable time frame and avoid insufficient setup decisions of the residential quarter.

The remainder of this section is organized as follows. The following subsection discusses the data requirements and availability, with a focus on PV and wind potential analyses within and around cities, as these represent an important input for energy system models. The focus on these two resources is justified through their dominance in the recent expansion of renewable energies. The subsequent section then addresses the socioeconomic factors that strongly affect energy demand but are not captured in many decentralized energy system models.

4.2. PV potential estimation

Further developing decentralized energy system models in cities/urban areas increasingly relies on larger amounts of, and more reliable data. Whilst much more geodata is becoming publicly available relating to infrastructure and renewable resources, for example, there are still large gaps. These especially relate to already installed power plants (of all types) and heating devices as well as the type, age and insulation state of the built environment. This lack of data can make the definition of the system boundaries and the measurement of energy flows for a local energy system model challenging (Keirstead et al., 2012).

For the determination of available areas for PV, the relevant data depends on the specific application, i.e. whether ground- or building-mounted, as well as the scope of the study. For the former, land-use data are most relevant (cf. section below), and for the latter, data relating to the form and distribution of the built environment is required. For larger scale analyses covering whole regions or nations, top-down methods based on statistical data are typically employed, such as those developed by Mainzer et al. (2014) for Germany and by Schallenberg-Rodriguez (2013) for the Canary Islands. For smaller-scale studies focusing on specific cities or districts, bottom-up approaches are employed with much more detailed building data. This includes so-called laserscanning/light-detection-and-ranging (LiDAR) and photogrammetry data, whereby the former are the most common (Schallenberg-Rodriguez, 2013). Amongst other things, this data can be employed to generate 3D city models, which have been employed relatively recently to estimate PV potentials (e.g. Mainzer et al., 2014, Fath et al., 2015, Strzalka et al., 2012). However, the high data-collection cost connected with the creation of such a 3D model has so far hindered a wide-spread application.

The most advanced PV potential studies in urban areas integrate an assessment of the total potential electricity generation from PV with an analysis of the integration of this energy into the local energy system. In the context of a top-down analysis, this was done by Mainzer et al. (2014) for the whole of Germany on the level of postcode/municipality level districts by employing publicly-available statistics relating to residential buildings. Based on generated electrical load profiles for all sectors in a municipality, the feasible additional development of PV capacity without feeding back into the electricity network outside the municipality was then determined. The same database was subsequently combined with detailed potentials for wind energy, in order to analyze how different combinations and orientations of PV and wind might best meet the local annual electricity demand in four different type-municipalities according to three key energy-political criteria (Killinger et al., 2015). More recently, bottom-up analyses have also considered the energy system integration aspects in individual case studies for Maribor, Slovenia (Sreckovic et al., 2016), and Conception, Chile (Wegertseder et al., 2016). But it remains unclear where the data relating to the distribution network topology comes from (Sreckovic et al., 2016) and what the logic behind the structure of the hypothetical distribution network is (Wegertseder et al., 2016), so there is clearly a need for additional research here.

One approach to overcome this problem of data availability and inhibitive costs is to employ open-source data such as satellite images and mapping data. Several open-source tools are available for automatic PV potential estimation on individual buildings, for example Google's Sunroof Project and the NREL's PV Watts tool[5]. In addition, Mainzer et al. (2016) have developed a new approach for the estimation of rooftop photovoltaic potentials by extracting building footprints from OpenStreetMap and combining these with orthographic satellite images from Bing Maps. These images are analyzed using image recognition techniques in order to identify the ridge line as well as structures like chimneys and windows on each building's roof. In combination with statistical assumptions about the roof's inclination angle, the exact shape, size and orientation of the partial roof areas can be calculated for each building. For the resulting areas, an irradiance simulation is conducted and combined with a PV electricity yield model in order to calculate electricity generation profiles with a high spatial and temporal resolution. The main advantages of this approach over methods which typically employ 3D models are, that no resources are required for data acquisition and it can be applied worldwide. The method is applied to German cities and an evaluation indicates a success rate of over 70%.

One of the main challenges for PV potential assessment relates to the fact that many interaction effects with solar irradiation within the built environment are not generally considered in such studies, including shadowing effects, vegetation, microclimate, slope/aspect, roof features, windows, ventilation ducts etc.

Mostly these aspects relate to the underlying data availability, so that if the data does not reflect them, they cannot be accounted for. But future advancements in the availability of data, especially relating to existing PV plants, should also enable them to be better dealt with. One example of an initiative in this area is the California Solar Initiative (CSI), which provides detailed data on all of the PV systems installed within its scope[6]. The method presented above (Mainzer et al., 2016) seems promising in this regard, but it still has significant potential to be improved with respect to recognizing flat and non-uniform roofs, chimneys and other obstacles. Secondly, the conversion of solar irradiation into a power output for a specific PV technology is associated with several uncertainties. As well as accounting for the performance ratio, the module efficiency and orientation, differentiating between manufacturers and models seems necessary due to differences in power functions between plants. But in practice this is not feasible due to the sheer number of manufacturers and models available, not to mention the lack of data. Hence why a more detailed understanding of how module-specific factors (over and above the ambient and module temperature) contribute to the power behavior of individual modules is required, as pointed out by Killinger et al. (2016).

[5] Google Sunroof: https://www.google.com/get/sunroof#p=0, NREL's PV Watts: http://pvwatts.nrel.gov/, checked 06.09.16.
[6] Within the so-called Power Clerk: https://csi.powerclerk.com/CSILogin.aspx, checked 19.09.16.

4.3. Wind potential estimation

For a detailed discussion of relevant the wind data sources and data processing techniques, the interested reader is referred the review by Angelis-Dimakis et al (2011). The remainder of this section concentrates on the challenges associated with wind potential estimation.

In general, one main challenge for wind potential studies is to obtain more accurate data on wind speeds and their temporal profiles. Whilst several large scale data sources such as NCEP/NCAR and ECMWF are freely available, these are based on the interpolation between data from globally-distributed met masts. Often the distance between these masts is very large, e.g. greater than 50 km, which especially for rough and/or heterogeneous terrain can lead to large uncertainties in the dataset. Whilst these large datasets provide a useful starting point for large-scale analyses, therefore, they cannot replace detailed bottom up analyses with location-specific data. One way in which this problem of a low spatial resolution of large scale wind datasets could be overcome, is to use existing wind parks in order to validate them. In certain European countries, Spain and Germany for example, where a large capacity of wind is already installed, this installed capacity, along with its electricity output over time, can be used as a reference dataset. Thus a country-specific calibration factor for the above wind datasets could be derived, in order to correct for systematic biases due to interpolation.

The greatest challenge for wind measurement is to make accurate measurements in complex and/or steep terrain (Miller et al., 2013). To accurately measure the wind speed at heights above 80 m, which is necessary for adequate wind forecasting, the mobile Light Detection and Ranging (LIDAR) and Sound/Sonic Detecting and Ranging (SODAR) methods will most likely be established in combination with forecast models. The reason is that, in contrast to conventional measuring masts, after a non-recurring investment, the device can be used for multiple measurements (Liu et al., 2008). Whilst the measurement of wind speeds with LIDAR is very accurate, the measurement of the turbulence intensity with LIDAR is limited at the time of writing. Hence it would be very useful to have more accurate measurements of the site-specific turbulences, in order to reduce the conservatism associated with turbulence estimations and load simulations (McKenna et al., 2015). However, these techniques are not yet fully refined, especially in complex terrain where they can be negatively influenced by turbulence (EWEA, 2012). They are also affected by the surface topography, as well as precipitation in the form of rain and fog.

4.4. Common challenges for PV and wind potential estimations

Several of the challenges relating to PV and wind potential assessments are common to both technologies. The first main challenge involves considering the competition for the use of areas and/or land. For PV, solar thermal and other uses on buildings, this is already done e.g. by Wegertseder et al. (2016), but it is not straightforward because it involves implicit assumptions about the respective preferences for different technologies, which may at least partly depend on the building use and its occupants. The situation is similar for wind studies: if the issue of land competition is to be considered, it implies a judgment about the relative importance of specific land use categories for different end uses. Typically, this problem is therefore dealt with indirectly, though suitability factors and the exclusion of some areas. In the future, the problem could be solved by including all relevant technologies (rather than just one) and/or coupling potential analyses with land use models.

The second main challenge relates to the consideration of the energy system integration of determined PV potentials. Whilst already carried out by some PV studies (e.g. Mainzer et al., 2014, Killinger et al., 2015, Sreckovic et al., 2016, Wegertseder et al., 2016), these aspects are typically not considered for wind potential studies. So there is definitely scope to improve these methods, e.g. by using real network topology and load flow data and/or also modelling other end-use sectors. Some progress in this regard has been made by Slednev et al. (2016a, 2016b).

A third challenge relates to the validation of these cost-potential methods. On the one hand this means validating the results against some reference plants, if data is available, on the other it means considering the existing plants and their location(s). In the absence of such data for reference plants, expert workshops can be carried out in order to discuss the results and obtain expert opinions on them. In some countries such as Germany and the UK, public databases are available containing information about the installed RES-E plants in the context of energy-political support schemes. For PV, there is evidence that the development is not at all correlated with those locations where the economics are most favorable (Linder, 2011), which makes the assumption of "economically-motivated" development invalid. As increasingly more mapping data become publicly available and the coverage of portals such as OSM increases, this severity of this challenge might be ameliorated.

Finally, the social acceptance of renewable energies should be considered in cost-potential studies, but the qualitative and heterogeneous nature of this effect make it very difficult to capture. One way in which this aspect can be better integrated into energy system modelling is through a combination of qualitative and quantitative methods, in which stakeholder workshops are used to elicit their preferences relating to specific technologies and measures (e.g. Trutnevyte et al., 2012). Whilst this is relevant for all renewable technologies, the rest of this section focusses on wind energy as an example, as this is one technology that has been subject to much attention in this regard.

For wind energy, the opposition to the visual impact, noise, effects on wildlife, and other related facts, can often mean that otherwise economically-attractive sites for wind energy are not developed, which results in an economically sub-optimal development[7]. Some studies have already attempted to account for such factors. For example, Höltinger et al. (2016) assessed the wind energy potential in Austria whilst considering some constraints due to social acceptance. Based on stakeholder workshops and interviews, "socially acceptable" sites for wind energy in Austria were identified. These sites are then used to assess the theoretical, technical and economic potential in the country. By involving a selection of stakeholders in the analysis, the authors are arguably able to capture diverse viewpoints, but one particularly important group, namely the public, seem absent from the consideration. In a recent study of the "feasible" wind energy potential for Baden-Württemberg, Jäger et al. (2016) actually did consider the public's views, at least with respect to one aspect of acceptance, namely the aesthetic appreciation of the landscape. In this work, wind turbines are placed and aggregated into wind parks based on the extension of existing methods for cost-potential analysis for wind (as presented in McKenna et al., 2015) , and shown in Figure 5 below). In this case, rules of local planning and the level of social acceptance of wind in specific landscapes. These two constraints resulted in a feasible potential at around a 50% of the previously-determine technical potential and a substantial shift in the location of this potential due to different wind park spacing and size assumptions. But it should be noted, that this "visual acceptance" as considered in this study cannot reliably be used as a proxy for social acceptance of wind in general. In addition, the extensive dataset for Baden-Württemberg relating to the public's appreciation of the landscape was a key input; where such data are not available, researchers must resort to interactive methods as in the case of Höltinger et al. (2016).

[7] Of course, one could argue here that these aspects are simply unpriced externalities, which, if they were considered, would demonstrate a different cost-optimal allocation/distribution.

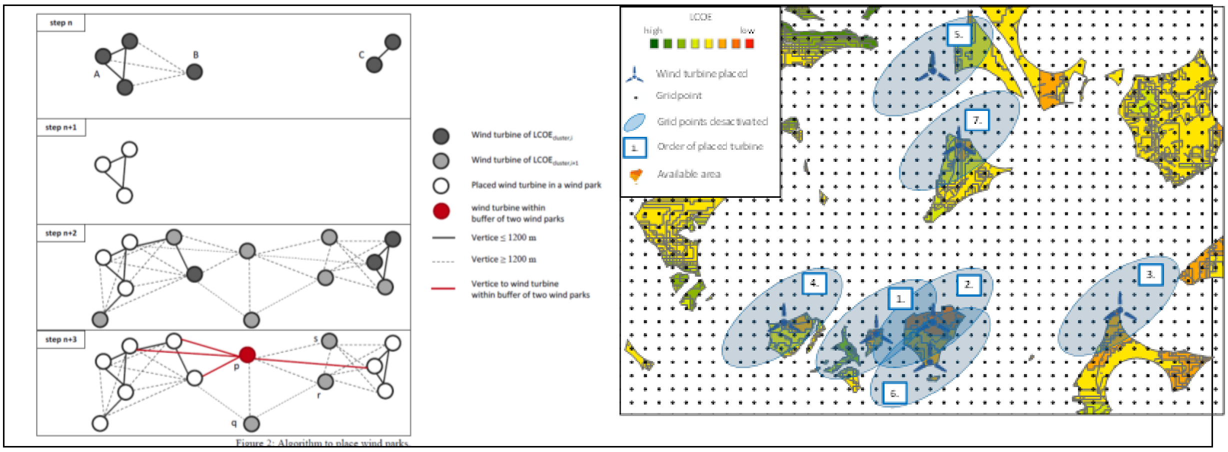

Figure 5: Developed algorithm for placing and clustering wind turbines (left) and a schematic of the algorithm being applied to place seven wind turbines (right) (Jäger et al., 2016)

As well as a better understanding of energy use on the domestic demand side, another related challenge for energy modelling is to deal with flexible loads, which are discussed in the following section.

5. Flexible loads and electric mobility in energy models

Finally, as already mentioned, another core change in the future electricity system modeling is the inclusion of flexible loads, which should consider technical as well as behavioral constraints. The ongoing increase in flexible loads has three main reasons. Firstly, the appliance endowment of households (but also industry) is changing and becomes less time reliant (such as heat pumps combined with heat storages, PV with stationary storages, laptops, charging of electric vehicles). Hence, the flexibility of electricity demand increases. Secondly and as already mentioned, the electricity generation becomes more decentralized and fluctuating, which increases the need for flexible loads. Thirdly, the possibility to communicate with electricity generation and other consumers as well as to (automatically) control appliances increased considerably during the last decades. Consequentially, an increase of available flexible loads in future energy systems is uncontroversial and should therefore be considered in electricity system modeling. In an extreme scenario an inversion of the supply-follows-demand principle in energy economics might occur.

5.1. Considering incentives for load adjustments

Already in the 1970s, during the first oil crisis, DR approaches for increasing load flexibilities have been applied. There, US electricity providers already implemented simple DR technologies (Hastings, 1980). In the following years many countries implemented a two stage electricity tariff with a reduced price rate for the nights (Kostková et al., 2013). The induced load change is used to reduce load peaks (to release the electricity network), to fill load valleys (in order to increase the full load hours of base-load power plants), to decrease emissions (by a considerable share of volatile renewable energy sources in the market) or to adapt to a volatile electricity supply (e.g. by wind installations) or to provide ancillary services to the grid (Pierluigi, 2014).

DR measures consists out of (direct) load control (e.g. by a direct control of appliances by the electricity provider or more generally by the DR integrator) and (indirect) load management, which is usually implemented by dynamic pricing but might be also based on other incentive, such as gamification or normative approaches. Literature often group four different dynamic tariffs, which focus on a flexible energy price (price per kWh): Time of use (TOU), Load variable tariffs (LVT), Critical peak pricing (CPP), and Real time pricing (RTP) (e.g. Dütschke and Paetz, 2013). Beside these, also tariffs with different demand charges are analyzed (cf. Hayn, 2015). The price signals may come from the national electricity market, or the (local) electricity network (Hillemacher et al., 2013).

So far, the load shifting potential from industry, medium-sized businesses and offices is only rarely considered in energy system models, even though these customers might focus more on price incentives, which is easier to consider in optimizing models. Most studies consider flexible loads in residential buildings (Faruqui et al., 2010), where decision makers are less price sensitive (Dütschke and Paetz, 2013). Hence, pure optimizing approaches neglecting user acceptance might be unsuitable to represent empirical load shift potentials from residential customers (Paetz et al., 2013).

Dütschke and Paetz (2013) analyzed the user acceptance of different electricity tariffs and load shift potentials and identified that residential customers are rather skeptical to complex pricing schemes, but prefer simple tariffs (Dütschke and Paetz, 2013; Grünewald et al., 2015). Another "simple", but widely accepted approach might be based on load flexible pricing schemes (Hayn, 2015). Energy interested customers seem to relish technical home automation and smart home applications, which increases their price elasticity significantly – at least for this user group (Paetz et al., 2012a). Overall, the analyses show that the users are very heterogeneous with regard to their price intensified load flexibilities and further research is required in order to harmonize this discrepancy between reality and modeling.

There are already several energy system models which consider some flexible loads on the decentralized level (e.g. Hillemacher, 2014; Jochem et al., 2015a) or national level (e.g. Heinrichs and Jochem, 2016). Further non-demand flexibility comes from battery storages (e.g. Babrowski, 2015) or power to gas (Heffels, 2015, Nolden et al., 2016). The underlying incentives are, however, mostly neglected in energy system models.

Due to long parking times and a significant electricity demand, electric vehicles provide a high potential for flexibilities. Ensslen et al. (2014) developed a comprehensive model, which considers the market penetration in Germany based on a Bass model, and secondly, a survey-based electricity tariff, which intensifies car users to provide load shift potentials to the electricity market. Thirdly, the aggregated load shift potential is then used in the electricity market model PowerACE for decreasing the overall costs. Further incentive focused approaches are under development.

5.2. Modeling main technologies for load adjustments in residential housings

Main technologies for providing load adjustments in the (future) residential sector are:

- **Power to heat applications** (such as heat pumps, night storage heating or electric boilers): Power to heat approaches have a high energy demand (mostly higher, than the overall residual electricity demand) and its demand is flexible due to heat storages. Hence, at least during the winter season, a shifting of heat production seems to be suitable (Jochem et al., 2015a).
- **Electric vehicles**: Similarly, the energy demand from an averagely used electric vehicle is in average comparable to the overall electricity consumption of a household. The parking time is in average above 23 hours whereas the required charging time is usually between one to three hours (Babrowski et al., 2014b). Technically, this leads, again, to a considerable load shift potential.
- **Stationary storages**: The current pricing scheme in Germany makes stationary batteries in combination with PV systems highly attractive and experts assume a significant market penetration in the next decade. Kaschub et al. (2016) developed an optimizing energy system model for a residential district and show, that the application of these system is profitable and

the effect on the electricity system might be substantial because the load pattern change considerably and some customers will become net electricity providers.

- **Other controllable applications (**such as washing machine, tremble dryer or fridge): Their overall flexibility of conventional domestic appliances is rather limited in comparison to the other technologies (Jochem et al., 2013).

One main focus in our research in this field was on electric vehicles. The technology was rediscovered in the early beginning of this century due to significant developments in battery technology. Now, most predictions of the future market developments show significant shares of electric vehicles (IEA, 2016). This will have an impact on the electricity system and mainly the load shift potential, which depends besides technical parameters (such as maximum charging rate) also on several other parameters such as mobility patterns (such as time and mileage), user acceptance etc.. Finally, we focused on some impacts on the electricity system, e.g. the indirectly generated CO_2 emissions from electric vehicles (Jochem et al.; 2015b). The emissions from electric vehicles are often calculated by multiplying the specific emissions factor of electricity generation (e.g. 500 grams of CO_2 per kWh) with the electricity demand from electric vehicles. Another approach is the marginal approach, which focuses on the marginal power plant, which is providing the electricity for charging electric vehicles. Not surprisingly the results show significant higher values, which might even exceed the emissions from conventional cars. Besides, carbon dioxide emissions, electric vehicles provide advantages in decreasing oil dependency, noise as well as local air emissions. Overall, the external effects from these emissions are, however, not by all means decreased by introducing electric vehicles (cf. Jochem et al., 2016).

5.3. Capturing socioeconomic factors and diversity on the demand side

Despite the very important role that socioeconomic diversity within and between households has been shown to play in shaping energy demand, its representation is often quite poor in many energy system models. This is especially the case for models that depict many sectors and have a large geographical scope, but arguably in this case the role that this diversity plays is relatively small. However, in energy system models at the regional level and below, the importance of this diversity becomes more significant, hence why this section focuses on these.

The ways in which socioeconomic diversity influences energy demand in households is summarized in the following. The upper and lower bounds for the annual energy consumption of a residential building are largely determined by the building's thermal characteristics (including geometry and insulation standard), the type of heating system, the climate, the number of persons and the number/type of appliances. But the precise energy consumption of a particular building between these two extremes depends heavily on the occupants and their behavior. For example, higher income tends to lead to higher overall energy demand (Druckman & Jackson, 2008), the age and number of householders has a positive influence on the energy demand (Jones et al., 2015), and the heating behavior (including heating patters and internal set temperatures) are also important. Overall, behavior can account for over 50% of the variance in energy demand in residential buildings (Haldi & Robinson, 2011), but it is also difficult/challenging to allocate the large variance in internal temperatures (Kelly et al., 2013) and energy demand (Hübner et al., 2015) to specific independent variables. The temporal patterns of energy consumption are also strongly affected by certain socioeconomic characteristics, including the size of the household, income and employment status (Hayn et al., 2015). Until now, the ownership and use frequency of particular appliances in households have only been moderately addressed. Finally, there are well known barriers to investments in energy efficiency and LCTs, as well as the rebound effect, all of which results in a lower level of uptake in practice than might be expected by purely economic-based modelling exercises that overlook some of these aspects.

Some attempts to explicitly consider this socioeconomic diversity are highlighted as follows, whereby this is not a comprehensive overview, rather serves to illustrate some examples. Some progress in this area has been made by Cayla et al. (2011) and Cayla & Maizi (2015), who have analyzed the expected (discounted) payback period and/or discount rate with respect to LCT investments based on survey in the French context and partly implemented them in the French TIMES model. Interestingly, they found that, whilst the willingness to invest in new space heating equipment actually increases with household income, the required rate of return also increases, in contrast to the results for vehicles and refrigerators. Another promising approach to modelling user-behavior is with agent-based models (cf. section 2). Especially the role of (social, cultural, spatial) network effects in the diffusion of energy technologies such as PV requires such approaches that do not revert to a central "control lever". The main challenges in the field of agent-based models for decentralized energy systems seem to lie in adequately validating them and improving their spatial representation (Rai & Henry, 2016). The former might be better achieved, for example, by comparing the results with those obtained using other approaches or with machine learning methods.

In addition, whilst smart meter data potentially represents a valuable data source for household load profiles, it often contains too little metadata to enable a rich differentiation between household types and/or end-use activities. Based on an econometric analysis whilst controlling for demographic and building variables, Boßmann et al. (2015) have obtained some valuable insights into the required differentiation, e.g. between weekdays and weekends and various appliances, and may have opened up a new avenue for further research. In addition, one of the few residential electricity demand models based on time-use data to enable a detailed socioeconomic differentiation between households is presented by Fischer et al. (2015), who develop a stochastic bottom-up model and apply it to German households, where the main novelty seems to be the level of socioeconomic differentiation achieved. Households are characterized by the number of people, the structure, the age, the dwelling type and the working pattern and results are validated with empirically-measured load curves and show a high level of accuracy.

5.4. Outlook over current and future challenges

The quantification of load shift potentials is cumbersome. The agents are heterogeneous and the aggregation is complex, because the load shift potential differs over time and is dependent on many system characteristics (see below). So far, the load shift potential is only considered strongly simplified by electricity market models– mostly with a single value of power or energy (e.g. Klobasa, 2007). However, the potential is strongly dependent on the current load level, the direction of the requested change (load increase vs. decrease), daytime, day and season (mainly night vs day, working day vs. weekend, winter vs. summer), duration of required load shift, budget for incentives, price sensitivity (e.g. automated control, user acceptance, technical endowment), and other parameters, such as temperature, sun irradiation, or special events (e.g. Christmas).

It might be technically possible to identify these parameters. However, the user acceptance is very heterogeneous and depends on many different aspects, thus a consideration in energy system models seems to be challenging and requires new methodological developments (e.g. by including stochastics). The user acceptance is also significantly influencing the market penetration of new technology developments such as electric vehicles, PV-storage-systems or heat pumps. Hence, user acceptance seems to be a core component in future energy system analysis when flexible loads are under consideration. Finally, if the uptake of electric vehicles and their corresponding impact on electricity loads is analyzed, a combination of transport and energy system modeling becomes a requisite.

6. Conclusions

As energy systems face structurally changes, a wide portfolio of modeling approaches has been developed in the last years at the Chair of Energy Economics at KIT. These approaches cover models for large energy systems and markets, such as national electricity markets or the European energy system, as well as for local energy systems of cities or neighborhoods (see Table 2).

Table 2: Overview of developed models

Name/Target	Method	Focus and application field	References
PERSEUS	Mixed-integer optimization	Energy system planning (capacity expansion and operation) based on cost minimization	Heinrichs et al., 2014, Möst and Perlwitz, 2009
PERSEUS-NET	Mixed-integer optimization	Energy system planning (capacity expansion and operation including network constraints) based on cost minimization	
HiRESO	Mixed-integer optimization	Capacity and transmission network expansion planning based on cost-minimization	
PowerACE	Agent-based-simulation	Energy market simulation (day-ahead market simulation and capacity expansion) based on behavior and perspective of market players	Genoese, 2010 Keles et al., 2016
ARMA model	Time-series modeling, ARMA process, regime switching	Electricity price simulation for a whole year including stochastic distribution of price components	
ANN model	Artificial Neural Network	Forecasting of day-ahead electricity prices	Keles et al., 2016b
RE^{3}ASON	Mixed-integer optimization	Energy system planning for municipalities and cities, largely based on publicly-available data, Cost, CO2, autonomy (etc.) optimization	
T3	System Dynamics	Market penetration of alternative drive trains in main passenger car markets.	
SpeicherOpt	Mixed-integer optimization	Investment and operation of PV-storage systems in private households	

The large-scale system and market models are applied to tackle research questions regarding the design of energy markets and further regulative measures. But they are also useful to generate long-term scenarios and to study possible impacts of a new market regulation on the exploitation of different energy resources within the entire energy system. With the help of PERSEUS-EU and the agent-based model PowerACE developed at KIT, we are able to analyze market dynamics and the effect of new policy implementations. Besides, time-series and econometric models are also developed to study electricity prices, whereas their focus is on the short and mid-term development. These models adopt a macro-economic perspective of the energy system without focusing on the details as the first two models do. Exemplarily, the PowerACE model incorporates beside technical components of the energy system also different market segments and their rules. However, also this model does not take into account all the characteristics and elements of the technical infrastructure. For instance, it still does not consider restrictions of the electricity network, such as congestion on the transmission lines, which becomes a major challenge due to the expansion of renewable power generation afar from consumption centers. Therefore, the relevance of transmission network modeling in energy system models is increasing. The integration of the network and the related power flow into the models is another challenge, as the corresponding mathematical equations drastically raise the complexity. At KIT we developed several methods to efficiently include network modeling into the system models. However, the interdependencies between energy markets and networks and the structural changes are expected to increase in the next years. That is why the existing approaches have to be developed further, especially to analyze not only national markets, but also the entire European energy system. The latter is gaining more and more in importance, as the European market coupling incorporates the physical power flow on the electricity network applying the so-called "flow-based market coupling". Furthermore, new methods are also necessary to address research questions related to the integration of different energy networks, such as the electricity, heat and gas networks, and coupling measures between them.

However, the inclusion of further technical infrastructure and economic framework not only requires new methods, but also large amount of data regarding the analyzed energy system. With increasing decentralized energy production, we also developed models for local and decentralized energy systems. Data availability and quality play a central role for decentralized energy system analysis, especially but not only relating to renewable energy resources. Whilst the amount of (publicly) available data is certainly increasing, its quality is not necessarily, and the challenge is often dealing with such large data quantities. Many of these models are therefore very application-specific: another challenge is to develop transferable methodologies that can work with limited data availability.

In addition, energy system models have to cover other changes in the system, such as decentralized production and utilization of flexible loads. There will be more flexible loads in the future electricity systems, which are, however, hardly incorporated in energy system models. Especially the potentials in industry and the interlinkage to electricity markets are missing in current models. In the residential sector especially new technologies for heat (e.g. heat pumps or mCHP with heat storage), storage (e.g. photovoltaic in combination with stationary batteries) and mobility (electric vehicles) are seen as promising contributions to increase the flexibility of loads. The underlying user acceptance of flexibility measures is, however, very heterogeneous and highly decisive. Therefore, further research should focus on analyzing the user acceptance of these technologies and the willingness to provide load flexibilities as well as methodologies to transfer these insights into energy system models.

Finally, accounting for socioeconomic characteristics, e.g. acceptance and behavior, in (decentralized) energy system models will remain another focus of future research. Whilst some inroads have been made in this regard with agent-based models, the main challenge is the calibration and validation of such models. Whatever modelling approach is applied, a superior quantitative understand of these characteristics and their effects on the energy system are required.

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