Modeling Smart Grid Systems

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Learning Objectives

- Be able to describe elements of smart grids that can be represented in models.
- Be able to classify and identify dimensions in energy system models.
- Be able to mathematically formulate smart energy system models.
- Be able to explain how the main drivers of smart grids impact model-based representations.

1 Introduction

This chapter is motivated by the transformation of the energy system toward a smart grid economy which also necessitates new solutions in the field of decision support tools that are used by system operators and market stakeholders. Trends that can be observed in the management of smart grids are an increasing orientation toward

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digital and intelligent solutions and a stronger coupling between different energy sectors as well as a growing interaction between different stakeholders. Examples include the electrification of district heating via heat pumps, mobility applications, e.g., electric vehicles, or consumers who provide energy from rooftop photovoltaic systems to grid operators to ensure grid stability enabled by smart grid devices. These developments also have implications for the model-based representation of smart grid systems.

Classic energy system models have a long history and are widely used since the two oil crises in the 1970s. Energy system models support decision-makers in questions regarding energy regulation and policies for infrastructure planning of energy generation, conversion, and transportation. Literature in the field of energy system modeling is vast and the reader of this book might ask how the modeling of smart grids differs from traditional modeling techniques. This chapter perceives a gap in the subject on model requirements that result in particular from smart grid economics and management. It provides an overview of different design aspects, challenges, and current trends associated with the model-based representation of smart grid systems, and additionally provides a detailed literature review of various modeling approaches in this research field.

The chapter is structured as follows: Sect. 2 gives an introduction to general modeling aspects of smart energy systems. For this purpose, a systematic taxonomy of smart grid systems is developed and different concepts are classified according to application scopes. Modeling of smart grid systems can be done at different scales and from various perspectives, thus different modeling approaches are introduced based on brief mathematical descriptions are presented in Sect. 3. These comprise small-, medium- and large-scale applications, bottom-up demand side models as well as bi-level approaches. Based on the structure of Sect. 3, Sect. 4 provides a comprehensive overview about literature with regard to smart grid modeling. Current trends in the modeling of smart grid systems are discussed in Sect. 5. In the final Sect. 6, a conclusion, an outlook and some exercises are presented.

2 Taxonomy and Classification of Smart Grid Systems

Modeling of energy systems has a long tradition and got a strong push with the two oil crises in the 1970s. In general, the purpose of energy system modeling and analysis is to improve and support the decision-making process in the energy sector with regard to technology choices, policies, and infrastructures for energy supply and energy conversion. Therefore, models try to consider “reality” in a systematic and knowledge-based manner. Depending on the question, a wide variety of factors and framework conditions must be considered. Developments in energy and key technologies, the limited nature of fossil resources and climate change, demographic change, the political, social, and economic framework conditions, the pursuit of sustainability—all these factors are only examples to be taken into account when analyzing and modeling an energy system. In general, energy system models can be classified in three main dimensions (see also Möst et al. 2009):

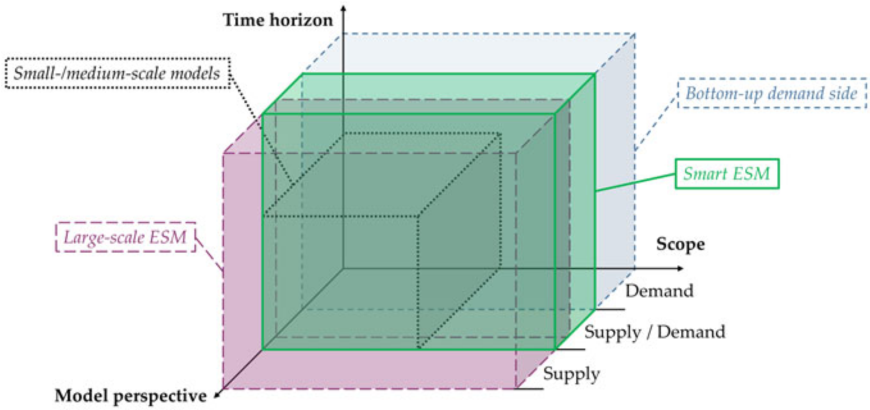

Fig. 1 Categorization of smart grid modeling approaches

- What is the energy system under consideration? The examined energy system can be the global one, the European, a national, that of a district, an industrial location, or a house. As a global energy system is not analyzed on the same level of detail as, e.g., a system on household level, system boundaries, and level of detail have to be defined.
- What time horizon and correspondingly what time resolution is addressed? The time horizon can range from a short time horizon and a high time resolution (e.g., analyzing the frequency behavior in a grid) to several decades and a lower time resolution (e.g., analyzing the development of the energy system until 2050).
- And finally, what is the model perspective? The perspective can be supply-oriented, grid-oriented, demand-oriented or even an integrated model approach.

Figure 1 depicts these three dimensions of energy system models: (1) The time horizon, describing the short-, medium- or long-term analysis, (2) the scope, which encompasses the level of detail and geographical range, (3) the model perspective, referring to a supply-oriented, demand-oriented, or integrated model approaches. This classification is also used in the course of this chapter.

It can also be applied to classic energy system models. Accordingly, the question arises what the difference to the modeling of *smart* grid systems is. “Smart” can refer to the system under consideration. Additionally, the other chapters of this book provide a good overview on what a smart energy system can entail. Modeling smart grids and the involved consumers or prosumers can be done on vastly different scales and from different perspectives. In the following, the differences in the aforementioned scope of smart grid systems are discussed by delimiting modeling approaches, although there is a fluent transition between the system and modeling boundaries.

In general, it can be stated that the main drivers of smart grid systems are the three Ds—Decarbonization, Digitalization, Decentralization—which are often considered to be the pillars of creating the green energy economy of the future. While these drivers were already introduced in chapter "Energy Systems Today and Tomorrow". However, this section explains how the three "Ds" stimulate and affect modeling.

Decarbonization
Decarbonization means that carbon-based fuels, such as oil, gas, coal, and lignite should no longer to be used for electricity generation. Renewable energy sources in particular are expected to replace these fuels and contribute to a more sustainable energy system. However, technologies with high potentials—such as wind energy and photovoltaic—are dependent on weather conditions. This creates challenges concerning the balance of electricity supply and demand. In addition, the potentials of these renewable energy sources are not necessarily close to demand, leading to longer transportation distances and hence the need for infrastructure adaptation.

Accordingly, the temporal and spatial resolution in energy system models must take into account the challenges posed by the higher share of renewable energy:

- Time component: Demand and supply have to be balanced and thus challenges in connection with the fluctuation of electricity generation (RES) and its balancing have to be addressed by smart grid modeling. In general, an hourly resolution or even a quarter-hourly resolution is state-of-the-art when modeling smart grid systems.
- Spatial component: As renewable sites are not necessarily located in close proximity to demand, transport and distribution of electricity pose new challenges for today's infrastructure. But also distribution grids are affected by new suppliers (e.g., photovoltaic) and demand technologies (e.g., electric mobility). The spatial component in high-resolution models is usually accounted for using at a NUTS3 level.[1]

In combination with new technologies on the supply and demand side, such as photovoltaic, electric mobility, heat pumps, etc., a further trend is decentralization.

Decentralization
Decentralization comes hand in hand with new technologies, providing decentralized feed-in of electricity and are intended to replace a "few" large generation plants in the long term. In consequence, electricity generation is dispersed across many smaller plants.[2] Furthermore, decentralization also refers to the increasing amount of embedded generation, for example, combined heat and power plants on industrial sites or solar panels on residential properties. As (larger) conventional power plants reach the end of their lifetimes, they are being replaced by wind farms, solar fields,

[1] Nomenclature des unités territoriales statistiques (NUTS) is a geo-code standard for referencing the subdivisions of countries for statistical purposes. NUTS3 refers to the district or municipalities level.

[2] However, this does not necessarily mean that energy based on renewable sources is always decentralized. While the power of single offshore wind energy plants is still small in comparison to large-scale fossil-fuel or nuclear-fuel based power plants, these single offshore plants are often grouped together to an entire farm resulting in connection points with large power injections (similar to the magnitude of large-scale plants).

hydropower, marine generation, and biomass, and thus decentralization is becoming more prevalent. Furthermore, sector coupling is also contributing to decentralization by providing additional electricity demand with high flexibility in general. This can help to balance supply and demand as decentralized as possible. Sector coupling is driven by so-called power-to-X (PtX) technologies, which means that electricity is used to provide energy services substituting common fossil energy carriers. Among others this is especially power-to-heat (e.g., district heating provided by heat pumps), power-to-vehicle (e.g., electric mobility) as well as power-to-chemicals, in particular power-to-gas (e.g., green hydrogen). This has given rise to so-called cellular concepts that directly address the topic of decentralization.

Decentralization poses a number of challenges, which also have to be analyzed with the modeling of smart grid systems:

- With decentralization, regional autarky and self-sufficiency are gaining in importance. Several questions in this context with regard to the level of decentralization are addressed by modeling smart grid systems.
- As renewable site potentials (e.g., wind offshore) are often far distanced from demand centers, there is still the duality of a centralized and decentralized supply of energy, resulting in several challenges for the infrastructure.
- Furthermore, interaction and participation of consumers are gaining in importance. Especially the possibility of generating electricity decentrally and controlling one's own consumption (smart demand) has led to so-called prosumers as new market participants. While, techno-economic modeling of energy systems was sufficient a few years ago, today behavioral and societal aspects pose additional challenges and barriers when it comes to making such a socio-technical transformation a reality. This requires further analysis techniques that also take behavioral and societal aspects into account. An example for considering behavior of agents is agent-based modeling, which has grown in importance.

Resulting from these developments, smart grid modeling is more specific and addresses topics at the level of households or industry site level and additionally considers societal concepts.

Finally, the last trend is digitalization.

Digitalization

With digitalization, several new possibilities and applications arise. Real-time information and control is just one example which provides new opportunities. Consequently, effective management and monitoring is essential and achievable with state-of-the-art digital technology when implemented across all areas of the electricity system, from generation to transmission, distribution, supply, and demand. The core infrastructure of the grid is still using similar switches to those used in the 1950s, and therefore requires some further upgrades in order to realize the full potential of digitalization. However, this process will steadily take place and provide new opportunities in the next years and decades. With digitalization, new technologies enter the market, which affect the energy system and thus have to be considered in modeling. Two selected examples are

- Smart metering: A smart meter is an electronic device that records consumption of electric energy and communicates the information to the electricity supplier for monitoring and billing. New concepts for controlling demand and appropriate incentive mechanisms are under development and the development is supported by analysis based on smart grid modeling.
- Smart grids[3]: The emergence of smart grids stimulated electric utilities, scientists, and vendors to develop comprehensive and sustainable solutions for the different elements of smart grids.

In general, digitalization allows for new business models behind the infrastructure, especially behind the metering devices. While traditional business models in the energy sector depend on infrastructure (large generators and power grids), which can be described by the principle of "produce big and sell small," many smart business models in the energy sector act behind the meter (e.g., smart communities, pooling of demand flexibility, electric vehicles, etc.) and use aggregation according to the principle: "buy small and sell big".

Along with digitalization, hard and software steadily improved and new software tools came up. Transparency and traceability is a must in modeling today. Open source modeling is already state-of-the-art and will displace black-box modeling and thinking (see Sect. 5.2). In consequence, new software tools as well as new modeling approaches (such as, e.g., bi-level programming for real-world applications—see Sect. 3.4) can also be applied to the field of modeling smart grid systems.

To further break down the term smart grid system and to derive a systematic taxonomy, smart grid systems can be divided into three sub-groups of application scopes: Small-scale, medium-scale, and large-scale applications. Table 1 classifies a variety of different concepts that are related to smart grid systems in accordance with the scope of application.

Smart home usually denotes residences equipped with smart technologies that enable to provide customers, i.e., residents, with tailored solutions that aim at enhancing the quality of living. Technical devices range from small household devices (e.g., refrigerator, washing machine), sensors, and domestic appliances that monitor and control lightning and heating all the way to integrate decentralized generation and storage applications that optimize the generation and utilization of energy within the smart home. Another strain of smart home solutions deals with energy efficiency and renewable generation integration, where household electricity consumption is optimized to provide electricity grid operators with flexibility in grid management and to avoid congestions in the transportation of electricity in the distribution grid. This can be achieved by direct (real-time) access of grid operators to household information on electricity consumption utilizing smart metering technologies and control of certain devices (e.g., charging of electric vehicles) but can be also controlled via incentive mechanisms. Time-of-use tariffs or dynamic retail tariff structures could provide end-users with real-time electricity price information that incentivize customers to adapt their consumption behavior in an electricity system beneficial way.

[3] A complete listing of all components of smart grids or a definition is out of the scope of this section.

Table 1 Classification of smart grid concepts

Smart grid systems		
Small-scale	Medium-scale	Large-scale
• Smart customer • Smart home • Smart technologies • Smart building • Smart meter	• Quarter solutions • Aggregators • Micro grids	• Smart demand • Renewable integration • Transmission monitoring

Another group of smart grid systems deals with smart applications on a community level. Here, several households in a street of a district or a compound of apartments of a multi-family house (sometimes denoted as quarter) are connected to a network with communication and information systems and optimized as a whole. So-called aggregators represent the group of households which manage the electricity sales and procurement of the entire quarter. The aggregator quite often is usually a service provided by a third-party energy utility. Since it accumulates the energy flows of all quarter members, larger total energy volumes are reached which allows to directly participate at wholesale markets. Again, a necessary prerequisite is that the aggregator is able to gather real-time information of the quarter members' energy consumption and decentralized generation which can be achieved by the installed smart metering systems. Sometimes smart grid systems at a communal level also relate to micro grids. In this context, smart grid systems are understood as an independent subsection of a distribution grid, that can be managed autonomously without being connected to the higher voltage level distribution grid either temporarily in case of fault events or even permanently due to the typology of the supply area, e.g., in very remote areas where geographic restrictions apply. Either way, it supports the grid operator with a higher degree of flexibility for increased integration of decentralized electricity generation and consumption appliances.

Smart grid systems also appear in large-scale applications of energy supply. In various analyses, demand side management (DSM) activities are a predominant characteristic of smart grid systems. DSM also referred to as demand side flexibility or demand response can be defined as the planning, monitoring, and management of activities that stimulate large-scale consumers, such as industrial utilities in changing their consumption behavior which essentially yields into optimized load profiles for system integration of variable generation sources. Again this can be achieved via incentive mechanisms or automated procedures through intelligent technical devices that initiate changes in the electricity consumption, e.g., an adjustment of the production plan. Apart from the generation and demand, smart grid systems can also be part of the transmission of electricity. In this context high-voltage power line monitoring enables optimized utilization of transportation lines. In this way, real-time information on the technical state of the power line (e.g., temperature and power flow) is delivered to the transmission system operator, which can then adjust transportation limits to avoid congestions in the electricity transport. As outlined in the introduction, digitalization is one driver of such emerging power line monitoring systems.

In the following, general model notations of large- and small- to medium-scale, bottom-up demand side modeling as well as bi-level programming will be introduced.

3 Mathematical Notations of Selected Smart Grid Problems

3.1 Large-Scale Models

Against the background of decarbonization as energy-policy target, the expansion of less carbon-intensive technologies related to the conversion, supply, and demand of energy requires the analysis of techno-economic uncertainties. Additionally, to capital-intensive rather central technologies with long lifetime (e.g., power plants or electricity grids), the trend of decentralized energy supply and flexible energy demand at distribution grid level increases the need for assessing positive and negative effects of the system transformation. Large-scale model analyses aim for the evaluation of these complex interactions between different available and future technologies. Besides equilibrium models, which represent the energy sector as part of the whole economy, simulation and optimization models are the main categories for large-scale energy and electricity system modeling. For both methodologies, it is crucial that impact assessment focus on insights from the interrelations between the modeling framework and the techno-economic implementation of the technologies, since models always simplify the real world. Taken this into account, energy and electricity system models enable the evaluation of system configurations to estimate optimal long-term investments and short-term dispatch decisions (optimization models) as well as efficient performances (simulation models) of different energy system components. As mentioned in the introduction, the digitalization and corresponding information and communication technology (ICT) are crucial elements for the decentralized interaction of the relevant components in a smart energy system. However, the modeling of these ICT in large-scale energy models is rather an implicit precondition than explicitly modeled. After giving an overview of central characteristics of large-scale energy system models, further aspects of the inclusion of smart grid technologies in these models will be discussed.

Both modeling methodologies usually apply a techno-economic bottom-up approach. In general, in optimizations models the objective function is formulated as cost minimization to identify least-cost solutions for electricity provision or welfare maximization. For a simplified dispatch model applied for a single node or market (in large-scale models usually an entire country) as illustrated in the following, the objective function minimizes total costs TC as the product of power plant dispatch $G_{i,t}$ and corresponding operational costs oc_i for each technology i and time step t, as shown in Eq. 1. Typically, the time-specific electricity generation costs are composed of plant-specific fuel costs, carbon allowance costs, ramping costs, and further variable costs. These operating costs take technology-specific efficiencies, emission factors, ramp rates as well as availabilities into account. While unit commitment and dispatch models minimize the time-specific electricity generation costs (composed of plant-specific fuel costs, carbon allowance costs, ramping costs, and further variable costs), system planning or investment decision models additionally include investments in relevant generation and storage technologies. Besides operational costs and fixed costs, technology-specific economic parameters like annualized investments are further included in this case.

$$\min_{G_{i,t}} \quad TC = \sum_{i} \sum_{t} G_{i,t} \cdot oc_i \tag{1}$$

The objective function is furthermore subjected to a range of restrictions. Thereby, the energy balance represents a key element of dispatch models. As an important constraint (see Eq. 2) in electricity system models, it ensures the balance between electricity generation and electricity demand d_t. Usually, in basic dispatch models the electricity demand is assumed to be inelastic to electricity prices, thus d_t is included as model-exogenous input parameter. For optimization problems, the energy balance as central equation of energy system models implies the variable costs of the dispatch of relevant technologies (including smart grid technologies) to meet the time-dependent electricity demand. Based on this energy balance equation electricity prices can be derived fundamentally. As a basic assumption, the marginal cost and thus, electricity price-driven dispatch of different components of the power system requires direct price signals and respective smart grid infrastructure (in particular information and communication technology (ICT)) for all participants. This is not only true for technologies on the supply side, but also when the demand side becomes more flexible.

$$d_t \ = \sum_{i \in I} G_{i,t} \qquad \forall\, t \tag{2}$$

For power plants, minimum restrictions forces the generation to be non-negative, while maximum capacities ensure that electricity generation is not exceeding the installed capacity pc_i. For weather-dependent RES wind and PV, generation time series (usually in hourly resolution) are included as parameters reflecting the weather dependency and the applied feed-in priority.

$$0 \ \leq \ G_{i,t} \ \leq \ pc_i \qquad \forall\, i, t \tag{3}$$

Based on this basic dispatch model, the equations can be extended, particularly when including additional technologies for smart applications and flexibility provision in energy system modeling. Storage provide temporal shifting flexibility to compensate for fluctuations in electricity demand and supply. Regarding a model implementation, storage charging and discharging has to be included in the energy balance, as displayed in Eq. 4. Thereby the set s is a subset of electricity generation technologies ($s \in S \subseteq I$). This allows for restricting the discharging of storages $G_{s,t}(s \in S)$ similarly to power plants. In addition, the charging of storages $P_{s,t}$ has to be restricted to be non-negative as well as to not exceed maximum charging power sp_i as in Eq. 5. Furthermore, the storage energy balance (see Eq. 6) describes the storage inflows and outflows (including a storage efficiency η_s) between two time steps. Thereby, in Eq. 7 the storage level $SL_{s,t}$ is restricted by maximum storage energy capacity sc_i.

$$d_t = \sum_{i \in I} G_{i,t} - \sum_{s \in S} P_{s,t} \qquad \forall\, t \tag{4}$$

$$0 \le P_{s,t} \le sp_s \qquad \forall\, s \in S, t \tag{5}$$

$$SL_{s,t} = SL_{s,t-1} - G_{s,t} + P_{s,t} \cdot \eta_s \qquad \forall\, s \in S, t \tag{6}$$

$$0 \le SL_{s,t} \le sc_i \qquad \forall\, s \in S, t \tag{7}$$

By increasing the system boundaries of the dispatch model to multiple nodes, the potential to exchange electricity between regions or countries can be included. In large-scale electricity systems the nodes typically represent countries reflecting the import/export of electricity as cross-border flows. This spatial shifting can be seen as crucial flexibility option, particularly in interconnected electricity systems like the European one. When considering numerous countries in dispatch models, an additional set has to be introduced (here c). Furthermore, the flow from one country c to another one is formulated by introducing an alias cc. With export and import, the energy balance of Eq. 2, has to be formulated for each node/country c (see Eq. 8). Additionally, the energy balance between electricity demand, electricity generation as well as storage charging and discharging is extended by imports $EX_{t,cc,c}$ and exports $EX_{t,c,cc}$. Available interconnections between countries are introduced by an adjacent matrix and restricted by existing hourly transfer capacities $ec_{t,c,cc}$ (Eq. 9).

$$\begin{aligned} d_{t,c} = &\sum_{i \in I} G_{i,t,c} - \sum_{s \in S} P_{s,t,c} \\ &+ \sum_{cc \in map(c)} (EX_{t,cc,c} - EX_{t,c,cc}) \qquad \forall\, t, c \end{aligned} \tag{8}$$

$$EX_{t,c,cc} \le ec_{t,c,cc} \qquad \forall c, t \tag{9}$$

The flexibilization of the demand side by demand response (DR) is of high importance in smart grid energy system analysis. To implement demand response measures, Eq. 8 can be further extended by both applications to increase ($LI_{t,c,a}$) and reduce

($LR_{t,c,a}$) electricity load with $a \in A$ as set of demand response (DR) applications, as shown in Eq. 10. The potential of each DR process has to be restricted considering several parameter and characteristics. First, the temporal availability has to be taken into account. While for load reduction the actual electricity demand $dr_{t,c,a}$ of the application forms the upper bound, for load increase the difference between maximum application capacity $drmax_{c,a}$ and current load restricts the availability (see Eqs. 11 and 12). In general, load shifting represents a subcategory of DR, characterized by a balance between the overall load increase and load reduction within a given time frame without influencing the total electricity demand. This is why DR shifting measures can be modeled as storage systems, as in Eq. 13 with $DRL_{t,c,a}$ as virtual storage level. However, since most of the DR processes and appliances have primary purposes (e.g., aluminum production for industry or dish washing for households), the shifting time $tbal_a$ has to be restricted by parameters combining the duration of activation as well as the time in which load reductions and increases must be balanced (Eq. 14). Further restrictions may be included to improve the representation of technical aspect of DR applications. Examples are the limitation of number of activations per day or year (if single processes are implemented). Subsets can be defined to assign applications for load shedding only (load reduction without compensating the load at a later time step), as well as for solely increasing electricity demand. The latter ones are typically introduced as sector coupling technologies (power-to-x) into existing dispatch models, increasing the load due to the electrification of further energy demand sector.

$$\begin{aligned} d_{t,c} = & \sum_{i \in I} G_{i,t,c} - \sum_{s \in S} P_{s,t,c} \\ & + \sum_{cc \in map(c)} (EX_{t,cc,c} - EX_{t,c,cc}) \\ & + \sum_{a \in A} (LR_{t,c,a} - LI_{t,c,a}) \qquad \forall\, t, c \end{aligned} \tag{10}$$

$$LR_{t,c,a} \leq dr_{t,c,a} \qquad \forall t, c, a \tag{11}$$

$$LI_{t,c,a} \leq drmax_{c,a} - dr_{t,c,a} \qquad \forall t, c, a \tag{12}$$

$$DRL_{t,c,a} = DRL_{t-1,c,a} - LR_{t,c,a} + LI_{t,c,a} \qquad \forall\, t, c, a \tag{13}$$

$$\sum_{t}^{t+tbal_a} \left(LR_{t,c,a} - LI_{t,c,a}\right) = 0 \qquad \forall\, t, c, a \tag{14}$$

With the implementation of power-to-X (PtX) technologies, intersections with other energy demand sectors are applied with direct impacts on the energy balance (Eq. 10) in the power system. Larger system boundaries and new actors potentially increase the need for smart communication between the technologies involved. In this sense, a multi-coupled energy system and the corresponding communication of the different sectors can be seen as smart energy system (Ringkjøb et al. 2018). In the model (variations) presented in Eqs. 1–14, particularly the implementation of demand side flexibility represents a simplified application of sector coupling, when flexibility is exploited with PtX technologies like heat pumps, electric vehicles or electrolyzer. These dispatch models still focus on the electricity market but include several options for the electrification of further energy sectors with a respective increase in (time-dependent) electricity demand without a detailed representation of additional energy sectors. Particularly, energy system models enable the comparison of electricity-based energy carriers and the complements of the respective energy sectors. With the expansion of the model system boundaries, further energy end-use sectors, like buildings, industry, and transport have to be included. Accordingly, further mathematical restrictions reflecting additional energy balances and techno-economic constraints have to be considered similarly to the electricity market models.

However, due to computational limitations, the level of detail is generally lower compared to sector-specific models. In general, the bottom-up modeling or simulation implies detailed data input. Therefore, the trade-off between techno-economic detail and computation time is of high relevance regarding large-scale models. Simplifications (i.e., aggregate technologies, countries, time steps) are often necessary to keep the models tractable. However, particularly due to the expansion of fluctuating renewable energies in smart energy system, the temporal resolution is of high importance to represent the increasing variability of the electricity feed-in. Besides the large-scale system perspective, the long-term planning horizon additionally increases the uncertainty of future developments. Especially in optimization models, compromises regarding the technical details are often addressed by applying scenarios and sensitivity analyses.

3.2 Small- to Medium-Scale Models

Models on a smaller spatial scale take on the perspective of a district, quarter, or individual houses. Fundamentally, these models are similar to large-scale models but with important distinctions, explained in the following.

The objective of such a model can be manifold (cf. Mohsenian-Rad and Leon-Garcia 2010; Yu et al. 2013 and Arabali et al. 2012 in Sect. 4.2). For instance, the objective can be the minimization of net costs. A quarter can aim for achieving the most inexpensive way of meeting its electricity demand. Here, c_t is the cost of procuring power, imported via the grid. r_t is remuneration for produced electricity, sold via the grid (Eq. 15). The objective function takes on the perspective of an aggregator which manages the selling and procurement of electricity for an entire quarter.

$$\min \quad NC = \sum_t (GRIDIM_t \cdot c_t - GRIDEX_t \cdot r_t) \tag{15}$$

The objective incorporates the goal of avoiding expensive power purchases and can therefore support the grid by reducing peak demand (cf. Mohsenian-Rad and Leon-Garcia 2010; Kahrobaee et al. 2012).

An important distinction to large-scale models is that the energy balance needs to hold for entities, not for market zones or countries. Entities can take on various forms, e.g., individual households. The trade in large-scale models now becomes an exchange with other entities, e.g., with neighbors (Eqs. 16, 17).

$$d_{t,e} = \sum_i (G_{t,i,e} + LR_{t,i,e} - LI_{t,i,e}) + \sum_{ee \in map(e)} (EX_{ee,e} - EX_{e,ee}) \qquad \forall t, e \tag{16}$$

Overall, an energy balance needs to be abided by, for the entire quarter. If there is a shortage, including all demand response activities, imports are needed; if generation plus load reduction exceeds the demand, electricity can be exported.

$$d_t = \sum_{i,e} (G_{t,i,e} + LR_{t,i,e} - LI_{t,i,e}) + GRIDIM_t - GRIDEX_t \qquad \forall t \tag{17}$$

$$T = \{1, \ldots, 24\}, \; I = \{1, 2, 3\}, \; E = \{1, \ldots, 300\}$$

Noticeably, also the variables for load reduction and increases take on the index t, i and e. This attests to the much higher granularity of small- and medium-scale model. Possibly, for each entity, different technologies can serve as flexible demand (cf. Gottwalt et al. 2016). These models then increase in size, by considering many entities, i.e., generally $|E| > |C|$. Also, the time resolution may increase from hourly to, e.g., quarter-hourly, considering $T = \{1, \ldots, 96\}$ instead (compare Sect. 4.2).

Importantly, generation capacity, demand response, and storage restrictions still apply, along the lines of the large-scale model.

With increasing regionalization the uncertainty in forecasts becomes greater and its consideration gains in importance. This pertains to predicted parameters especially, for instance, demand and availability of renewable energy. For renewable energy it becomes more difficult to accurately predict the availability in a small region. For entire countries, load can often be aggregated by standard load profiles. On a small- or medium scale, the load profiles of smaller entities have to be predicted which is generally more challenging. One method to handle this uncertainty is stochastic optimization (see also Yu et al. 2013).

Consider a quarter which has generation capacities based on renewable energy as well as some flexibility option. The objective of this quarter is the minimization of net costs, comprised of costs for grid imports and negative costs (revenues) for the export to the grid (Eq. 18).

$$\begin{aligned} \min \quad NC = & \sum_{t} \left(GRIDIM_t^{\mathrm{DA}} \cdot c_t^{\mathrm{DA}} - GRIDEX_t^{\mathrm{DA}} \cdot r_t^{\mathrm{DA}} \right) \quad + \\ & \sum_{t,s} p_s \cdot \left(GRIDIM_{t,s}^{\mathrm{ID}} \cdot c_{t,s}^{\mathrm{ID}} - GRIDEX_{t,s}^{\mathrm{ID}} \cdot r_{t,s}^{\mathrm{ID}} \right) \end{aligned} \tag{18}$$

The forecasts for demand $d_{t,s}$ and generation availability $cap_{t,i,s}$ are uncertain, i.e., there are a number of possible scenarios s for these parameters. In a first stage, the quarter purchases energy from and sells it to the day-ahead market ($GRIDIM_t^{\mathrm{DA}}$ and $GRIDEX_t^{\mathrm{DA}}$), taking into account the various scenarios. Depending on the realization of scenarios, intraday adjustments have to be made in a second stage ($GRIDIM_{t,s}^{\mathrm{ID}}$ and $GRIDEX_{t,s}^{\mathrm{DA}}$) which, importantly, are scenario-dependent. The scenarios can be weighted by means of p_s, depending on how probable these scenarios are considered to be.

As in the example above, the capacity constraint has to be abided by in each scenario. Also, the energy balance will differ in each scenario with constant elements, such as the day-ahead decisions (from the first stage), as well as scenario-dependent elements like demand, intraday imports/export and load flexibility decisions (Eqs. 19, 20).

$$G_{t,i,e,s} \leq \quad cap_{t,i,e,s} \qquad \forall t, i, e, s \tag{19}$$

$$\begin{aligned} d_{t,s} = \quad & \sum_{i,e} (G_{t,i,e,s} + LR_{t,i,e,s} - LI_{t,i,e,s}) + \\ & GRIDIM_t^{\mathrm{DA}} - GRIDEX_t^{\mathrm{DA}} + \\ & GRIDIM_{t,s}^{\mathrm{ID}} - GRIDEX_{t,s}^{\mathrm{ID}} \qquad \forall t, s \end{aligned} \tag{20}$$

$$I = \{1, 2, 3\}\,,\ T = \{1, \ldots, 24\}\,,\ E = \{1, \ldots, 300\}\,,\ S = \{1, \ldots, 10\}$$

A key element of stochastic optimization is the consideration of scenarios to account for uncertainties. Questions emerge regarding which and how many scenarios to consider. For instance, scenarios can follow from observed time series or simulated ones, taking into account the key distribution characteristics. To maintain the feasibility of model computations, often scenario reduction techniques are applied (e.g., see Heitsch and Römisch 2003). This becomes especially important with a growing amount of considered entities and a higher time resolution, increasing model complexity. Stochastic programming can, of course, be applied to any model scale. For instance, the effects of intermittent renewable energy feed-in on electricity market are of great interest (Abrell and Kunz 2015).

3.3 Bottom-Up Demand Side Models

The modeling of the future energy demand is of crucial importance for investment and dispatch planning, in particular due to its rising influence on the success for a sustainable energy transition, integration of renewable energy, and smart energy systems. Influencing factors of the energy demand are multiple—for instance, weather and climate conditions, the economic development, technology change as well as changes in policy and consumption behavior. However, several models take only few of these factors into consideration, ensuing incomplete information. Usually in projection models the final energy demand can be carried out for individual energy carriers such as gas, heating oil, district heating, biomass, solar thermal, or electricity (Herbst et al. 2017), whereby in this section the focus is on modeling and projecting electricity demand of individual sectors in a smart grid energy system.

Bottom-up energy demand models derive long-term projections for the future annual energy demand of individual countries based on assumptions on socio-economic data (e.g., gross domestic product, population, evolution of energy carrier prices) and techno-economic data (such as specific consumption, equipment rate, operation time, life time, investment costs). In most bottom-up demand side models the projected annual electricity demand can be further distinguished by year, country, sector, application, and technology (Boßmann et al. 2013). Compared to other sectors, the industrial sector reflects the highest degree of heterogeneity with regard to technologies and energy end-uses. For instance, the industrial sector can be categorized by several sub-sectors such as the iron and steel, non-ferrous metal, paper and printing, chemical, food and drink, tobacco, or engineering industry, to name few. Moreover, a variety of industrial process technologies exist for instance the primary aluminum production, paper production, cement production, electric arc furnace steel, and blast furnace steel production (Herbst et al. 2017). A further distinction can be carried out by defining cross-cutting technologies like lightening or electric motors etc. In contrast, the tertiary sector can be categorized into sub-sectors like trade, hotels, and restaurants, traffic and data transmission, finance, public administration, or health. Those sub-sectors include different energy end-uses such as lightening, electric heating, ventilation, refrigeration and cooling, cooking, data centers, etc. (Herbst et al. 2017). In the residential sector different energy demand groups are distinguished between lightening, sanitary hot water, space heating, among others. Those residential energy demand groups are further categorized in energy end-uses like air conditioning, dish washers, washing machines, dryers, lightening, stoves, computer screens, or television. The energy end-uses can further be classified into technologies and their different efficiency classes (Herbst et al. 2017).

The particularities of each sector such as the granularity, technology structure, and actor heterogeneity as well as the data availability emphasize how complex future energy demand forecasts are. For instance, drivers of the projected energy demand for the tertiary and residential sector are more population-related by, e.g., number of employees and households (Herbst et al. 2017). Whereby, the electricity demand for the sub-sector space cooling in the tertiary sector can be calculated by considering the specific energy demand per m^2 floor area to be cooled and the quantity of the energy service driver, which is the share of cooled floor area per employee. Therefore, the employment in the tertiary sub-sector is an influencing factor which further depends on the development of the gross value added in the sector, demographic trends, and the gross domestic product per capita (Herbst et al. 2017).

Next to the annual electricity demand of a sector, also the hourly electricity load curve is of high importance for designing the future smart grid energy system since the electricity demand and supply needs to be balanced at any time step of the year. The most common and simplified approach in long-term projections is scaling a historical load curve by assuming the future annual electricity demand. This approach implies specific errors as changes in the future electricity load curve are not considered and therefore, the load curve correlates precisely with the historical hourly electricity demand (Boßmann et al. 2013). An alternative approach is the decomposition of the historical load curve by means of sector and application specific electricity loads (cf. Elsland et al. 2013). In this case, the individual load curves are scaled corresponding to the sector and application-discrete annual electricity demand forecast and aggregated to a total sector and/or system load curve.

In the following the disaggregation of the annual electricity demand to the hourly electricity demand for a (smart) energy system is described (based on IAEA 2006): The electricity demand is derived for a given hour (t) of a certain day (d), and period (j, e.g., week, month, etc.) for a specified year by considering the following factors:

1. The average growth rate of the electricity demand over the year (trend).
2. The seasonal variation of electricity demand (e.g., semesters, quarters, months, etc.).
3. The impact of day types (k) in the electricity consumption (i.e., consideration of working days, weekend days).
4. The daily variation of electricity consumption due to certain periods (i.e., morning hours, lunchtime, evening hours, etc.).

These influencing factors are considered by different coefficients which represent the variation of electricity consumption in a sector by referring to the standard load of the sector that is usually calculated for an equivalent working day (IAEA 2006). Before starting to model the annual and hourly electricity demand, the variations in the electricity consumption pattern need to be identified by defining different seasons (*seas*) and day types (k). Therefore, the starting and ending dates of each season during a year need to be defined, similar to the dates of special holiday periods. Further, the sequence of weekdays and representative days (e.g., working days and weekend days) for hourly load variations are to specified.

The coefficient T_j is a correction factor of general trends for the electricity consumption growth during a year. The growth trend coefficient of the gross electricity consumption is calculated on a weekly (*j*) basis with 52 values for a year (Eq. 21). *GROWTH* is defined as the absolute difference of the annual electricity demand between the current and the reference (past) year related to the total annual electricity demand of the current year.

$$T_j = \quad [1 + GROWTH]^{\left(\frac{j-26}{52}\right)} \quad \forall j \in J = \{1, \ldots, 52\} \tag{21}$$

The seasonal coefficient K_j considers the impact of different seasons on the electricity consumption pattern in a sector for a certain time period (*j*) which can be a semester, a quarter, a month or a week. Assuming weeks as specified time period, K_j can be defined as the average weekly weight of the yearly electricity consumption. The sum of the coefficients of a year equals the value of the total number of periods into which the year is divided (e.g., 52 weeks).

The daily ponderation coefficient $P_{j,d}$ considers the fluctuations within the electricity consumption pattern of different day types, i.e., working days, Saturdays and Sundays. Therefore, the electricity demand of every time step of the reference (past) year is compared to the electricity demand of an equivalent working day, which has the relative weight of 1. At first, the yearly average electricity demand of each working day needs to be calculated. The value which is nearest to the mean of all working days can be considered as equivalent working day. The other day types are weighted to their relative electricity demand compared to the equivalent working day (e.g., Saturday might achieve a 0.8 of a working day, etc.). The coefficient $P_{j,d}$ varies over the year depending on the defined seasonal periods (j) and the day types.

Subsequently, the average electricity demand of an equivalent working day can be calculated dividing the total annual electricity demand of the current year by the total number of equivalent working days, which is the sum product of the trend coefficient T_j, the seasonal coefficient K_j and the daily ponderation coefficient $P_{j,d}$ over all calendar days cd of a year (Eq. 22).

$$D_{cd} = D \quad / \sum_{j,d \in map(cd)} \left(T_j \cdot K_j{}^* P_{j,d}\right), \tag{22}$$

$$\forall cd \in CD = \{1, \ldots, 365\}, j \in J = \{1, \ldots, 52\}, d \in D = \{1, \ldots, 7\}.$$

To disaggregate the average electricity demand of an equivalent working day D_{wd}, the hourly load coefficient $LC_{t,d}$ is needed. $LC_{t,d}$ reflects the weighted hourly electricity demand over 24 h of a day. The coefficient is calculated by the hourly electricity demand related to the daily electricity demand of the reference year multiplied by 24 h. The sum of all coefficients of a day is equal to 24. Consequently, the hourly electricity demand can be calculated by multiplying the average electricity demand of an equivalent working day with the hourly coefficient divided by 24 h (Eq. 23).

$$D_t = \quad D_{cd} \cdot LC_{t,d}/24 \qquad \forall t \in T = \{1, \ldots, 8760\}, d \in D = \{1, \ldots, 7\}. \qquad (23)$$

In context of modeling smart grids, the electricity demand side needs to be flexible to balance the electricity supply at any time (e.g., facilitating the integration of high shares of intermittent). As described in Sects. 3.1 and 3.2, the flexibilization of the electricity demand side can be achieved by integrating demand response applications ($a \in A$) which can increase ($LI_{t,a}$) and reduce ($LR_{t,a}$) electricity load in certain time periods when needed. The potentials of DR applications are constrained by several parameters and characteristics as described before in Sect. 3.1 and in Eqs. 11–14.

3.4 Bi-level Programs

The above formulated large-, medium- and small-scale models represent typical decision problems of individual energy stakeholders in a smart grid environment that can be modeled as a single linear or non-linear optimization problem. While these models are useful approaches to investigate the various interactions in smart grid systems, they sometimes fall short of representing the heterogeneity in the preferences of multiple stakeholders and the potentially involved interaction between them. Forms of interactions between sub-systems of a smart grid can create a stronger coupling between the demand- and supply side. For example the participation of end-users which own distributed flexible energy applications, e.g., electric vehicles or heat pumps, in corresponding electricity markets. Whenever sub-systems of a smart grid are managed by individual stakeholders, the model-based representation entails the inclusion of different objectives in the optimization problem, which requires other modeling techniques than those discussed above.

Let us assume the following example: Consider an aggregator, which buys energy at the wholesale markets to serve a given load of a residential quarter. The aggregator can decide on a dynamic tariff scheme offered to the customers representing the members of the quarter. Since wholesale prices vary over the course of a day the aggregator tries to design a tariff scheme that incentivizes the customers to shift their energy consumption into times with low wholesale prices. Aggregators usually try to maximize their profits, which can be calculated by subtracting the energy procurement cost at the wholesale market from the revenues from electricity consumption of the quarter. An intelligent communication infrastructure allows the aggregator to have full information on the customer's demand profile.

Furthermore, members of the quarter adjust their electricity consumption behavior in a way that minimizes their total expenses for electricity supply, which is strongly affected by the provided electricity tariff. However, usually only a fraction of the quarter's electricity demand can be considered flexible as specific technical limitations of the household devices prevent a full flexible operation.

As we can see here, the optimal decision on the design of the tariff scheme in the optimization problem of the aggregator is constrained to be optimal solutions to the optimization problem of the members of the living quarter. Such a framework refers to the class of bi-level optimization programs, in which one optimization problem is nested into another. In the outlined example the lower level optimization problem of the quarter members is included in the upper level optimization problem of the aggregator. Since the upper level variables are considered as fixed parameters and not decision variables in the lower level problem, i.e., the provided dynamic electricity tariff cannot be actively controlled by the quarter members, the optimization problem follows a hierarchical structure as in the well-known Stackelberg leader/follower game.

It is important to understand that the raised example is just one possible application of a bi-level program in the smart grid context. More generally, the upper level can be considered as a strategic decision-maker, who anticipates a feed-back from the lower level problem. Strategic decisions could be manifold, e.g., investment decisions, tariff-design or other regulatory questions. The lower level problem could be a response from the energy management of a single household, an integrated residential quarter, or an entire electricity market. As a smart grid typically exhibits a strong interaction between different sub-systems of an energy system, bi-level programming can be seen as a powerful tool for its model-based investigation.

In the generalized mathematical form we can write a bi-level program as follows (Bylling 2018):

$$\min \mathrm{f}_1(\mathrm{x}, \mathrm{y}^*) \tag{24}$$

$$\text{s.t. } \mathrm{g}_1(\mathrm{x}, \mathrm{y}^*) \leq 0 \tag{25}$$

$$\mathrm{h}_1(\mathrm{x}, \mathrm{y}^*) = 0 \tag{26}$$

$$\mathrm{y}^* \in \operatorname{argmin} \{\mathrm{f}_2(\mathrm{x}, \mathrm{y}) \tag{27}$$

$$\text{s.t.} \quad \mathrm{g}_2(\mathrm{x}, \mathrm{y}) \leq 0 \tag{28}$$

$$\mathrm{h}_2(\mathrm{x}, \mathrm{y}) = 0\}. \tag{29}$$

In this formulation, f_1 represents the objective function of the upper-level with the decision vector x (Eq. 24) and f_2 the objective of the lower level with the decision vector y (Eq. 27). Likewise, we have two sets of constraints represented by g_1 and h_1 (Eqs. 25, 26) as well as g_2 and h_2 (Eqs. 28, 29). The upper level decides on the values of x which minimize the objective f_1 anticipating the response of the lower level summarized in the values of the decision vector y, which minimizes the objective f_2. Due to the nested structure, solving bi-level programs is sometimes a challenge. Existing solution methods involve the replacement of the lower level problem by their necessary and sufficient Karush-Kuhn-Tucker (KKT) system following complementarity theory. The KKT system represents optimality conditions that must hold in the optimal solution of the lower level problem and which again can be reformulated as a set of additional inequality constraints. The newly derived set of constraints can then be taken together with the upper-level problem, recasting a single optimization problem that can be solved with commercial solvers for linear and non-linear programs.

4 Overview of Existing Modeling Approaches of Smart Grid Systems

The following subsections provide an overview of existing modeling approaches addressing smart grid components in large-scale energy models with a system perspective. Secondly, an overview of existing small- to medium-scale models narrowing down the scope on consumers' perspective is provided. Thirdly, to further increase the detail of the energy demand side modeling, bottom-up demand side models are examined. In general, the distinction between "traditional" energy models and smart energy models is fluid, and a strict differentiation is not possible.

4.1 Literature on Large-Scale Models

Among others, model descriptions for large-scale energy system models can be found in Panos and Lehtilä (2016) or Hidalgo Gonzalez et al. (2014). Examples for investment models can be found in Gils et al. (2017) or Zerrahn and Schill (2015). In addition to operational costs and fixed costs as well as technology-specific economic and technological parameter, relevant energy policies such as feed-in priorities of (weather-dependent) renewable energies are usually employed with country-specific time-dependent feed-in time series (e.g., in Child et al. 2019; Nitsch et al. 2012). The EU emissions trading scheme (ETS) can be represented by explicitly implementing a carbon cap or budget constraining the total amount of emissions allowed, as in Hobbie et al. (2019), Capros et al. (2016), Möst and Keles (2010) or by implicitly specifying prices for emission allowances, as for example in Zöphel et al. (2019) and Oei et al. (2014).

Generally, in a smart grid system with different levels of (de-) decentralization in supply and demand balancing, combinations of flexibility options are object of large-scale energy system analysis. Various technologies for supplying electricity (e.g., power plants), shifting energy (e.g., storages or transmission grids) or increasing electricity load (i.e., power-to-X (PtX), such as heat pumps, electrolyzer for hydrogen production or battery electric vehicles) are analyzed with different scopes. While for example Cebulla and Fichter (2017) analyze the influence of different renewable energy sources (RES) shares on investments in power plants and storages in a regional case study, Brijs et al. (2017) apply their analysis in a similar set-up for Belgium. In contrast, examples for an increase in system boundaries can be found in Connolly et al. (2016) or Koch et al. (2015), where additionally investments in transmission grid expansions, demand side management (DSM) and PtX technologies are analyzed for Europe and different shares of RES. These models still focus on the electricity market but include several options for the electrification of further energy sectors (sector coupling) with a respective increase in (time-dependent) electricity demand without a detailed representation of additional energy sectors. As an example, Lund and Kempton (2008) simulate the interaction between different electric vehicle charging strategies and levels of wind expansion on the amount of RES-based excess generation on national level. In general, the majority of optimization problems for electricity markets and energy system is a linear or mixed integer program. Nevertheless, non-linear formulations exist as well (e.g., when optimizing the number of power plants or including price elastic demand). An overview is given for example in Fernández-Blanco Carramolino et al. (2017) or Möst and Keles (2010). Further examples for smart grid applications are methods on the electricity supply side like real-time RES generation (as in Bottaccioli et al. 2017) or real-time pricing to balance electricity demand (as in Tao and Gao 2020). Furthermore, an emerging research field and application for simulations models is the estimation of time of arrival for vehicle-to-grid measures as in Luo et al. (2016). A combination of optimization and simulation models is often applied to derive optimal scenarios also for mid-term and long-term time horizons as well as to evaluate the efficiency of these scenarios in simulations with higher temporal resolution on shorter time scale. An example can be found in Rosen (2007), where optimization and simulation approaches are used to capture both, long-term changes and variability of renewable integration.

In a large-scale electricity market perspectives, the aspect of decentralization, introduced in Sect. 1, is often assessed by comparing scenario frameworks including technologies generally assessed as decentral, as for example photovoltaics (PV) rooftop system and decentral heat pumps, with more central systems characterized by a higher share of for example wind offshore farms and combined heat and power (CHP) plants. These kinds of modeling approaches are described for example in Zöphel et al. (2019) with a European system perspective. Furthermore, with large-scale energy system models selected decentral or central approaches can be analyzed. On the one side, both simulation and optimization models are applied in the literature to evaluate possible system effects of scaling-up small-scale smart applications and examine the large-scale impacts of an expansion of decentral smart technologies. While, as already mentioned, the application of optimization models tends to assume the presence of smart grid technology, simulations often focus on the efficiency of suitable algorithms and control strategies for the communications between the components involved. In Bazan et al. (2015), a smart grid simulation including an explicitly simulated controller for single houses is up-scaled and applied for 200,000 households to evaluate the influence of battery and PV size on the average electricity costs in different system configurations. Similarly, in Schill et al. (2017) an optimization model is used to analyze the interactions between different prosumage strategies for PV-battery systems with varying levels of self-consumption and optimal storage investments in Germany. Thereby, the optimal coverage of the prosumer electricity demand is modeled as minimum restriction, while the realization of the self-consumption is a result of the optimization. On the other side, rather central smart grid applications address the optimization of grid operation, usage, and infrastructure as well as integrating large-scale intermittent generation. As an example, Hinz (2017) discusses the impact of decentralization and RES expansion in the German electricity system on the provision of voltage stability and reactive power management in a combination of non-linear and a linearized techno-economic grid models.

Within this range of model applications and system boundaries, the flexibilization of the energy demand side in general (see for example in Müller and Möst (2018) and Ladwig (2018)) and sector coupling in particular with corresponding ICT and the resulting bi-directional power flows, as in Mathiesen et al. (2015), are in the focus of smart grid model analyses.

4.2 *Literature on Small- to Medium-Scale Models*

Conejo et al. (2010) state that most existing literature assumes a "consumer sufficiently large to participate in the electricity market to minimize its energy procurement costs." Due to the small and distributed nature of end consumers, individual households are often considered in an aggregated way. Nevertheless, this necessitates the consideration of consumers' or prosumers' involvement and behavior as active participants in energy systems and markets, coming along with smart grids and new contractual agreements, such as real-time pricing, resulting in new decision-making models. This brings forth new challenges as described in Sect. 1.

Optimization in smart grids from a consumer perspective often involves the formulation of a cost minimization or utility maximization problem. The objective function typically is the reduction of the end-users' electricity payments. For this, residential load control schemes are designed and deployed, deciding on energy consumption in the household. Because of the manifold objectives of end consumers, optimization tasks can deviate from purely technical and cost-minimizing perspectives and involve factors regarding customers' satisfaction and comfort. Further objectives can include, for instance, a trade-off between electricity bill and waiting time for operation, as in Mohsenian-Rad and Leon-Garcia (2010) or similarly a trade-off between costs and quality of services in Yu et al. (2013), with a minimization in consumer dissatisfaction, measured by temperature deviations. From a system perspective, more technical objectives can be accounted for, such as Arabali et al. (2012), who evaluate a compromise between risk of failure to meet demand and generation cost for different levels of wind and PV. Lastly, with growing shares of decentralized energy generation, individual consumers or energy communities can pursue targets for certain levels of autarky or also complete self-sufficiency. As described in the introduction, this presents new challenges and model objectives beside cost-minimizing considerations.

While most load management approaches take on the grid's perspective, with smart grids, "bi-directional data flow and interoperability between homes and the grid" (Kahrobaee et al. 2012) cause the possibility to optimize individual consumption. Existing literature repeatedly indicates that these cost-reducing schemes on an individual basis often simultaneously create benefits for utility companies and the operation of the grid due to the reduction of peak-to-average load ratios, e.g., Mohsenian-Rad and Leon-Garcia (2010), Kahrobaee et al. (2012). The maximization of individual utilities through cost-saving incentives, brought forth by pricing signals and technical possibilities for flexible demand, usually also leads to overall welfare benefits. This goes along with the grid infrastructure-related questions mentioned in Sect. 1, which arise with a growing expansion of smart grids, namely adequate transmission capacities to properly integrate consumers and steering their behavior to be beneficial for the grid.

As mentioned before, demand has to become increasingly flexible with growing utilization of renewable energy sources. Thus, cost-reducing decisions not only involve demand response, as e.g., modeled in Conejo et al. (2010), but additionally the generation and storage of electricity. Kahrobaee et al. (2012) mention that models in earlier literature have not fully utilized smart home features, they mention the oversimplification and overly restricted model in Pipattanasomporn et al. (2009), the inability to generate power in Ramchurn et al. (2011) or the lack of demand response in Vytelingum et al. (2010). When all possible consumer decisions are taken into account in the modeling of smart grids and their separate entities, passive load curves do not suffice due to the active participation of end-users or smart homes. Beside these modeling aspects, questions emerge regarding the "proper" storage technologies to balance renewable energy feed-in, which are characterized by technical considerations, e.g., storage capacity and discharge time, and feasibility requirements.

Often, linear optimization is used, as in Conejo et al. (2010) and Mohsenian-Rad and Leon-Garcia (2010). Yu et al. (2013) use a mixed integer multi-time scale stochastic optimization to model a home energy management that controls energy consumption in response to dynamic pricing. Studies have increasingly used multiagent-system-based approaches, e.g., Kahrobaee et al. (2012), in which smart homes are agents in a smart grid environment that can consume, generate and store electricity, making autonomous decisions to manage these components while interacting with the grid. The objective is to minimize the cost of electricity. As pointed out in Sect. 1, agent-based models will likely gain in importance. Kahrobaee et al. (2012) describe that multiagent systems are advantageous due to their versatility and scalability. Furthermore, they are able to model stochastic and dynamic interactions among agents, i.e., end-users or homes, and between homes and the grid. With multiagent models, transition periods in the simulation result in an equilibrium "as an emergent behavior of the agents".

The time resolution of smart grid models is often hourly (e.g., Mohsenian-Rad and Leon-Garcia 2010; Gottwalt et al. 2016). Case studies range from covering one day up to several months. The geographical scope is similarly diverse, ranging from single households to an accumulation of hundreds or thousands of consumers. This attests to the vastly different perspectives of smart grid modeling, ranging from micro/household to macro/community perspectives.

One strand of literature considers single households or consumers, e.g., Conejo et al. (2010), Mohsenian-Rad and Leon-Garcia (2010), Yu et al. (2013) and Adika and Wang (2013). More comprehensive approaches consider numerous households with different household devices, which directly respond to different load and renewable energy generation. Stadler et al. (2009), electric vehicles in Schuller et al. (2015), heating/cooling systems in Hakimi and Moghaddas-Tafreshi (2014) or control approaches for stationary batteries in van de Ven et al. (2013). Considering numerous devices necessitates a categorization regarding the technical possibilities for demand flexibility. For instance, Gottwalt et al. (2016) differentiate between automatically controlled devices, such as refrigerators and storages for water heaters as well as semi-automatic devices like dishwashers and washing machines, which require previous user interactions.

When numerous households are considered, their participation can be modeled as aggregators, e.g., Ottesen et al. (2016) and Iria et al. (2018). The aggregator can control the prosumers' flexible energy units. Ottesen et al. (2016) model a two-stage stochastic mixed integer linear program with bidding decisions in the first stage and scheduling in the second. The case study with a diverse portfolio of prosumers attests to the heterogeneity of consumers and behavior. Iria et al. (2018) model an aggregator of small prosumers in the energy and tertiary reserve markets by means of a two-stage scenario-based stochastic optimization model. It becomes evident that a multitude of uncertainties have to be considered, such as renewable power generation, electricity demand, outdoor temperature, end-users' behavior, and preferences. Results include that system flexibility increases with an aggregator (Ottesen et al. 2016) and the reduction of bidding net costs under the consideration of flexible strategies (Iria et al. 2018).

A further example for the modeling of aggregators includes Gottwalt et al. (2016), who investigate the interactions between different shares of renewable energy and the utilization of demand side flexibility. For this, the authors provide a comprehensive centralized scheduling model to make use of demand flexibility in a residential microgrid. An aggregator with full information dispatches controllable devices with the objective of cost minimization, considering power system balances and device constraints. The problem is formulated as a mixed integer linear program. The analysis derives cost reduction potentials of flexible loads and recommendations for electric utilities to structure their renewable portfolio. Recommendations include that aggregators should incentivize customers to own the according appliances depending on the renewable mix. This attests to the importance of interactions between the aggregated level and individual consumer behavior.

Besides the challenge of modeling smart grids and their participants, existing studies also point out the lack of opportunities and incentives for small consumers to participate in the market, e.g., Zepter et al. (2019). This suggests that beside the consideration of technical constraints and cost-minimizing approaches, consumer involvement poses another challenge. For instance, Mohsenian-Rad and Leon-Garcia (2010) argue that the two major barriers for the full potential utilization of real-time pricing are the lacking knowledge of consumers regarding the response to time-varying prices and effective building automation systems.

Zepter et al. (2019) highlight that the challenge of integrating local markets into the wholesale market has not been sufficiently addressed. They propose a framework, the Smart elecTricity Exchange Platform (STEP), which involves the coordination of operation of supply-demand decisions and provides an interface between wholesale electricity markets and prosumer communities. Rather than considering aggregated distributed energy generation, as is the case in most existing literature, Zepter et al.

(2019) take into account the local distribution and peer-to-peer trading, which enables households to balance out deviations from the community's day-ahead market commitment in the intraday market. This addresses the above-mentioned question regarding the interlinkage of markets to contribute to the integration of renewable energy sources. The authors state that approaches like their proposed one bear great cost reduction potentials. The study attests to multitude of modeling aspects, which need to be addressed to adequately map the different options that end-users can utilize in (future) smart grids.

The modeling of smart grids on a small- to medium-scale encompasses a wide array of approaches and perspectives. When individual households are considered, pure cost-oriented objectives do not capture all facets of consumer behavior. While demand response as well as the decentralized generation and storage of energy are subject to technical constraints, consumers likely have expectations regarding their comfort and convenience level. Aggregators can help to bundle, coordinate and market the potential of communities. Utilizing the full potential of prosumers and smart grids necessitates the technical implementation as well as the provision of information to end consumers.

4.3 Literature on Bottom-Up Demand Side Models

With the crucial role of energy end-users in smart grid systems, energy demand models are of high importance as forecasting energy demand and supply is essential for ensuring a reliable and secure energy system. Furthermore, demand side models allow analyses in the context of decarbonization, decentralization, and digitalization (cf. Sect. 2).

In a system perspective, the annual energy demand is strongly related to energy prices, the gross domestic product (GDP), and population growth (Suganthi and Samuel 2012). The electricity demand is influenced by technological and socio-economic drivers, such as economic growth, energy efficiency, urbanization, per capita income, support schemes for renewable energy sources and other low-carbon energy carriers, as well as by electrification and technological progress in electricity generation technologies. To measure the impact of intermittent RES and to estimate operational flexibility of the future power system, the need arises to model and forecast electricity demand in high resolution (Adeoye and Spataru 2019). National hourly electricity demand pursue a periodic and predictable daily pattern. Changes in the pattern of electricity demand depend mainly on energy efficiency improvements, de-industrialization, and the increasing electrification of the industry, heat, and transport sector (Boßmann and Staffell 2015).

However, most recent studies forecast the future electricity demand by neglecting the further development of the electricity consumption pattern. The studies assume simplified that the hourly electricity load curve maintains its shape by scaling up equally in all hours. Consequently, capacity requirements for flexibility options and peak load technologies increase, and full load hours as well as the profitability of conventional base-load and mid-load power plants decrease (Boßmann and Staffell 2015). Hence, significant transformations of the electricity load curve can evolve in future with the diffusion of new and the phase-out of existing technologies. The changes can have substantial effects, which are crucial to integrate in the modeling of smart grid systems. For instance, the need to cover greater residual load peaks could arise which can be balanced with storages, DSM applications, interconnections, and peak load capacities or the need to flatten hours with negative residual load by curtailing the excess of renewable energy sources (Boßmann and Staffell 2015).

Several studies have modeled and projected the hourly electricity demand and the annual electricity demand by aggregating the individual sectors on country, regional, and sector level. Typical sectors are the industrial, tertiary, residential, and transport sector. Different methodologies to forecast electricity demand on annual or hourly consumption exist. Suganthi and Samuel (2012) have conducted a literature review that provides a comprehensive overview of energy demand forecasting techniques.

The following section focus on bottom-up energy demand models as these models are common for modeling smart grid energy systems. Bottom-up energy demand models are characterized by their high degree of technological detail, which allows to model several, and clearly defined technologies to assess future energy demand and supply (Fleiter et al. 2011). As already mentioned, due to its technological accuracy and explicitness, bottom-up models are applied to model effects of sector- or technology-oriented policies (Gillingham et al. 2008).

Different mathematical formulations of bottom-up models have been developed that can be categorized in partial equilibrium models, optimization models, simulation models, and multiagent models (Herbst et al. 2012). The development of energy end-uses and their respective energy efficiencies estimates the future energy demand. Within all bottom-up energy demand models the demand forecasts are directly linked with the technological structure of the energy system (Fleiter et al. 2011). In the following, bottom-up energy demand models are classified in annual energy demand (Sect. 4.3.1) and in hourly electricity demand projection models (Sect. 4.3.2).

4.3.1 Bottom-Up Modeling of Annual Energy Demand

New challenges have to be faced by policymakers, therefore annual energy forecasting models are applied to assess the potential impact of new policies and to support the decision-making process (Worrell et al. 2004). In general, though optimization and partial equilibrium models are applied as well, the majority of the approaches are simulations. There exist various scopes for both, the geographical coverage ranging from national to international level as well as to system boundaries. Regarding the latter one, analyses can focus on a single sectors, like the industry sector, or on multi-coupled sectors including different energy end-use sectors.

Bottom-up energy demand models are applied to support scenario designs and analyses for the long-term evolution of energy demand and GHG emissions in different sectoral and geographical scales. Annual energy demand models aim to integrate policies and changes in the socio-economic framework including the consideration of a broad range of greenhouse gases (GHG) mitigation options with high degree of technological detail. Usually the three sectors—industrial, tertiary, and residential sector—are depicted by those models and characterized by different specific data requirements, e.g., the production in the industry sector, number of employees in the tertiary sector or number of households in the residential sector. Further input parameters are the main drivers as gross domestic product, populations growth, energy prices by energy carrier, temperature (heating and cooling degree days), and business cycles. Furthermore, price-based policies are considered as taxes, CO_2 prices, market-based instruments (e.g., the EU emissions trading scheme (ETS)), subsidies as well as operational expenditures. Additionally, structural information as the energy balance, CO_2 balance, and the technology distribution as well as technology parameters including behavioral assumptions are reflected (Herbst et al. 2017). The outcome of annual energy demand models can be disaggregated in high resolution from sectors (e.g., residential) and sub-sectors (e.g., industrial combined heat and power (CHP)), as well as energy end-uses (e.g., space heating), technologies like industrial CHP and energy carriers (e.g., natural gas). The diffusion of technologies is the result of individual investment decisions over a specific time period to cover the energy demand in different sectors. Therefore, the investment decisions are commonly modeled as discrete choice process, where companies and households have miscellaneous technology choices to satisfy a specific energy demand (Herbst et al. 2017). This is typically implemented as logit approach considering the total cost of ownership (TCO). Thus, the simulation algorithm considers market heterogeneity and non-rational behavior that leads to price sensitive technology and energy demand developments (Herbst et al. 2017).

In the recent past, especially due to decarbonization targets for all sectors, the importance for building park models has increased. Building park models are bottom-up demand side models that simulate the development of energy-related equipment and the resulting energy demand in the building sector. For this purpose, building technology, construction engineering, energy-specific, and economic parameters, such as investments and life cycle costs as well as influencing factors as energy end-user prices, interest rates, energy and emissions taxes as well as subsidies, are considered. Building park models show future costs and technology developments in the field of energy efficiency and for the use and provision of decentralized heating, cooling, and electricity (TEP 2020). Furthermore, demand side models for the building sector are used to define energy and climate targets, for impact analyses and evaluations of energy climate and policy measures (ex-ante and ex-post), strategic and operational energy planning, urban planning, network expansion planning, and evaluation of network renewal projects (electricity, gas, heating, cooling, etc.). Additionally, the models support the creation of emission and energy statistics, material flow analyses as well as the management of building portfolios or the conduction of market studies. Therefore, past and future changes in national, regional, urban or municipal building parks are simulated over several decades to receive evaluation indicators such as the electricity and energy demand for energy sources, maximum load (electricity, heat), primary energy consumption, carbon and GHG or material flows (new buildings, existing buildings, dismantling). Moreover, the building specific modeling provides insights concerning the optimal choice of heating systems for new buildings and renovations, or of repairing vs. energy-efficient renovation. Furthermore, results as the efficiency level of renovations, devices, and building technology components can be gained.

4.3.2 Bottom-Up Modeling of Hourly Electricity Demand

As stated before, most studies apply a simplified scaling approach of a historical load curve corresponding to an annual demand forecast to assess the future load curve. Within the scope of long-term energy system modeling more sophisticated approaches are required as the diffusion of new technologies and the phase-out of existing technologies may lead to significant changes within the pattern of the hourly future load curve (Boßmann and Staffell 2015). The majority of the studies assess load curve projections for single sectors or consumers (Voulis et al. 2017; Hayn et al. 2018; Lee et al. 2019). Other studies focus on regional load curve projections in a specific country (Riva et al. 2019; Boßmann and Staffell 2015). Further literature analyzes specific characteristics of the hourly future load curve as the hourly peak electricity demand (Hainoun 2009) or the load duration curve (Poulin et al. 2008).

Most bottom-up models assess the hourly electricity demand in the residential sector for an entire year. Hourly electricity load curves for households have been modeled for the United States (Capasso et al. 1994), India (Riva et al. 2019), United Kingdom (Richardson et al. 2010), and Finland (Paatero and Lund 2006) to name few. These models integrate behavioral, social, technical, and economic data, as well as weather data to model the electricity demand for representative households and its consumers (Adeoye and Spataru 2019). Typically, these are simulation models taking for instance the increasing diffusion of e-mobility and further decentralized electricity generation appliances into account. Commonly, electricity load curves for specific household appliances (e.g., heating technologies) or the electricity consumption by electric vehicles in households are estimated. For instance, the hourly load curve of e-mobility in the residential sector can be derived from the number of battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV), the electric driving share of plug-in hybrid electric vehicle (PHEV), the traveled kilometers per year, the energy consumption of battery electric vehicle (BEV) and PHEV, multiplied by the share of charged electricity (Elsland et al. 2013). The future residential electricity demand is characterized by increasing volatility due to demand shifts from night-time to day-time hours caused by a growing number of information and communication technologies, while electro-mobility increases evening demand peaks. Electricity generation by photovoltaic can compensate the additional demand due to electric vehicles, if the decentralized electricity generation can encounter the electricity demand of demand side management applications and storage systems.

In contrast to the modeling of the residential sector, there exist only few studies and bottom-up models that focus on the hourly electric load forecasting for all sectors (industry, tertiary, residential, and transport sector). For instance, Pina et al. (2011), Hainoun (2009), or Boßmann and Staffell (2015) assess user specific load profiles of representative customers to composite the future load curve within the industry, tertiary, and residential sector, based on empirical data. Therefore, the profiles are scaled to the annual electricity demand forecast and aggregated to estimate the entire hourly electricity load curve. Hourly electric load forecast models are applied to assess the future pattern of the electricity system load curve at national level for the long-term (e.g., until 2050) by considering all demand side sectors. In general, the projection of hourly electricity load curves can be realized by the deformation of the load curve due to structural changes on the demand side and due to the diffusion of new appliances (e.g., e-mobility) by applying a partial decomposition approach (cf. Boßmann and Staffell 2015). The annual electricity demand projection is an exogenous model input and is necessary to identify significant electricity consumption increases or decreases by relevant appliances over the long-term perspective (Zöphel et al. 2019). Appliance specific load profiles from surveys, official databases, or simulation models are used, to generate load curves for all appliances, according to the annual demand in the base year. Consequently, the specific appliance load curves and the remaining load curve are scaled for all projection years with regard to the electricity demand evolution. Further, the load curve can be adjusted by the flexible dispatch of DSM applications. The DSM appliances' load is based on day-ahead price signals, and scheduled from hours with high prices to hours with low prices. With this approach the least-cost dispatch of DSM appliances from a consumer perspective can be estimated in order to smooth the residual load (Boßmann and Staffell 2015).

Finally, forecasting hourly electricity load curves across different sectors is of crucial importance for modeling smart grid systems, since the future electricity demand will transform significantly as the diffusion of new and the phase-out of existing technologies have a great impact on the daily electricity consumption pattern.

5 New and Other Modeling Trends

5.1 Forecasting: High Resolution of Weather Data and Time Series

The combination of more decentralized power generation and more active consumer behavior, which arises from the proliferation of prosumers, also contributes to new challenges of forecasting tasks. In a smart energy system with high shares of weather-dependent renewable energies, especially weather forecasts are gaining strongly in significance. Da Silva et al. (2013) describe that the transition toward an information-driven smart grid as well as local electricity markets depends on accurate forecasts of its participants' demand and generation. Predictions for renewable energy generation at a higher geographical resolution will become increasingly important when planning and operating local energy systems and communities. The analysis by Schönheit and Möst (2019) describes the different distributions of day-ahead prediction errors for wind speeds. The authors find that the error distributions differ across Germany, which affects the uncertainty connected with local availability of wind energy. This highlights the necessity of accurate prediction techniques on a small-scale level.

Sobri et al. (2018) and Das et al. (2018), which both provide overviews of photovoltaic power forecasting techniques, point out that PV is an often-used technology, also for "stand-alone" or "off-grid" networks. This pertains to small grid-connected consumers as well due to the integration of PV in the buildings of prosumers. Lorenz et al. (2012) describe that on a local level, smart grid applications result in an increased need for PV power forecasting. The authors propose an approach for regional PV power, specifically focusing on snow detection. Das et al. (2018) describe that PV capacities have grown substantially on the past year, but their effect on the grid necessitates accurate forecasting techniques to maintain stability and reliability and aid the modeling and planning of solar photovoltaic plants. To meet the complex task of taking into account the weather dependency when predicting solar energy generation, often neural network-based approaches are used, as in Rodriguez et al. (2018). Shang and Wei (2018) deploy support vector forecast solar power output.

Additionally, with rising participation of consumers in the electricity markets, electricity price predictions may also gain in importance at household level. In general, electricity price predictions are already at high importance since liberalization. Wang et al. (2019) describe that day-ahead electricity price forecasting is an important element for decision-making of market participants. This includes consumers in a market-oriented environment as stated by Zhang et al. (2019). Neural networks are also applied for price predictions, e.g., in Kuo and Huang (2018) or Chow et al. (2012). Wang et al. (2019) use a weighted voting mechanism to combine numerous predictions and achieve better performance than with unified modeling. Forecasting combination, i.e., taking the (weighted) average of multiple forecasts, is also used by Ziel and Weron (2018).

Finally, forecasts are not only needed for generation and prices but also demand. When demand is considered in models on the level of households or communities, e.g., as opposed to high-voltage grid nodes, a higher geographical resolution is necessary for forecasting models. Yu et al. (2015) state that energy resource management in smart grids face the challenge of fluctuations, both on the demand and the supply side. They deploy several machine learning-based approaches and neural networks to forecast energy usage. Goude et al. (2013) state that innovative technologies, such as smart grids, create challenges for electric load forecasting. They propose a semi-parametric approach based on generalized additive models theory to predict electric load at substations. Da Silva et al. (2013) tackle the challenge of forecasting individual demand by the creation of groups. They also show that groups can act as a single unit on the market and use the positive effects of aggregation on forecasting accuracy.

5.2 *Open Source, Transparency, and New Software Tools*

As a general shift toward open methods can be recognized in the energy system modeling community, this development has also influenced research in the context of smart grid modeling. Open methods generally refer to the disclosure of associated source codes, datasets, and documentation with appropriate licensing for reuse, modification, and republication of modeling works. Open modeling is often accompanied by the development and maintenance of open power system data bases that share modeling data among researchers. As summarized in Morrison (2018) main drivers that can explain this shift in modeling paradigms include the desire for improved public transparency, the need for scientific reproducibility and the believe that open methods potentially improve academic productivity and quality.

While reproducibility of research results and general research performance strongly relates to academia, a high degree of transparency is also of great importance in real-world smart grid applications. With a strong involvement of energy end-users or other stakeholders into energy management activities a clear communication of energy utilization and market prices is necessary. This can be achieved by emerging smart home technical devices or apps for energy visualization but also be driven by legislating institutions. One example is the German smart metering legislation which ensures the (gradual) introduction of smart metering concepts with mandatory installations of smart meters in new buildings or during major renovation works. Smart metering not only enables the communication between end-users and energy utilities. It can also create a stronger awareness of energy consumption in society that potentially contributes to energy efficiency and carbon emission reduction.

6 Summary

Many different concepts are used to model smart grid systems and a high variety of approaches exists. Although the focus of the introduced model categories (large-scale, small-to-medium scale, and bottom-up demand side models) can overlap, differences exist regarding the dimensions time horizon, scope, and model perspective. Large-scale energy system models are rather applied to long-term analysis of challenges in terms of RES integration and flexibility provision. From a system perspective, the role of the energy demand side becomes more relevant in energy systems with higher shares of weather-dependent renewables. Besides the digitalization, allowing for an automated flexibilization of the energy demand, one of the main drivers of this development is sector coupling. Thus, the new additional power demands and their impacts, both on the yearly demand and on the hourly (or quarter-hourly) demand profile, have to be considered. The increase in number of actors with new technologies and the role of decentralization on the supply and demand side, emerge the importance of modeling approaches on small-to-medium scale. Since the interaction of prosumers and the respective optimization of individual or regionally aggregated energy supply and demand is located on a decentral level, a narrower geographical scope as well as time horizon is more suitable for these models. While the demand side hasn't played that crucial role in former years in energy system modeling approaches, today, a detailed bottom-up consideration is often required to address the impact of new demand technologies and its control. The corresponding disaggregation of demand (and supply) data in these demand side models enables the assessment of potentials of flexible demand to integrate higher shares of RES in a short- to long-term perspective.

Further key trends of smart grid modeling can be recognized due to the increasing role of policy and society in participating in future energy systems. To analyze the interplay of the different players, besides common modeling approaches, also new modeling approaches such as bi-level programming, and agent-based simulation will allow for more applications and thus contribute to the different research activities. Thereby, transparency and traceability are getting further in importance. In consequence, open source approaches will become standard. Additionally, the weather-dependent character of renewables necessitates on the one side a high timely resolution (as already mentioned above), but on the other side it also requires a significant improvement of forecasts. In consequence, weather forecasting will increasingly gain in importance. It has to be mentioned that complexity in modeling smart grid systems will continue to increase, also because hard- and software will further develop and allow for solving larger and even more complex models. Finally, when modeling smart grids, the trade-off between model complexity and additional insights with regard to the research question at hand must be considered.

Review Question

- What are the three main drivers which necessitate smart grid modeling?
- List five elements that are often considered in model-based representations of smart grids.
- Name and explain the three dimensions of energy system model (ESM). How are they commonly modeled in smart energy system models (ESMs)?
- Classify smart energy supply models (ESMs) by means of a visualization, considering the three dimensions of ESMs, and distinguish them from "traditional" ESMs.
- Why is the importance of modeling demand increasing for smart grids?
- Why and how is modeling of energy systems affected by uncertainties resulting from weather forecasts?
- Explain the idea of bi-level programming in the context of smart grid modeling.

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