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Chapter 11

Modeling, simulation and decision support

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ABSTRACT

Energy markets are intertwined and complex systems that influence and are affected by various sectors such as transportation, industry, and electric power. Solely focusing on the power sector without considering the up-and downstream of the supply chain may produce misleading results. For instance, the mixture of primary energy carriers and the procurement source affect the generation cost of electricity and consequently may alter the decisions of generation companies about future investments. Therefore, researchers should carefully decide a reasonable trade-off between complexity and simplicity based on the determined level of detail and questions at hand. In this section, top-down and bottom-up modeling approaches are discussed, with their corresponding pros and cons, in the broader context of energy markets. Then, we focus on different modeling techniques in the established electricity markets. Finally, we demonstrate the unique modeling challenges that should be dealt with in emerging local electricity markets.

KEYWORDS

Energy markets, Top-down macroeconomic approach, Bottom-up engineering approach, Optimization models, Simulation

11.1 INTRODUCTION

Determining correct policies requires accurate observations and predictions of future trends. Yet, neither would be achieved without quantitative methods, by which the underlying system, and its components, are represented using mathematical formulations. Energy systems are complex systems that influence, and

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are affected by, other techno-socio-economic sub-systems. In order to study such complicated interactions, researchers rely on two well-known modeling perspectives: the top-down macroeconomic approach and the bottom-up engineering approach, which are synonymous with *aggregated* and *disaggregated* models, respectively [40]. These approaches have their strengths and shortcomings; therefore, choosing a suitable modeling approach is profoundly subject to the problem at hand. For instance, while bottom-up models are better suited for analyzing energy systems in which parameters and technologies may evolve over time, they require an extensive effort in data collection. Hence, researchers should determine a suitable trade-off between the complexity and simplicity.

In this chapter, we categorize various modeling techniques in the context of energy and electricity markets. The advantages and disadvantages of each method are explained to assist researchers in choosing proper methodologies to cope with their problems. Figure 11.1 depicts an abstract illustration of the chosen pathway in the following sections. As one can perceive, the reviewed papers in this chapter show only one possible path, which is closer to the agenda of this book; thus, it is by no means complete.

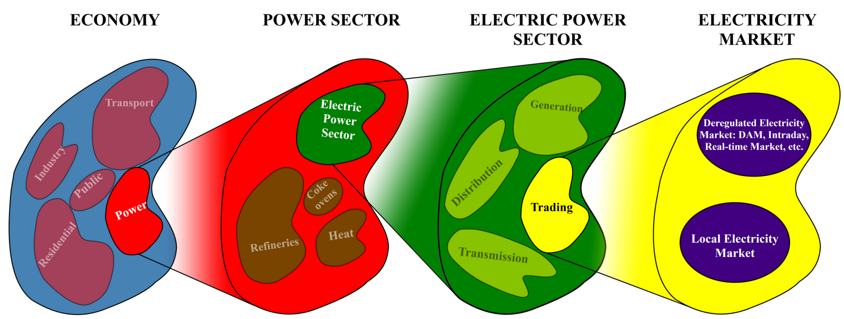

FIGURE 11.1 The guideline for the following sections. We content ourselves to only few instances inside each hyper-bubble for the sake of clarity.

This chapter unfolds as follows. In the next section, we elaborate on basic modeling approaches through which researchers produce insights. Section 11.3 focuses on electricity markets and examines various modeling techniques with their corresponding pros and cons. Studies that are related to local electricity markets are investigated in Section 11.4. Finally, Section 11.5 concludes.

11.2 MODELING APPROACHES

There are two fundamental modeling approaches to investigate interrelated energy systems [40]:

- **The top-down macroeconomic approach** that emphasizes the possibilities to substitute multiple inputs in order to achieve better outputs. Top-down models focus on economy-wide features.

- **The bottom-up engineering approach**, which is taking into account technological and sectorial details. Bottom-up models can be divided into optimization (including partial equilibrium models), simulation, multi-agent, and accounting models [47].

In top-down models, energy, like other inputs, is a production factor and interacts with other factors in the production function to generate economic growth. Top-down models mostly account for macroeconomic feedback and microeconomics realism [7]; however, for the sake of simplicity and tractability, top-down models ignore technical aspects and assume an institutionally, behaviourally and technologically stable world [116]. We can associate any top-down model to one of the following categories [49, 101, 41]:

- *Input-output (IO) models*: These models are characterized through a system of linear equations that describe the financial flow of products among economic sectors for both intermediate and end-use deliveries. IO life cycle assessment (IO LCA) extends economic IO models to include externality costs such as environmental impacts [72, 48]. Although these models allow us to study the impacts of structural changes and economic shocks on the whole economy, they assume that prices are provided exogenously [47]. Another drawback of these models is that they often consider sectors in an extremely aggregated form, which may introduce inaccuracy in the results [82, 24].
- *Econometric models*: They utilize economic data and statistical inference techniques to examine statistical relations among economic variables with respect to time. Econometric models are ranging from simple linear regression to more rigorous methods in time series analysis [32, 1]. While econometric models are used to calculate projections, their ability to project the relation of economic variables into decades ahead is limited, since the correlations among statistical variables may change over time [69].
- *Computable general equilibrium (CGE) models*: CGE models are built upon general equilibrium theory to analyze equilibrium conditions in an economy with rational economic agents. These models can be seen as the general form of the partial equilibrium models, in which interactions between energy markets and the rest of the economy are considered. Models in this category can be conveniently connected to bottom-up models.
- *System dynamics models*: Complex non-linear simulations can be produced by specifying rules to describe different agents' behavior in these models; nonetheless, they often have narrower focus than CGE models.

Top-down models, which are normally used to make projections, become less reliable as the underlying parameters in these models change over time. For example, the past projections of natural gas prices in the United States turned out to be so unreliable that they resulted in billions of wasted dollars in investments in U.S. regasification plants that were constructed to import foreign sourced Liquid Natural Gas (LNG) into the United States. In this case, top-down models failed to anticipate the application of known technologies to the production of natural gas from reserves that were previously thought to be too expensive to produce (i.e., shale gas) [108, 109]. Unlike top-down models in which parameters will remain unchanged, the bottom-up models provide specific opportunities to introduce new technologies and understand how they can affect future energy market fundamentals; therefore, bottom-up models serve as the only practical choice to estimate energy trends beyond a few years.

Bottom-up models are qualified to describe the whole energy sector in detail considering different forms of energy and various technologies. In bottom-up models, technologies are characterized based on technical (e.g., availability factor, efficiency), and economic properties (e.g., investment cost, operation and maintenance cost). Parallel technologies compete in the bottom-up frameworks to satisfy demand with low cost and in a sustainable manner. As competing technologies are assumed to be perfect substitutes, it can lead to a market that is dominated by the cheapest technology; therefore, despite the technological explicitness, these models suffer from the lack of behavioral realism [20] and feedback stemmed from economic growth (e.g., income and GDP)[40]. Figure 11.2 depicts a schematic diagram of a Reference Energy System (RES) in a generic bottom-up model from the supply of primary energy sources, energy conversion, transmission, distribution down to consumption by services.

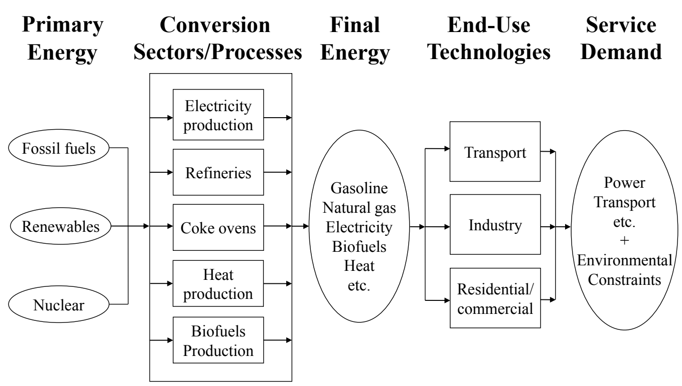

FIGURE 11.2 Simplified Reference Energy System.

Major top-down models can be counted as EPPA [85], GEMINI-E3 [17], MACRO [71], GTAP [50], and BaHaMa [12]. MESSAGE [77] and its successor TIMES [68], and LEAP [46] are popular software tools for the bottom-up modeling of energy systems[5]. The bottom-up modeling approach has been used in World Energy Outlook (WEO) since 2008 by the International Energy Agency (IEA).

As bottom-up and top-down approaches can complete one another, researchers propose hybrid models, in which they consider the joint impact of

5. Please check Table 1 in [47] for the extensive list of models in each category

macroeconomic factors and technological development [117, 7]. These hybrid models can be created by either soft-linking or hard-linking of top-down and bottom-up models. The soft-linking strategy seeks to align these two basic modeling approaches through an iterative process such that the convergence condition of central parameters and variables are fulfilled. However, the hard-linking strategy attempts to unify these two modeling approaches into a single model; thus, the resulted model is often simplified either in the top-down or bottom-up side (e.g., Bohringer and Loschel [20] develop a hybrid CGE model, in which the electric power sector is modeled using bottom-up approach and other sectors are modeled using a CGE model). Figure 11.3 depicts soft-linking and hard-linking strategies of two approaches with the interactions between them. MARKAL-MACRO [71] and TIMES-MACRO [62] are the known instances of hybrid frameworks.

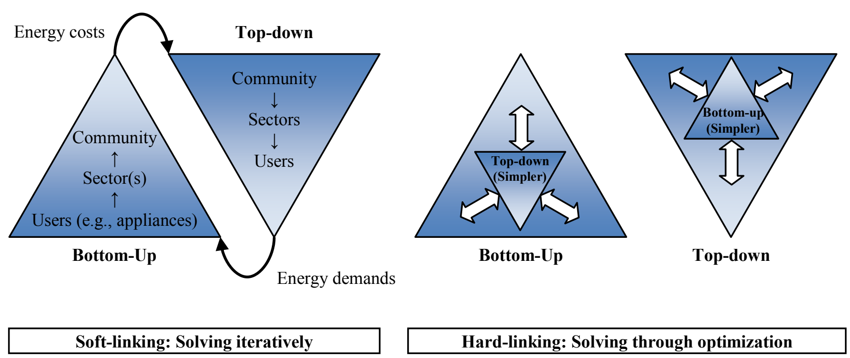

FIGURE 11.3 A simplified demonstration of building hybrid models through hard-or soft-linking. Two models may partially or entirely overlap each other when hard-linking strategy is applied.

Since these frameworks are comprehensively covering energy, economy, and environment modules, they require substantial effort on data gathering and organization processes for the region of interest (e.g., city, province, country, or world) based on the desired level of detail. For example, in [36], the bottom-up model is disaggregated to individual processes instead of employed technologies (see Figure 11.4), which demands multiple gigabytes of raw data to provide accurate representations. Thus, instead of taking a holistic view, researchers may confine the boundary of their study to a subset of these sectors and consider the interaction with other sectors as exogenous input parameters to simplify the interactions.

In the next section, we concentrate on various methodologies that replicate and analyze electricity markets.

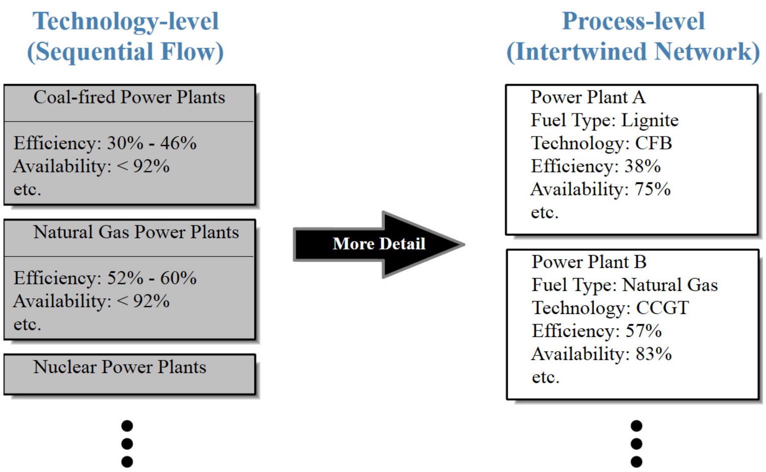

FIGURE 11.4 A power sector representation in the RES that is modeled down to individual power plants instead of employed technologies for enhancing accuracy. As the level of detail increases, the RES becomes more complex and intertwined.

11.3 MODELING ELECTRICITY MARKETS

Unlike storable commodities, electricity consumption should be instantaneously balanced with generation. This feature introduces technical, managerial, and economical complexity to trading structures. Electricity industry commenced with vertically integrated monopolies; however, unsatisfactory performance of such regulated monopolies as a result of expensive construction and operation costs called for the liberalization [54, 55]. Nowadays, power delivery consists of many services, including generation, trading, transmission, and distribution. Trading and generation layers regard electricity as a tradable merchandise, whereas distribution and transmission layers concentrate on resolving technical issues and providing electricity services.

The main objective of deregulated (or liberalized) electricity markets is to maximize social welfare via competition. Nevertheless, designing a perfectly competitive liberalized market is tremendously difficult. In fact, it has been shown that some electricity markets act more like oligopolies [31, 120]. Few reasons for this oligopolistic behaviour can be reported as

- restricted number of generators due to entry barriers (e.g., high capital investment) for smaller companies,
- limitations in transmission and distribution networks (e.g., congestion) that isolates certain generators from some consumers, and
- losses in transmission lines that discourage consumers to purchase electricity from remote producers [31].

An unfavorable by-product of oligopolistic markets is the likelihood of participants engaging in collusion. Collusion is an agreement among multiple parties to evade perfect competition. In electricity markets, explicit collusion is prohibited, yet another form of collusion, which is called tacit collusion, exists in the absence of explicit agreement. Market designers and policymakers struggle to mitigate collusion between competitors to attain a competitive market. In general, detecting collusive behavior is of no simple task for regulators [3, 23]; nonetheless, researchers in [103], [44], and [38] have demonstrated that players might have engaged in tacit collusion in Wales and England, California, and Spain, respectively. These negative outcomes can be alleviated by employing innovative concepts such as the Local Electricity Markets (LEMs). In LEMs, the number of small generators is more than conventional markets, and this alone can make the market more competitive even though there is a growing body of the literature investigating the optimal coalition in LEMs [66]. The LEM also mitigates the congestion in the network. In Section 11.4, we will discuss this concept in more detail.

In the literature, three separate market modeling paradigms exist: equilibrium, optimization, and simulation models. While equilibrium models exhibit the general behavior of markets factoring into account individual participant models, optimization models concentrate on a single entity. In equilibrium models, price-taking behavior relates to perfect competition whereas strategic behavior pertains to imperfect competition. Equilibrium models that regard imperfect competition are ranging from simple economic models (e.g., Cournot and Bertrand competition) to more sophisticated mathematical models (e.g., Conjectural Variation (CV) and Supply Function Equilibria (SFE)). Finally, when the underlying problem is very complex to be addressed with equilibrium models, simulation models can be used as alternatives to generate insights.

Some researchers prefer equilibrium models, in which the solution can be computed rather straightforwardly using analytical methods. Nonetheless, because of strict simplifying assumptions, there is no guarantee that these outcomes are spotted in practice [30]. One of these streamlining assumptions is associated with the characterization and the length of the time period: Most analytical methods are restricted to monitor the system during a short and fixed time horizon (e.g., Cournot [97, 56], CV [98, 34] and Equilibrium Problem with Equilibrium Constraints (EPEC) [99]). These models implicitly assume a fixed-behavior for the Power Generation Companies (GenCos) over time. In addition, analytically solvable equilibrium models typically do not regard the physical constraints of the transmission network [97, 98, 99, 100]; for instance, Ruiz et al. [99] admit that introducing physical limitations of transmission lines makes their suggested analytical method intractable; therefore, they demand employing a numerical method instead of an analytical one.

On the other side of the spectrum, simulation models enable us to capture the dynamic behavior of participants in a real-life environment. For example, when one GenCo modifies its bidding strategy, other stakeholders observe this new arrangement, and will eventually respond to the new conditions such that serve their interests. A countless number of studies simulated electricity markets using agent-based models [102, 22, 112, 5, 4, 91]. Researchers believe that Agent-based Modeling and Simulation (ABMS) is a practical approach that can produce realistic knowledge about players' interactions within complex markets [64].

In the upcoming sections, each method is explained briefly with their advantages and disadvantages. Figure 11.5 categorizes various modeling techniques in the context of energy markets. Although equilibrium models are shown in top-down and bottom-up methodologies, their level of detail is different: CGE models are more aggregated, focusing on the whole economy; but, equilibrium models that are connected to bottom-up methods are mostly concentrated on the electric power sector. Hybrid models cause *modeling electricity markets* and *top-down approach* to intersect since the future consumption of demand services are often projected using top-down models.

In [33, 1], the authors provide an extensive review of the forecasting techniques used in the literature with respect to their time frame. The forecasting time frame can be categorized into three groups: short, medium, and long. In the short-term forecasting, researchers consider temporary inputs such as weather and past consumption to calculate projections for the next hour or the next week [39, 45]. Beyond a week to a year, researchers use medium-term forecasts [16, 15]. In the long-term forecast, socio-economic parameters such as GDP and population are used to develop projections beyond a year [121].

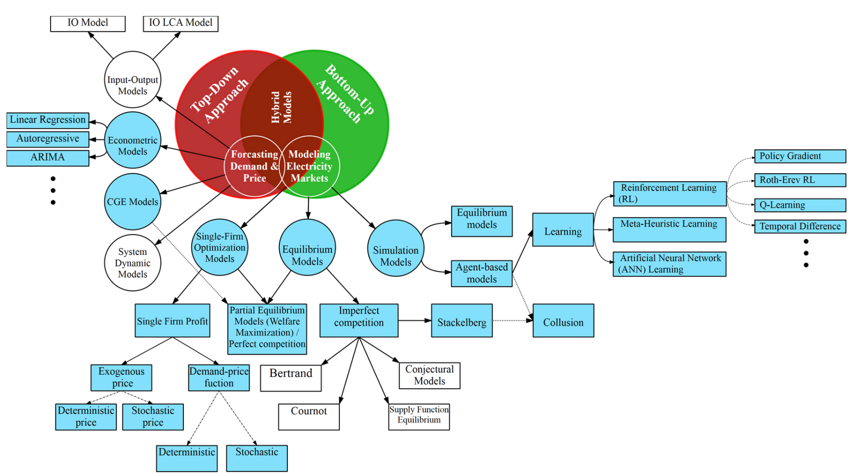

FIGURE 11.5 The taxonomy of various modeling approaches in the energy market. Blue elements are relevant to both local electricity markets and generic electricity markets.

11.3.1 Single Firm Optimization Models

Single firm optimization models mostly focus on the maximization (minimization) of profit (cost) or utility. The price of electricity, which is essential for the profit calculation, can be dictated either exogenously [42, 107, 90] or as a function of the demand [8, 13].

11.3.2 Multiple-Firm Equilibrium Models

A number of equilibrium models have been offered to study the oligopolistic behavior of deregulated markets: Cournot, Bertrand, and SFE are amid the famous models, while others, such as the CV and Stackelberg, have also been employed to analyze electricity markets.

11.3.2.1 Cournot Competition

In Cournot models, power producers compete over the amount of dispatched power, and the price of electricity is determined via an inverse price-demand function. Pros and cons are as follows:

+ Cournot models are well-established in the literature of microeconomics.
+ With a lower computational burden, it allows researchers to model producers' behavior in electricity markets with adequate detail that represent the real-world.
– Each producer presumes that its output can change the market price, but not competitors' production level.
– The cost function of every single GenCo is considered to be known to others; however, in reality, these pieces of information are confidential [89].
– Cournot models are highly sensitive to the demand elasticity.

11.3.2.2 Bertrand Competition

Unlike Cournot competition where quantities are the strategic decision variables of players, prices are assumed as the strategic decision variables in Bertrand models. Bertrand models consider no bound on the GenCos' production level, which is not a realistic assumption in electricity markets.

11.3.2.3 Supply Function Equilibrium (SFE)

Bidding supply-curves instead of quantities or prices provide better adaptability for players in dynamic environments. At the equilibrium solution of the supply function game, each GenCo specifies its optimal offer, which is a supply-curve, such that maximizes its payoff with respect to other GenCos' reactions concerning developments in market conditions, anticipating their strategies. The quantity and price in any SFE model are bounded by outcomes in Bertrand and Cournot models [58]. Advantages and disadvantages are as follows:

+ By gaming in both quantity and price, SFEs represent realistic pictures of electricity markets; thus, their price predictions are more reliable.

+ SFE prices are not as sensitive as Cournot models to the demand elasticity.
+ Unlike Cournot models, SFE models provide the possibility of developing insights into the bidding behavior.
– Solving SFEs are computationally burdensome; in fact, the equilibrium solution of an SFE model is obtained by solving a system of differential equations whereas solving a system of algebraic equations in a Cournot model; therefore, one can hardly obtain the closed-form expressions of a solution.
– Proving the existence of a solution, or its uniqueness, is hard except in trivial cases.
– It is not clear which solution better represents GenCos' strategic behavior when multiple SFE solutions exist.
– Transmission lines constraints are regarded solely in simplified SFEs.

11.3.2.4 Conjectural Variation (CV)

The CV method is employed to evaluate players' strategic behavior while reflecting the reactions of others with different competition levels. Many game theoretical bidding strategies and traditional market structures, such as Stackelberg, monopoly, perfect competition, and Cournot, are particular manifestations of CV strategies. Pros and cons are as follows:

+ Similar to SFE models, CV models also overcome the demand elasticity issue.
+ Several market competition levels can be modeled using CV parameters.
– There are discussions opposed to CV models regarding the stability of the conjectures and the likelihood of multiple equilibria.
– The necessity of identifying all rivals' CV parameters makes the method virtually impossible to be utilized in a real-life scenario.

CV models can easily be rendered intractable when transmission networks are being introduced [99].

11.3.2.5 Stackelberg and Multi-leader-follower Games

The Stackelberg model investigates non-cooperative games, in which a dominating leader in the market behaves strategically while followers act upon leader's decision. The multi-leader-follower game is the extended form of the Stackelberg game, where multiple leaders behave strategically and compete with one another. In a typical electricity pool market, the Independent System Operator (ISO) is considered as a follower while GenCos represent leaders; however, the role of leaders and followers might be different in other contexts. For instance, in [37], the follower is a virtual entity that determines the unit investment cost of a novel technology based on leaders' (i.e., GenCos) investment decisions.

As the process of decision-making in the multi-leader-follower and Stackelberg games are sequential, their equilibrium solution may suit better than other oligopolistic models to the long-term investment-decision problem according to microeconomics. Generally, Stackelberg games are modeled using Mathematical Programming with Equilibrium Constraints (MPEC) [113, 26], whereas multi-leader-follower games (e.g., [81, 63]) are formulated using Equilibrium Problem with Equilibrium Constraints (EPEC) since multiple leaders with dissimilar interests exist. EPEC models are mostly unsolvable by mathematical-based optimization techniques [94], which is why heuristics and meta-heuristics algorithms are proposed to resolve the issue [11].

11.3.3 Simulation Models

Simulation models exploit an alternative approach to calculate the solution of the equilibrium models for the complex problems when they cannot be addressed using conventional frameworks. Typically, simulation models describe agents' strategic decision dynamics using a collection of sequential commands and rules. The main advantage of the simulation approaches is the flexibility to model almost every type of strategic behavior.

11.3.3.1 Equilibrium Models

Often, simulation models are connected to a family of equilibrium models. In this class of simulation models, market players ignore learning and achieve the possible equilibrium by following predetermined rules. For instance, researchers may use Cournot models to support the efficacy of simulation models, in which GenCos' decisions are in the form of quantities. In order to find the CV parameters, Song et al. [100] introduce a simulation model, in which GenCos optimize their bid using CV method such that minimize their perceptual errors about rivals' competition levels at every iteration.

11.3.3.2 Agent-based models

In various disciplines, *agent-based modeling* and *multi-agent system* have been used interchangeably [84]; nonetheless, despite similarities, they are distinct from one another. Broadly speaking, multi-agent systems are emerging in real-world phenomena; however, agent-based models strive for replicating such systems for analytical purposes in simulation frameworks. Thus, the nature of agent-based models is to study the collective behaviors of agents who follow certain rules rather than solving a specific engineering problem.

In the agent-based models, modeling learning and intelligence are indispensable to a certain extent as agents have to decide and act autonomously in unknown environments [95]. Learning can assist GenCos in obtaining and enriching helpful information to display desirable performance in the future. Learning is particularly important in the electricity markets as the act of bidding is occurring repetitively.

The current economic theory widely imposes rational expectations assumption, by which the learning problem is being short-circuited [106]. To the greatest extent, the absence of (dynamic) learning in the game theory-based models may cause miscalculation in results and conclusions [115]. Nonetheless, agent-based models provide adequate flexibility to examine the impact of learning on GenCos' strategic behavior [93]. Various methods are employed to simulate learning in electricity markets; however, researchers emphasize more on reinforcement learning (RL) algorithms, especially model-free RL algorithms such as Q-learning due to the ease of implementation together with acceptable accuracy and convergence. In an environment that can be stated in the form of a finite Markov Decision Process (MDP), RL algorithms can be utilized to discover an optimal action-selection policy. Krause and Andersson [59] analyze multiple congestion management mechanisms employing an agent-based model, in which GenCos learn according to the Q-learning algorithm.

Using a generic Q-learning framework, Krause et al. [60, 61] study GenCos' strategic behavior and infer that in the presence of several Nash equilibria, GenCos' cognitive ability may fail to function properly. Thus, to improve Q-learning performance, researchers exploit features of other algorithms. For example, Bakirtzis and Tellidou [14], Tellidou and Bakirtzis [105], and Wang [115] combine Simulated Annealing with generic Q-learning to adjust exploitation versus exploration. In their method, exploitation rate increases as time progresses from a low value; simultaneously, exploration rate decreases to a minimum value at the end of simulation. Fine-tuning Q-Learning parameters using simulated annealing is regarded as a remedy to cope with the slow convergence or divergence.

Roth-Erev learning is a streamlined version of RL when a finite number of pure strategies are played by multiple players [96, 35]. Unlike Q-learning, Roth-Erev considers only one state for every agent; therefore, practitioners can avoid dimensionality curse and process the collected data faster. Veit et al. [112] employ Roth-Erev RL algorithm to study the impact of several congestion management mechanisms on the German electricity market. Li and Shi [64] use Roth-Erev RL algorithm in an agent-based simulation framework to analyze the link between weather forecasting and the net earnings of Wind GenCos.

The combined impact of risk sensitivity and learning behavior on GenCos' profits are explored in [5]. In their work, the authors develop an agent-based simulation model for dynamic electricity markets considering time-varying learning parameters and transmission constraints. They demonstrate that risk aversion to a certain level can increase GenCos' profits, whereas extreme level of risk aversion can cause intense price competition. In contrast, the model proposed in [91] focuses on the perspective of a supported player, with the unique aim at supporting its decisions to achieve the maximum profit.

11.4 LOCAL ELECTRICITY MARKETS

In order to create a competitive liberal electricity market, policymakers have envisioned a greater contribution from consumers in generating electricity [27]. In established electricity markets, exorbitant capital investment has prevented end-users from becoming active market players; however, thanks to the development of new technologies such as solar photovoltaic (PV) cells, electricity production at smaller scales is gradually becoming affordable, even without any support mechanism. The steep drop in cost and modularity of solar PV supports the building of an environment, the so-called Local Electricity Market (LEM), in which end-users (i.e., prosumers) with limited budgets can generate and trade electricity. However, the higher participation of prosumers corresponds with the following managerial difficulties:

- As the number of active players grows, the organization of the distributed generation (DG) becomes challenging.
- The power delivery is structured unidirectionally to transfer the electricity generated by large-scale fossil-fired power plants to end-users to be consumed instantaneously. Nevertheless, this paradigm is rapidly becoming obsolete since battery storage systems are getting cheaper, and prosumers can feed electricity into the grid. Thus, as the prosumers' share in the market increases, the transmission and distribution networks must transform to enable the bidirectional flow of electricity. To increase the stability of distribution networks, the use of smart grid technology is being advertised, through which aggregators can minimize and manage the reverse flow of power to low- and medium-voltage substations [75].
- Payments to prosumers should be negotiated with electric utilities. These utilities which have already invested heavily in conventional generation systems are reluctant to accommodate their business models to the new market conditions; therefore, prosumers often face resistance [80].

Simulation and optimization models have a proven record of solving managerial problems. Simulation models are mostly employed in disaggregated systems, whereas optimization models are common in centralized decision making. In [51, 95], the authors show that managing DG is feasible by means of multi-agent systems. Pinto et al. [92] use an agent-based model to simulate Virtual Power Plants (VPPs), whose premise is to bring flexibility to DG. However, due to the characteristics of LEMs, mixed models might be a better fit to answer research questions. For instance, Li and Willman [65] utilize a scenario-based analysis to conduct the simulation, in which various aspects of ocean energy penetrating local energy systems in remote areas are analyzed; therefore, in [65], the authors propose a mixed framework that combines optimization methods in sub-modules with a simulation method that generates scenarios.

In the following sections, we review various modeling approaches in the context of LEMs from different angles: market designs, the integration of renewables and energy storage systems, demand side management, and power system reliability.

11.4.1 Market Designs

Among multiple network structures, some researchers suggest the peer-to-peer (P2P) market mechanism to facilitate direct and secure trading between prosumers and consumers in the grid [25, 70, 74, 73].

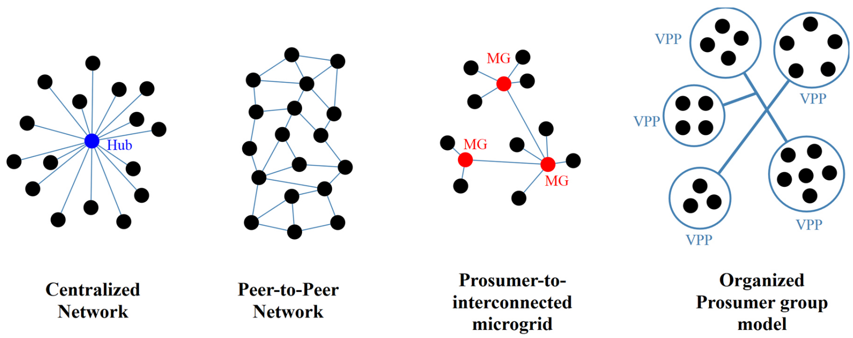

FIGURE 11.6 The network of prosumers in LEMs (for more detail, check Parag and Sovacool [87]).

In [74], the authors investigate two market designs using an agent-based model: a direct P2P market and a closed order book market. They conclude that the P2P market design with intelligent agents achieves a lower average electricity price. To facilitate decentralized coordination among non-trusting parties, Münsing et al. [80] propose exercising blockchain technology and smart contracts. Using the Alternating Direction Method of Multipliers (ADMM), the authors decompose their decentralized optimization model and implement it in the blockchain.

11.4.2 Renewable and Energy Storage Systems

Integrating an energy system with unpredictable renewables can make the whole system unstable. To prevent instability that can cause electricity outage, researchers have pursued three main approaches: developing better prediction models [88, 114], managing consumption, and utilizing storage systems to smooth out volatility in renewables.

In [73], agent-based simulation is utilized to analyze the impact of community electricity storage in a decentralized P2P local electricity market. Lüth et al. [70] implement an optimization model to represent P2P interactions in the presence of battery storage for a small community in London. They compare the contribution of centralized storage to that of decentralized storage. Unlike Lüth et al. [70], Xiao et al. [119] model a market in which not only electricity but also hydrogen can be stored and traded. A decentralized iterative procedure is developed to clear this market securely. The impacts of centralized and decentralized integration of battery storage and renewables are also studied in [53] using a Stackelberg game model. In the proposed model, the retailer sets the electricity price, and consumers adjust the consumption level to maximize their surplus accordingly. Their simplified analytic model helped to gain a better understanding of the *death spiral hypothesis* for retail utilities. Also, various control methodologies are studied in [118] to manage battery storage in residential energy systems based on three control architectures: centralized, decentralized, and distributed control. The objective of their optimization models is to minimize the variation in energy consumption across the network. According to their results, the centralized model offers the minimum variance; therefore, it is used as the basis of comparison to evaluate the performance of other methods.

Unfortunately, the current PV-battery systems are not managed optimally; to mitigate this issue, Klein et al. [57] suggest using scarcity signals to align prosumers with the electricity wholesale market and measure its efficiency using a so-called Market Alignment Indicator (MAI). They illustrate the performance of multiple policy instruments using MAI in a simulation framework, in which technical limitations of battery systems are formulated as a Mixed-Integer Linear Programming (MILP) problem. Using agents that exhibit no intelligence in a simulation framework, Ampatzis et al. [6] examine the efficiency of an LEM, in which solar PV and fuel-based generators provide electricity for local consumers and prosumers. In another study, Menniti et al. [76] employ a simulation framework to illustrate the performance of their optimization model (i.e., StLM) for managing distributed storage systems.

As experts expect to witness a growing demand for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) in the market, a body of literature is interested in the idea of exploiting these vehicles as a distributed electricity storage systems. Vayá and Andersson [111] introduce a Stackelberg game model, in which the upper-level minimizes the charging cost of electric vehicles, while the lower-level clears the market. They convert their MPEC model to a MILP problem and solve it using CPLEX. Tan et al. [104] propose a distributed optimization algorithm based on the ADMM that solves an optimization problem, by which renewable distributed generators and EVs are integrated. In [110], a three-tier approach is developed, in which the electricity demand of all PHEVs are aggregated; then an optimization problem is solved to minimize costs for electricity supply, and finally, an incentive signal is created for all PHEVs. Vandael et al. [110] put their method to the test via simulation runs. To the best of our knowledge, utilizing simulation frameworks to validate distributed optimization models is a well accepted approach in the LEM literature.

11.4.3 Demand Side Management

Another subject of study in LEMs is demand-side management. New technologies, such as the smart grid, assist us in applying innovative methodologies to shape demand so as to minimize costs and variation in energy consumption, and omitting network congestion [118, 2]. Demand Response (DR) can be implemented using load response and price-based programs.

In [75], the authors simulate a DR program for prosumers in a smart network. Ahmadi et al. [2] devise an optimization model to control residential loads which takes into account their necessity, re-schedulability, and controllability. In the proposed model, the authors consider both DR and control models. Giordano et al. [43] offer a two-stage optimization model that schedules prosumers' load/storage/production in the first stage and refines the solution by redistributing electricity surplus within the district instead of selling at a cheaper wholesale electricity price to the grid. Similar to Ahmadi et al. [2], electricity loads are divided to schedulable and nonschedulable loads.

11.4.4 Power Reliability and Resilience

Typically, the reliability of the power systems are secured using the $N - k$ contingency constraint [19]; thereby, the system will be able to satisfy the demand, even though k components (out of N) fail. However, resilience expands the definition of reliability as the system capability to predict, prepare for, endure and efficiently return to normal conditions [18]. Throughout the Iraq war, saboteurs and looters in Baghdad damaged and stole valuable parts of the electrical systems [78]. To cope with threats of this kind and strengthen national security, experts advise DG technologies by which one can remove vulnerable targets to terrorists [10]. Despite the importance of security measures against hostile actors, sound security measures should encompass natural disasters as well. The last example of such a necessity for DG occurred in California, where the wildfire caused a protracted blackout [79].

The damage induced by wildfires or earthquakes, even on a massive scale, is no match against bioterrorism and infectious diseases: The unprecedented economic crisis ensuing the COVID-19 outbreak caused the demand for all energy sources to fall [52]. Partial and full lockdowns reduced the electricity demand by 20% [29]; it also changed the demand shape since most industries were closed. The COVID-19 pandemic damaged many utility-scale power producers (i.e., burning coal, oil, and natural gas) as they are labor-intensive industries. Nevertheless, residential solar PVs, due to their autonomous nature and near-zero marginal cost, can unfold new opportunities to increase the reliability and resilience of communities against natural disasters of such scale [28].

Considering system reliability and supply-security, Arefifar et al. [9] suggest a systematic approach to construct an optimal design of microgrids with DG of many different types. The authors formulate their problem as a multi-objective programming model and solved using Tabu search, graph-theory techniques, and probabilistic power-flow methods. In [83], the authors develop a MILP model to design a defense strategy for the grid, in which transmission lines are protected against man-made attacks while considering the threshold risks and investment costs. The computation time of the developed model grows exponentially as the number of buses increases from 6 to 57. To improve the resilience of power systems, Lin and Bie [67] propose a tri-level defender-attacker-defender (DAD) model and solve using a column-and-row generation method. According to Panteli and Mancarella [86], one can enhance the resilience through hardening and operational measures; therefore, the developed model determines the best hardening strategy on the first level. Then, attacker optimizes its actions to have maximum damage on the second level. Finally, given the damage after hardening plans, the defender finds the best operational plan including DG islanding formation to restore the system on the third level. Although the proposed model is solvable in a matter of hours for two case studies with 33 and 94 buses, the computation efficiency of DAD models should be improved. With some caveats [21], heuristics might be a better fit to solve DAD problems for networks with a huge number of microgrids.

11.5 CONCLUDING REMARKS

Deregulation of electricity markets, although motivated by various reasons in different regions, was considered as revolutionary. However, the challenges came along. To begin with, it requires an elaborate analysis to understand whether deregulation had served the purpose of intention while the outcomes heavily relies on various external parameters. While the biggest challenge lies in recognizing and interpreting the behaviors of players in the market, imperfect conditions are usually detected to result in unwanted outcomes. In this respect, while the top-down macroeconomic approaches are only conducive in constructing hypothesis on principals of fundamental market design issues, the bottom-up engineering approaches bear more potential in predicting behaviors of market players and prescribing solutions to prevent undesirable outcomes. Nonetheless, to address certain questions that may arise in analyzing energy and climate policies, scientists suggest combining these basic approaches to benefit from technological explicitness and behavioral realism, simultaneously.

A more recent milestone in deregulation and liberalization of markets has emerged as the advancement in DG technologies; their deployment throughout distribution systems have led to a rapid increase in new players, i.e., prosumers, in local supply of electricity. While this development dictates reconsideration of market designs in an unstructured manner, renewables and energy storage systems as well as demand side management have also risen together with LEMs. There are many new challenges ahead for integrating LEMs into existing power grids originally designed for centralized generation. However, both the technical and market-wise integration of LEMs into the conventional grid would provide many benefits including the following aspects:

- Current wholesale competition among generation companies would be spread over all players in the market; hence, small consumers would benefit by participating in the market directly as well as through increasing energy autonomy.

- Incorporation of renewable and DG would facilitate decarbonization of existing power sector.
- DG, especially when it is equipped with the rooftop solar PV systems, can improve the network security.
- Transmission system losses due to centralized power system would diminish due to local generation.
- Energy for remote areas would be easily and conveniently provided.
- These new resources may provide ancillary services for the power system.
- Last but not least, integration of new players in the market would eliminate opportunities for market power and collusive behavior of players.

On the other hand, there are also some very likely threats that come along with this new era. Uncertain and intermittent nature, near-zero marginal cost, strong site specificity of DG and its penetration in LEMs creates new challenges in day-ahead scheduling, real-time dispatch and network security for system operator. Furthermore, bidirectional power flows introduced by these resources in the power system that is designed for unidirectional flows creates new technical challenges, i.e., emerging system configuration and setup.

Both the expected benefits and the impacts of upcoming threats are to be reflected in the analytical models including and not limited to optimization, simulation and decision-making tools. The existence of DG through LEMs change the span and scope of such tools. Integration of these new agents into the existing grid system requires new methodologies and approaches. In addition, both the degree of uncertainty and the degree of freedom in decisions are magnified; it will naturally require more sophisticated analytical modelling tools not only to analyze and understand the market but also to provide decision support for various players in the market. While such developments are inexorable from the point of view of policy makers and practitioners, novel propositions are to emerge in research immediately.

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