Applied Energy 357 (2024) 122495

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Power market models for the clean energy transition: State of the art and future research needs

Mari Haugen [a,b,1,**], Paris L. Blaisdell-Pijuan [c,d,1], Audun Botterud [d,e,*], Todd Levin [d], Zhi Zhou [d], Michael Belsnes [b], Magnus Korpås [a], Abhishek Somani [f]

[a] Norwegian University of Science and Technology, Department of Electric Energy, Norway
[b] SINTEF Energy Research, Department of Energy Systems, Norway
[c] Princeton University, Department of Electrical Engineering, United States of America
[d] Argonne National Laboratory, Center for Energy, Environmental, and Economic Systems Analysis, United States of America
[e] Massachusetts Institute of Technology, Laboratory for Information and Decision Systems, United States of America
[f] Pacific Northwest National Laboratory, Distributed Systems Group, United States of America

HIGHLIGHTS

- Review methodologies and assumptions commonly used in power market models.
- Identify model design features critical to analyzing the clean energy transition.
- Survey current state-of-the-art in modeling low-carbon power markets.
- Identify key model improvements needed for future deep decarbonization scenarios.
- Highlight importance of tailoring tools for specific power market applications.

ARTICLE INFO

Keywords:
Power market modeling
Flexibility
Hydropower
Energy storage
Grid services
Price formation

ABSTRACT

As power systems around the world are rapidly evolving to achieve decarbonization objectives, it is crucial that power system planners and operators use appropriate models and tools to analyze and address the associated challenges. This paper provides a detailed overview of the properties of power market models in the context of the clean energy transition. We review common power market model methodologies, their readiness for low- and zero-carbon grids, and new power market trends. Based on the review, we suggest model improvements and new designs to increase modeling capabilities for future grids. The paper highlights key modeling concepts related to power system flexibility, with a particular focus on hydropower and energy storage, as well as the representation of grid services, price formation, temporal structure, and the importance of uncertainty. We find that a changing resource mix, market restructuring, and growing price uncertainty require more precise modeling techniques to adequately capture the new technology constraints and the dynamics of future power markets. In particular, models must adequately represent resource opportunity costs, multi-horizon flexibility, and energy storage capabilities across the full range of grid services. Moreover, at the system level, it is increasingly important to consider sub-hourly time resolution, enhanced uncertainty representation, and introduce co-optimization for dual market clearing of energy and grid services. Likewise, models should capture interdependencies between multiple energy carriers and demand sectors.

* Corresponding author at: Argonne National Laboratory, Center for Energy, Environmental, and Economic Systems Analysis, United States.
** Corresponding author at: Norwegian University of Science and Technology, Department of Electric Energy, Norway.
E-mail addresses: mari.haugen@ntnu.no (M. Haugen), abotterud@anl.gov (A. Botterud).
[1] First authors.

https://doi.org/10.1016/j.apenergy.2023.122495
Received 20 June 2023; Received in revised form 1 December 2023; Accepted 11 December 2023
Available online 25 December 2023

1. Introduction

The global urgency to decarbonize is typified by the rapid growth in research and deployment of new low-carbon infrastructure throughout the energy economy. These changes are driven by national initiatives such as the United States' commitment to create a carbon-free power sector by 2035 and a net-zero emissions economy by 2050, the European Union's law to cut emissions 55% by 2030 and to be net-zero by 2050, and China's goal to achieve net-zero emissions by 2060 [1]. Meeting these goals will require energy infrastructure changes at an unprecedented rate, a process that is already well underway. The power sector is the linchpin in these efforts because of the potential to deploy zero-carbon electricity generation technologies and supporting technologies such as energy storage and for its role in decarbonizing other sectors of the economy, such as transportation, heating, and manufacturing. Thus, the power sector is undergoing a paradigm shift characterized by the rapid deployment of variable renewable energy (VRE) resources. Such rapid change creates several integration challenges for power grids and markets, where maintaining system reliability with increasing shares of variable and uncertain power production is a critical high-level challenge. Power market models help to identify effective solutions to these challenges by simulating the planning and operation of different future power system configurations.

One crucial aspect of securing a reliable energy transition is ensuring that the increasing demand for system flexibility is met. Flexibility can be broadly defined as the system's ability to adjust to variability and uncertainty across all time scales, from milliseconds to days, weeks, and years [2,3]. Traditionally, many components of system flexibility, such as fast-start resources or ramping capabilities, have been taken for granted and not provided with direct incentives or compensation due to either low system requirements or high supply levels. However, in future grids with high levels of VRE, demand for flexibility may increase while availability decreases. It will therefore be essential to revisit market-based incentive mechanisms for flexibility to ensure sufficient investments are made in flexible technologies, e.g., energy storage, flexible generation such as hydropower, demand-side management and demand response, transmission infrastructure, and infrastructure that enables sector-coupling [2–5].

In addition to requiring additional flexibility, future zero-carbon systems will likely be characterized primarily by resources that have zero or close to zero marginal costs. This may substantially impact price formation in markets for energy and ancillary services, and some studies have already found a significant reduction in prices in areas with high VRE penetration, i.e., the so-called “merit order effect” [6]. Reduced short-term prices caused by increasing shares of zero-carbon resources may decrease incentives for investments in new generation capacity, which can ultimately impact system resource adequacy and reliability. Several market design approaches have been proposed to ensure resource adequacy and revenue sufficiency in future low-carbon power systems [7]. Proposed ideas range from refinements to existing market solutions, such as improving price formation in energy and capacity markets and increasing reliance on long-term auctions and contracts to reduce risk exposure for investors, to more substantial re-design of electricity markets. However, no consensus has emerged regarding optimal electricity market design solutions for the energy transition. In reality, multiple market designs and regulatory mechanisms will likely be needed to accelerate investments in clean energy resources and maintain reliability in the power system cost-effectively.

Addressing these challenges requires power system models that accurately represent the nuances of a rapidly changing grid and provide insights into the dynamics of future power markets. Specifically, power market models, a subset of power system models, aim to provide insights into the scheduling, dispatch, and pricing of energy and reserves. These models are critical tools to help power system planners, operators, policymakers, and regulators assess future system needs and understand how evolving market designs and price formation mechanisms impact the incentive-driven investment and operational decision-making of market participants. Power market models are already evolving in response to these challenges and the specific needs that have emerged from the ongoing transition. For example, in recent years, new models have been developed to assess long-term market contracts for energy and capacity, to provide price forecasting and resource valuation, to study resource participation in ancillary markets, to integrate the power system with other energy sectors, to optimize microgrid design and their interaction with power markets, and more [3,8,9]. These models serve different purposes and are driven by different assumptions and mathematical formulations. Therefore, their results and conclusions may differ, even when applied to analyze the same system. Identifying, discussing, and understanding the differences between power market models will elucidate new insights that are important for improving models and implementing innovative solutions in future power markets.

It is critical for power market models to accurately represent resources such as hydropower and energy storage that provide real-time balancing and essential grid services with fast response time and low marginal cost, yet such resources are often misrepresented or undervalued in power market models [10–12]. Specifically, studies must account for the future availability and operational strategies of these resources and their effect on market prices to ensure proper remuneration and incentives for flexible resources. Hydropower is given particular attention in this study as it is the most widely available and utilized source of dispatchable zero-carbon generation capacity and accounts for more than 90% of all energy storage capacity globally [13].

In practice, limits on computational resources and data availability constrain the level of detail that can be included in a power market model. It is therefore important for modelers to consider the intended application of the model and assess cost-benefit tradeoffs when determining how to structure model formulations and simplifying assumptions. Model developers face many challenges, including the need to capture highly resolved spatial and temporal representation, accurately represent resource cost and performance characteristics, incorporate new market designs and grid services, model long-term contracts for ancillary services, energy, and capacity, overcome data limitations, maintain computational tractability, and more [14].

In this paper, we review power market models, identify key model design characteristics, and how they affect the model's ability to provide insights into market dynamics and inform decision-making for the clean energy transition. As previous model reviews primarily focus on general energy system modeling, we target power market modeling in this review. In particular, we address the limited understanding of how the design features of models translate to their ability to represent future power markets and to provide insights into specific questions about market design. Through our review, we identify how power market models need to evolve to study next-generation low- and zero-carbon power markets.

The main contributions of the manuscript include:

- A comprehensive literature review of market model methodologies, design features, and market trends as they pertain to future low-carbon power systems.
- Identification of how the ongoing energy transition and corresponding electricity market trends translate into design characteristics and needs for future power market models.
- Identification of the various approaches in representing system flexibility in power market models and a discussion of their benefits and drawbacks.
- A discussion of the model representation of hydropower and storage resources and their growing role in low-carbon power markets.

In Section 2, we provide a summary of previous related work and elaborate on how our review offers additional insights. Section 3 provides a basic review of power market model methodologies, defining general approaches to optimizing or simulating power markets. The

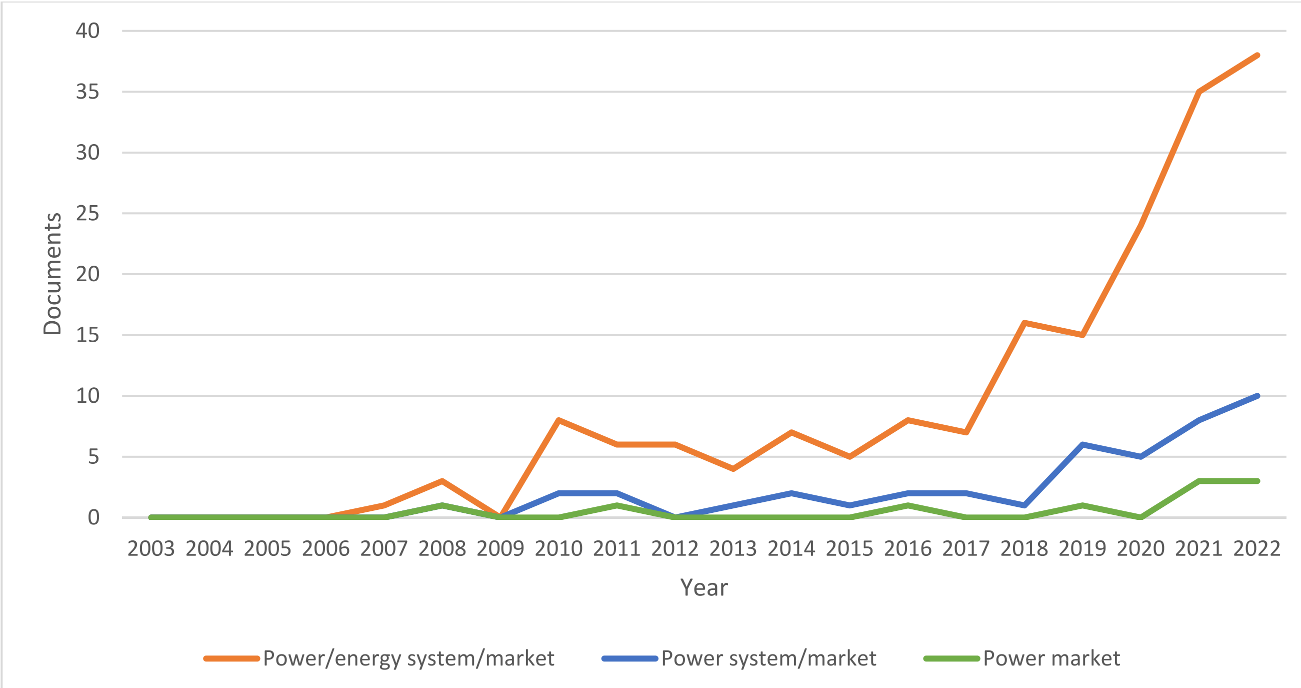

Fig. 1. Total yearly publications reviewing models used in energy and/or power systems related to decarbonization or energy transition. Based on searches in the Scopus database for papers including variants of the words "power/electricity/energy system/market model", "power/electricity system/market model", or "power/electricity market model" along with "review/survey" and "decarbonization/low-carbon/zero-carbon/renewable/transition/green". (Source: Scopus). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

section is focused on providing a foundation of several fundamental methodologies commonly utilized in current literature and sets the stage for the design features we introduce in Section 4. In Section 4, we provide more detail on the common treatment of different model design features as well as their respective limitations and benefits. We then draw upon these insights to identify tradeoffs across current market models, highlight how model methodologies correlate with their results across different applications, and establish key considerations for future model development and application. Section 5 reviews how power market models have been applied to analyze and address decarbonization goals, with a focus on how the design features introduced in Section 4 have been utilized and how market trends correspond to future model needs. Finally, Section 6 concludes with a summary of key findings, including proposed directions for future work.

2. Previous work

Energy and power system models are receiving increasing attention in the existing literature. Fig. 1 shows how the number of review publications has grown over the last 20 years and illustrates the importance of assessing modeling tools under fast-changing conditions. The figure also reveals that the broader scope of energy system modeling has gained the most attention. There are fewer review publications related to power systems and fewer yet related to power markets.

Review papers on modeling tools serve different purposes and cover a wide range of perspectives, ranging from providing a classification of models to assessing the suitability of models for various applications and identifying challenges or trends [15,16]. Many papers review specific models or frameworks, some consider models proposed by academia, and others focus more on general findings. We find that most model review papers focus more broadly on energy system modeling and the challenges they face in the energy transition [17–21]. These challenges are dominated by issues related to VRE integration, although some recent papers focus on the ability of models to account for social aspects and energy justice [22,23]. Some review papers focus specifically on a subset of models, like open source/access models and their performance compared to conventional models [24,25]. In contrast, others focus on a specific technology, like nuclear [26] or hydrogen [27]. Some review papers on energy system modeling also cover power market models. For example, Pfenninger et al. review different categories of energy system models, including power system and power market models [28]. Savvidis et al. classify energy system models, including power market models, to identify gaps between low-carbon energy policy challenges and modeling capabilities [16]. Chang et al. identify current trends in energy system modeling and review 54 tools, including power market models [15]. Yoro et al. review recent advances in modeling and simulation for renewable and sustainable energy systems, including those related to power market models, with a particular focus on current approaches, challenges, and prospects [29]. Després et al. focus both on power sector and long-term energy system models and the need to evaluate long-term scenarios for energy system decarbonization [30].

Other review papers focus strictly on the power sector. Foley et al. review power system models broadly in the context of market liberalization and VRE integration and also discuss several existing models, including some power market models [31]. Koppelaar et al. review the characteristics of power system models in general, and German models in particular, and study their suitability for policy analysis [32]. Deng and Lv review the evolution of optimization models for power system planning with increasing shares of VRE and find a need for more detailed modeling of flexible generation, energy storage, and demand response [33]. Oikonomou et al. review power system models ranging from power flow, and production cost to planning models, classify the relationships between them, and suggest a range of model improvements [34]. Many review papers provide an overview or survey of existing tools and address their suitability for different use cases, for example, to study VRE integration, expansion planning, or to inform policy decisions. Both Connolly et al. and Ringkjøb et al. describe and review a wide range of energy and power system modeling tools and focus on their suitability for analyzing VRE integration [8,35]. Neither of the above-mentioned papers provide an in-depth review of specific market

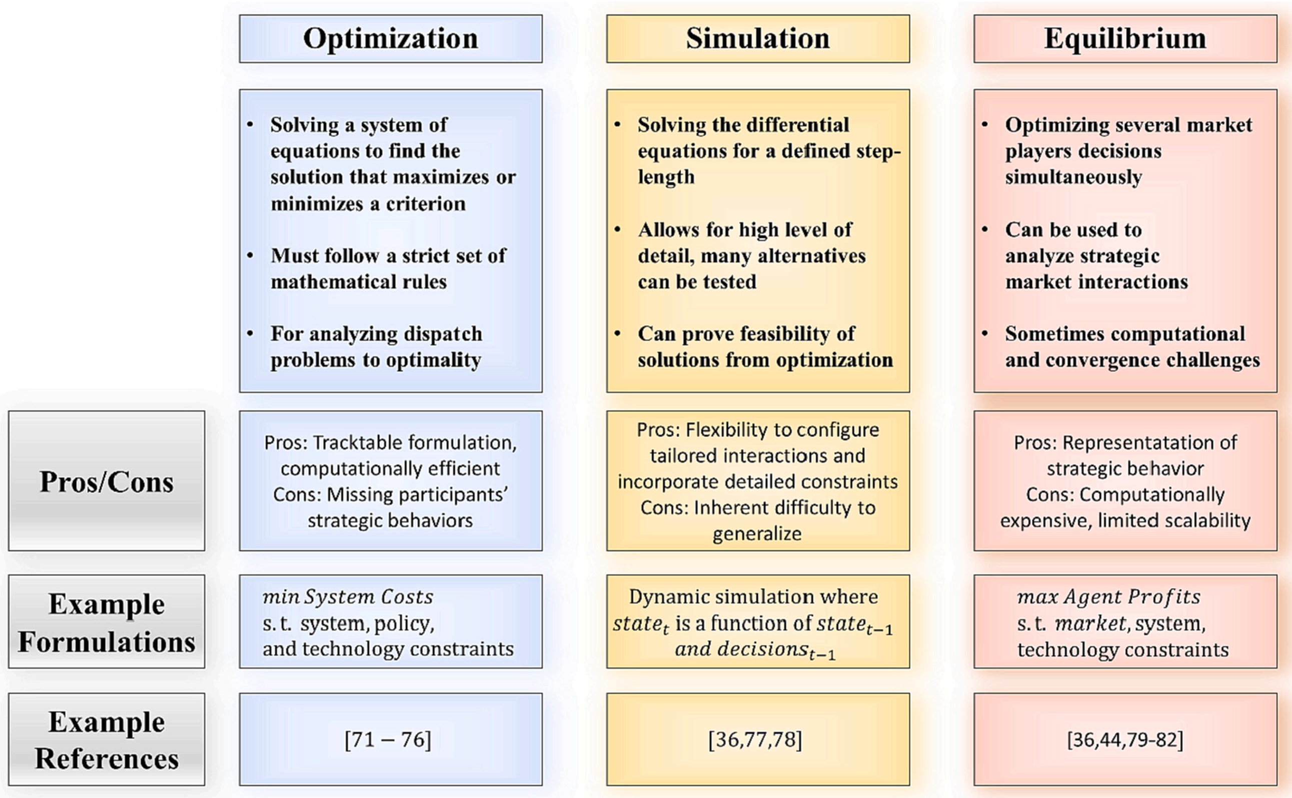

Fig. 2. Three fundamental model methodologies from which a power market model can be formulated: optimization [71–76], simulation [36,77,78], and equilibrium [36,44,79–82].

modeling challenges.

A smaller subset of the review literature focuses specifically on power market models. Early on, Ventosa et al. classified models as single-firm optimization, equilibrium, or simulation models and provided a detailed discussion on subtopics, including strategic interactions, Nash equilibrium, electricity price projections, stochasticity and risk analysis, and agent-based models [36]. The work is an excellent starting point for introducing the scope and dynamics of power market models. More recent market model reviews have followed a similar structure, covering new power system challenges, such as the need for higher time resolution, time-domain reduction methods, sector-coupling, and new market products [2,37,38].

Many reviews focus on specific aspects of power systems, such as power market design, the representation and valuation of VRE and energy storage, expansion planning, uncertainty modeling, or flexibility-related challenges. Hu et al. [39], Sequeria et al. [40], and Johnathon et al. [41] reviewed market design problems and political barriers in high VRE systems but left out consideration of market modeling. Honkapuro et al. review European market design and examine methods used for modeling market mechanisms [42]. Menegaki et al. studied early methods for VRE valuation but didn't consider other aspects of power market modeling, such as dispatch considerations, resource representation, and grid service representation [43].

Other VRE modeling reviews focus more on the planning problem and less on market issues [44,45]. Bistline et al. review the representation of VRE in long-term power sector models and complementary technologies like energy storage [46]. Levin et al. review challenges and opportunities for capacity expansion modeling with a particular focus on the role of energy storage in decarbonizing the grid [47]. In Oree et al., the authors reviewed how environmental considerations are integrated into planning models and categorized methods based on external costs and constraints, multi-objective approaches, methods for handling uncertainty in VREs, and dispatch and pricing behavior under high VRE penetration [45]. Ballireddy and Modi reviewed solution algorithm techniques for planning models in the context of reliability and uncertainty [48]. However, they do not discuss the design characteristics of market models, the challenges they face in integrating solutions, or how they are used in practice. Siala et al. compare five power market models applied to analyze generation expansion in Europe, but the investigation is limited to how model type (optimization or simulation), planning horizon, and temporal and spatial resolution affect model results [49]. Gacitua et al. also review expansion planning models but focus on their potential for energy policy analysis with an emphasis on policy instruments for VRE integration [50]. There are also power market model reviews specifically focused on agent-based power market models, reviewing both the methodologies and availability of these tools [9,51–53] or more specific details like the use of machine learning in such tools [54].

Flexibility and uncertainty have attracted increasing focus as power systems and markets adopt higher levels of weather-dependent production, and some papers study how uncertainty can be or is represented in current models [55,56]. Lund et al. reviewed trends in alleviating flexibility issues, including demand-side management, supply-side solutions, and grid services, but did not cover the design consideration of models and how their characteristics affect their ability to model such solutions accurately [3]. Villar et al. reviewed system flexibility, grid services, and market design but did not cover related challenges of modeling tools, particularly the main design features representing these critical areas [57]. Other reviews focus on modeling specific flexible technologies, like the ability of models to accurately represent and value energy storage resources with different technology types and operational practices [11,46,58–60]. Similarly, there have been several reviews on hydropower modeling, including pumped storage hydropower (PSH) [61], resource utilization, and sustainability [12,62,63]. There are also reviews on demand response and sector-coupling, focusing on the utility these mechanisms provide [64–70]. However, these technology-specific reviews only lightly touch on the larger scope of power markets and how accurate representation of these resources fits within the requirements of future market models.

As demonstrated by our review of previous related research outlined above, a growing emphasis in literature lies in the capability of models to keep up with different needs brought on by the energy transition. Nevertheless, it is evident that most literature reviews concentrate on energy system models, while the specific details of power market modeling have gained less attention. Furthermore, numerous studies delve into specific tools, a subset of models, the representation of a particular technology, or specific aspects of market modeling without covering a broader picture of the underlying design considerations. In this paper, we address this gap in the literature by providing new insights through an up-to-date review of power market modeling, with a special focus on model design features we identify as critical for accurate representation of future renewables-dominated systems that are likely to follow from the clean energy transition.

3. Power market model methodologies

It is common to distinguish power market models based on their mathematical foundation, solution approach, and target application [8,36,38,44,45]. In this section, we review several different power market models methodologies and provide a brief overview of common use cases. A variety of optimization and modeling methodologies are utilized in power market modeling. Modeling approaches can be grouped into three categories (Fig. 2): optimization-based, simulation-based, and equilibrium-based methodologies. Optimization models are typically used in power systems and markets that are planned and operated to achieve specific objectives, usually related to system cost. Simulation methods are applied when investigating interactions among subsystems or market participants with different objectives. They can model detailed interactions between physical system components and strategic behaviors, such as bidding behaviors of generation resources in a competitive wholesale market. Alternatively, if economic equilibrium solutions emerging from strategic interactions are of particular interest, the problems can be formulated as equilibrium models. These three groups of methodologies are not mutually exclusive, as simulation- and equilibrium-based models can be embedded with optimization-based subproblems or converted to traditional optimization-based models.

These three categories are intended to provide a structure for introducing how models are commonly constructed and applied. A detailed review of all solution approaches and use cases is beyond the scope of this manuscript. Rather, we provide this general description of model methodologies and typical uses to give context for the key model characteristics introduced in Section 4. This may aid in understanding the tradeoffs between key characteristics and model results as they pertain to the different model methodologies.

3.1. Optimization models

Optimization models seek to capture the dynamics of a power market and individual power system assets by minimizing/maximizing an objective function subject to a set of constraints. It is common to categorize optimization models as linear or nonlinear and deterministic or stochastic. The linearity refers to the relationship between decision variables in the objective function and model constraints, while the stochasticity of a model refers to whether uncertainty is modeled in selected input parameters or if inputs are treated deterministically. The most straightforward market models are deterministic and linear and can be solved with linear programming (LP) methods. Often, these models include integer variables to better represent operational constraints in the system and are, therefore, solved with mixed integer linear programming (MILP) methods. These models do not consider strategic behaviors among market participants, and decision variables are solved for by minimizing the total system cost based on the reported cost structure of generation resources. They are commonly adopted by current electricity market operators.

In the research literature, nonlinear objectives have been applied recently for modeling demand response and time-of-use retail rates [83–85]. Stochastic optimization has been used to manage various power market uncertainties, including but not limited to demand, weather, and renewable energy [86,87]. A variety of stochastic modeling techniques have been proposed to model uncertainties in a market, including stochastic programming [73,88], robust optimization [74,89,90], and chance-constrained optimization [75,91–93]. In addition to different mathematical formulations, each stochastic modeling technique may represent different risk preferences. For example, stochastic programming models are typically risk-neutral since they consider all possible scenarios based on their probability. In contrast, robust optimization models are more risk-averse since they make decisions based on the possible outcome of the worst scenario. In addition, market models can be single- or multi-stage, based on the decision-making process of underlying systems [76,94–96].

The main challenge in applying optimization models in power market analysis lies in the computational requirements of solving problems with highly resolved spatial, temporal, or system representation. Generally, the more variables and constraints in a problem formulation, the harder the problem is to solve. Thus, these models must be developed and applied with the tradeoffs between design feature choices and computational difficulty in mind. On the other hand, in addition to conventional exact solution search techniques, heuristic search algorithms have been proposed, such as particle-swarm optimization [97], genetic algorithms [98–100], and machine learning techniques recently [101–106]. Aguila-Leon et al. utilizes particle-swarm optimization to optimize a set of artificial neural networks managing self-adaptable energy microgrids, demonstrating the potential of learning algorithms in contained energy systems [97]. Additional processes may also be used to overcome computational challenges. Teichgraeber et al. utilized a time-series aggregation method that reduces computational time by 1–3 orders of magnitude while maintaining similar or more granular results across multiple optimization methods [107].

3.2. Simulation models

Other reviews of power market models have clearly distinguished between simulation-based models and optimization models [36,77]. In general, simulation-based models do not utilize a single system objective function but instead establish rule structures that govern interactions between system components. These interactions can be iterated algorithmically or can be determined by solving sets of independent optimization problems. Hence, optimization and simulation models are not necessarily mutually exclusive. One example of this is an agent-based model, in which the behavior of each individual market participant - or agent - is parametrized and solved for based on their assumptions regarding the behaviors of the other agents. This iterative process is completed for each time step until a convergence or another stopping criterion is reached [36,78]. Some of the advantages of simulations include the flexibility to configure interactions, in certain cases reduced computational burden and therefore the possibility of including more detailed operational constraints, and the ability to represent asymmetric market behavior. Drawbacks include the inherent difficulty of generalizing simulation results to all markets, especially systems that have time dependencies, such as those relying on long-duration storage technologies.

3.3. Equilibrium models

Power market equilibrium models are based on the formal economic definition of solving for market equilibria. Equilibrium models can be used to analyze the design of an individual market or multiple related

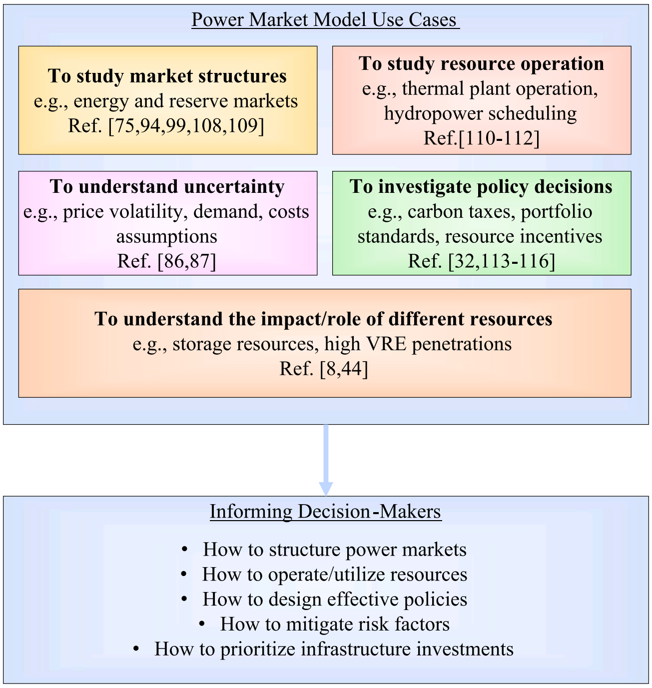

Fig. 3. Examples of different market model use cases and ways they can be used to inform decision-makers in the power sector, e.g., to analyze market structures [75,94,99,108,109], resource operation [110–112], uncertainty [86,87], policy decisions [32,113–116], the role of different resources [8,44].

markets. In a partial equilibrium model, feedback from related markets is either fixed or ignored, while a general equilibrium model incorporates feedback mechanisms from related markets. For instance, agents' bidding strategies in day-ahead and real-time energy markets can be highly interdependent. However, a partial equilibrium model of day ahead market behavior will typically assume fixed behavior in the real-time market and not capture the dependencies between the two markets [36,44]. More complex examples can include interactions and feedback between long-term capacity markets and financial transmission rights markets.

Equilibrium models are usually applied to analyze the strategic interactions of multiple agents in either a partial or general equilibrium framework. The concept of equilibrium in these models is based on the known or assumed competitive environment in the market of interest, and agents compete by strategically submitting bids and offers into the market. For instance, in a power market model based on Cournot competition, the equilibrium model determines generator quantities or outputs. The distinction between equilibrium and optimization models can also be blurred, as often, market equilibria are determined by formulating and solving multiple optimization problems.

The type of optimization approach that is utilized determines how these models are mathematically constructed and how their equilibrium outcomes are determined. In general, equilibrium models are formulated as some form of a mixed complementarity problem to account for the interactions between different markets or multiple agents' strategic behaviors within the markets. For instance, the strategic bidding behavior of multiple agents in a day-ahead energy market can be formulated as an equilibrium problem with equilibrium constraints (EPEC). In such a setup, an individual agent's optimization problem consists of equilibrium constraints representing known or assumed response functions, which guide the choice of optimal price and/or offer quantity.

In summary, equilibrium models incorporate feedback between different markets and between multiple agents in a single market or multiple interdependent markets. These models can be used to analyze

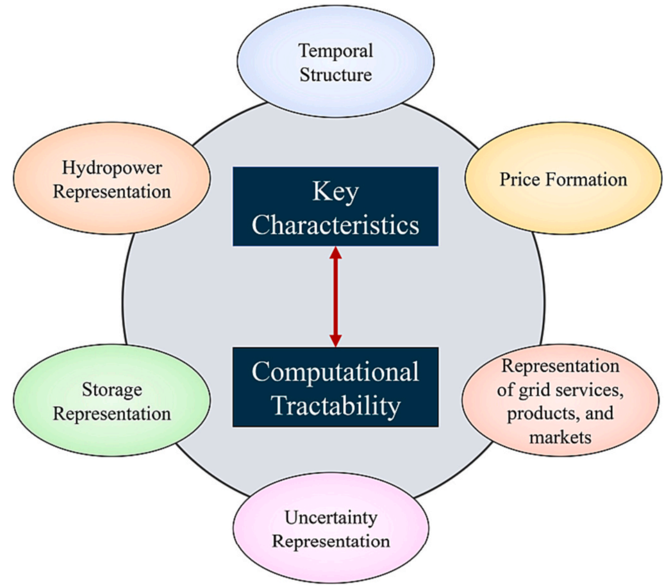

Fig. 4. Illustration of selected power market model characteristics of particular relevance for the clean energy transition and the tradeoff between key characteristics and computational tractability.

market designs by identifying conditions under which participants can exert market power or test incentive compatibility based on known or assumed agent behaviors.

3.4. Market model use cases

The results generated from applications of the three categories of models discussed above may reveal market trends, system requirements, and other nuanced behaviors of power markets and their agents under projected or hypothesized future system conditions. These model outputs inform decisions in the power sector, complementing information obtained from other sources, including analysis of historical market data, economic and political trends, and results from production cost simulations and long-term power system planning models. The value of power market models resides in their ability to analyze how different operational strategies, participant behavior profiles, uncertainty representation, policy decisions, market design options, and system sensitivities impact outcomes for the market as a whole and for different individual resources. Since it is impossible to model every dependency and uncertainty in a power market, the main benefit of market models is found in their ability to identify trends and understand the behavior of power markets under a range of different assumptions. A summary of selected market model use cases and how they support decision-making in the electric power sector is given in Fig. 3.

4. Power market model design features

This section reviews key design features of power market models that are particularly relevant to the clean energy transition. We identify trends in how markets are represented and propose considerations for modelers to evaluate when balancing tradeoffs in model design. The design features we cover are shown in Fig. 4. Each feature plays a critical role in developing high-fidelity model representation when modeling low-carbon power markets. We start each review with a basic introduction of the design feature and its tradeoffs, then summarize trends in the relevant literature and describe how these tradeoffs should be considered when designing a power market model. In Section 5, we review studies of low-carbon power markets to illustrate the importance of these design features and analyze the advantages and limitations of different design choices.

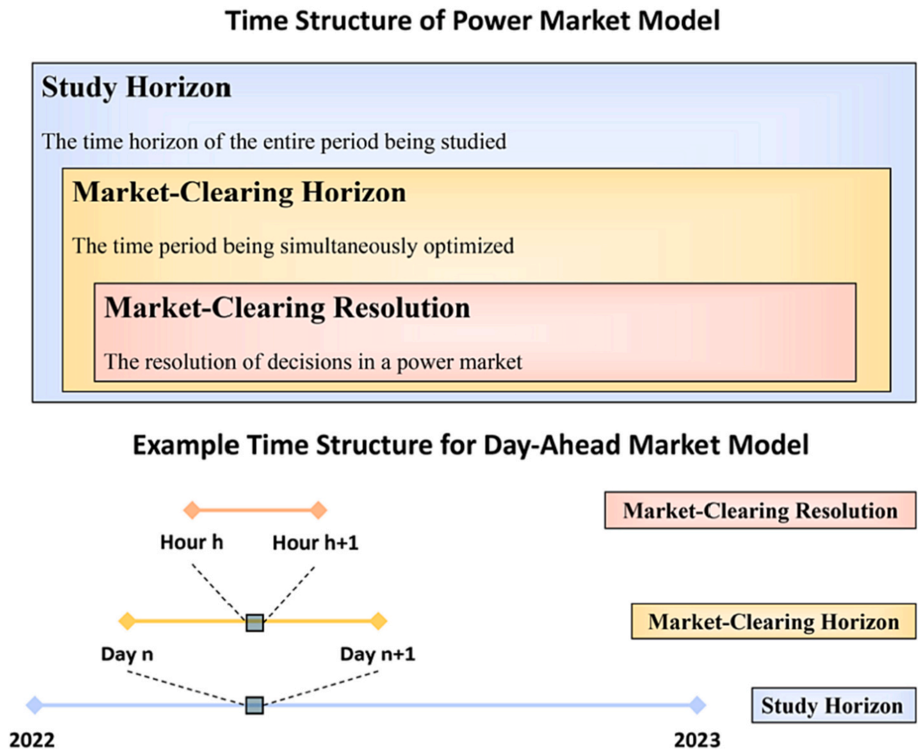

Fig. 5. The three basic temporal dimensions within a power market model.

4.1. Temporal structure

Temporal structure is one of the most fundamental design features of a power market model. It provides a framework for model constraints, defines the representation of the dynamics of dispatch and generator behavior, and dictates how markets will be cleared. The fundamental temporal structure of a model (described in Fig. 5) has many components, including the study horizon, the market clearing horizon, and the market clearing resolution. The choice of this structure presents a tradeoff in model design, where increasing the detail of any of these components also increases the computational burden of the model [77,117]. The study horizon defines the entire timeframe that the model considers and analyzes. The market clearing horizon represents the time period during which decisions are simultaneously made or optimized by the market operator. In contrast, the market clearing resolution represents the granularity of individual model time steps, i.e., the resolution of decision variables.

The market clearing resolution in a model should ideally reflect the time resolution used in the actual market clearing. Likewise, the market clearing horizon should be aligned with the actual market clearing timeframe, although it is sometimes shortened to reduce the underlying problem size or lengthened to mitigate edge effects at the end of the clearing timeframe. A short-term market is cleared for a fixed horizon (e.g., 24 h for day-ahead and one to a few hours for real-time). This can be changed, especially when considering resources with longer decision horizons, such as long-duration energy storage (e.g., hydro reservoirs) [11]. The decision horizon influences problem size and the size of each time step within this horizon. Commonly, day-ahead markets have 24-h decision horizons with 1-h time steps, meaning that each hour, a new decision is made regarding the state of the system 24 h in the future. Additional look-ahead periods are sometimes added to address inter-temporal constraints and end effects. Models that resolve on sub-hourly scales can capture the dynamics of intra-hour market contracts, which would have their own decision horizon, separate from the fundamental time structure components in Fig. 5. Importantly, changing the temporal structure of a model may impact the model results. Reducing a model's time resolution to improve computational performance is a standard process, though this can influence model results across multiple dimensions [77,117–121].

Another common approach that can be used to reduce the time domain of a model is to consider representative time periods, e.g., a set of days less than 365 that collectively approximate the characteristics of an entire year. When using this method, the results obtained from modeling the representative time periods ideally are similar to those obtained from modeling the whole year. This approach is common in long-term planning models and less common in short-term market models. The main difficulty in representative time period selection is accurately capturing daily and seasonal changes in demand and weather-driven variables such as wind and solar availability. Representing a year with a set of non-sequential representative hourly periods can also eliminate consideration of intraday volatility in time series parameters, such as demand or renewable generation profiles, and hinder the ability to capture the operational capability of long-duration energy storage resources. Furthermore, by considering fewer non-sequential representative days, a modeler may sacrifice important multi-day considerations like the effects of extreme weather conditions, such as the so-called “Dunkelflaute” when periods of low VRE production extend for multiple days. Hence, there has been work on developing methods for the proper selection of representative days, the most common of which involve hierarchal clustering or error quantification metrics [118,122]. It is challenging to generalize methods for choosing the optimal model time reduction, as this decision depends significantly on the specific choice of model and the application. Modelers exploring time domain reduction should be aware that their results may depend on their choice of temporal representation and should, therefore, take care to perform robust sensitivity analyses and interpret results in the context of these limitations [123].

4.2. Representation of other grid services, products, and markets

Models may represent the provision of several grid services in addition to energy; these include operating reserves, flexibility products,

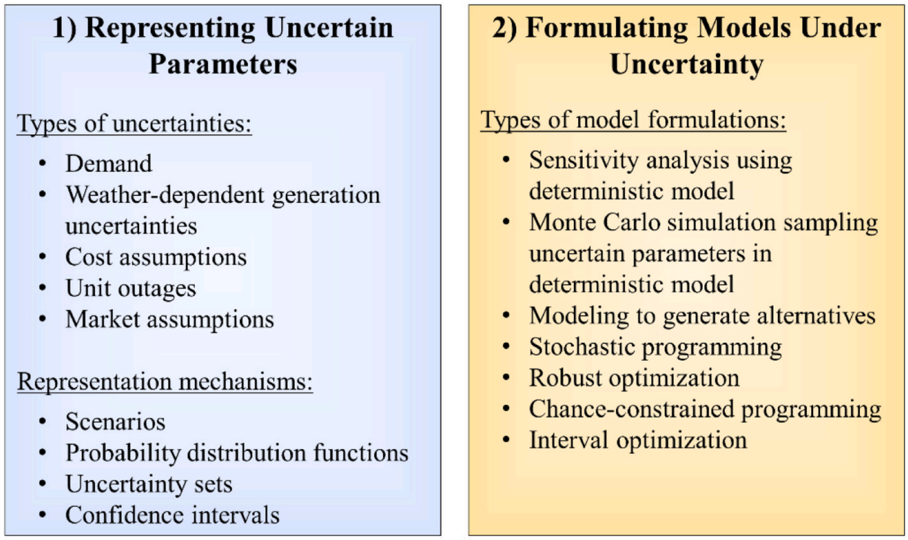

Fig. 6. Distinction of the two main steps in addressing uncertainty in power market models: 1) representing uncertain parameters and 2) formulating a decision problem under uncertainty.

long-term capacity, and demand response. Traditionally, market models are designed with the primary objective of representing the energy market clearing process, but as power markets continue to decarbonize and evolve to allow greater operational flexibility, modeling these additional services will become increasingly important. These markets can be cleared separately or co-optimized [124,125] with energy or other products. Operating reserve products are the most commonly considered non-energy grid services, however, they are often represented in a relatively straightforward manner. For example, the full spectrum of physical and opportunity costs that market participants face when providing these services, may be overlooked [5]. Moreover, reserve requirements may be determined through simplified heuristics based on a percentage of anticipated peak demand or anticipated hourly demand, which may not be fully reflective of reserve procurements in actual market operations or the physical need for reserves to maintain system reliability [126,127]. Furthermore, the underlying uncertainty driving operating reserve requirements is typically not explicitly represented in market models [128].

Capacity products are largely underrepresented in short-term power market models but are a growing and critical market modeling feature [129,130]. It can be challenging to model competitive capacity markets since market rules and market processes can vary significantly in different regions, and it may be hard to capture all such distinctions in a single model framework. When these products are modeled, capacity requirements are often represented by implementing one or more capacity demand curves [131].

Capturing demand response in models is increasingly important as power systems look to become more flexible. Demand response can be modeled in wholesale power market models by including price-elastic demand as a portion of the total demand [64,65,69,132]. The price-responsive demand portion is represented as a stepwise curve for power demand so that less energy is required during periods of supply scarcity. However, price-responsive demand changes the independent nature of the demand input and tends to increase the size of the optimization problem. Other demand response models include retail pricing models, typically large nonlinear optimization models directly interacting with wholesale markets and their corresponding optimization problems [65,69]. Pricing schemes such as time-of-use, real-time pricing, and critical peak pricing are challenging to linearize without losing significant accuracy or limiting the scope of the model.

4.3. *Uncertainty representation*

Many power market parameters are inherently uncertain, and these uncertainties must be accounted for in order to represent system behavior properly. Such uncertainties arise from multiple sources in the power market, including demand, VRE generation profiles, assumptions about technology and fuel costs, and other input parameters. A variety of uncertainty techniques are commonly applied in power market modeling, including stochastic modeling, probabilistic modeling, possibilistic modeling, information gap decision theory, robust optimization, modeling to generate alternatives, and interval modeling [4,86,88]. In general, there are two main challenges in uncertainty modeling: 1) representation of the individual uncertainties and their correlations (e.g., as scenarios or probability distributions), and 2) how this uncertainty is considered when the power market model is formulated and solved (e.g., through stochastic or robust programming). These considerations are summarized in Fig. 6. In both cases, there are numerous tradeoffs across the various uncertainty representation approaches related to data requirements, computational limitations, and the fidelity of model outputs.

The representation of uncertainty in a power market model depends on the type of modeling problem at hand and the assumed risk preferences of the decision-makers, as different approaches are tailored to specific risks and tolerances. With a deterministic model formulation, the most common way to consider uncertainty is to perform sensitivity analysis on input parameters. However, new advancements in uncertainty representation and computational capabilities are paving the way for modelers to explore other options. For example, one approach called "modeling to generate alternatives" allows modelers to determine the maximally different investment decisions that fall within a set error tolerance of the objective function [133]. This allows for considerations of maximum variety in decision mixes that meet the same objective.

In the case of formulating models under uncertainty, such as in stochastic programming, models can be configured to augment risk constraints and objective functions, for example, to understand how reserve requirements may change with increasing VRE penetrations [79,88,134]. In this case, one must characterize the probability distributions of stochastic input parameters such as demand, unit outages, or weather-driven electricity generation. These uncertainties may have different probability distributions and can be modeled using different approaches [135]. Uncertain parameters can generally be represented in various forms, depending on data availability and the problem

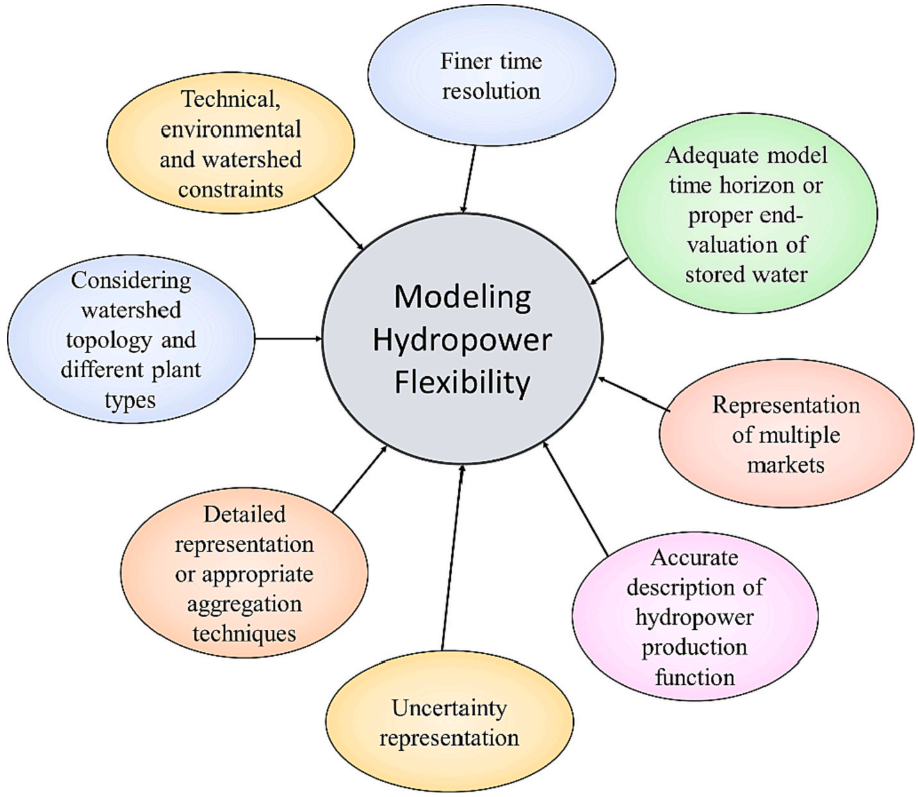

Fig. 7. Key challenges in modeling hydropower flexibility.

formulation of the power market model. For example, uncertain wind power generation can be represented by a set of scenarios [125], a set of intervals [136], or an uncertainty set [137].

Lastly, some uncertainty measures can be incorporated into deterministic formulations directly. For example, Monte Carlo simulation can be utilized. Here an uncertain input parameter space is sampled repeatedly, and multiple executions of the deterministic model yield a joint distribution of results over the parameter space [138]. Other approaches to address uncertainty require more significant departures from deterministic models. For example, a stochastic optimization model is implemented by optimizing over a set of scenarios representing the uncertainty of stochastic parameters within the model formulation. In robust optimization the distribution of the uncertain parameter is similarly unknown, and an uncertainty set is defined. The problem is then optimized over all possible realizations to yield a least-cost solution that is robust against a worst-case future, even if it is unlikely, e.g., to minimize the system cost given the worst-case realization of a technology's future capital cost [110,137,139]. Including uncertainty measures enhances a model's ability to represent the risk preferences of decision-makers, thereby providing improved insights into the dynamics of these complex systems.

4.4. Energy storage representation

As power systems restructure, new storage technologies are continually developed and deployed to address future flexibility needs. Storage resources, such as PSH, batteries, flywheels, and compressed air, are also being utilized in new ways to provide flexibility to the grid. As storage resources become increasingly diverse and gain access to new revenue streams in electricity markets, simple storage formulations will fail to capture the optimal utilization and full value of these resources [11,140]. For example, storage technologies vary in terms of efficiencies, power limits, ramp rates, and lifetimes, and these parameters also vary as a function of usage patterns and, therefore, require individual treatment [10]. Furthermore, these resources can participate in wholesale markets, reserve markets, and retail markets as a distributed resource and demand response provider. This means models cannot simply represent storage as a combined energy producer and consumer with one revenue stream and expect proper valuation and dispatch of these technologies [10,11,140]. While balancing markets and distributed energy provision currently constitute a relatively small portion of the revenues many storage assets earn, they may provide a more significant fraction of storage revenues in future systems.

The temporal representation of storage resource operations also plays a critical role in accurately modeling their dispatch and evaluating their role in the power system [141]. In a short-term setting, these resources benefit from sub-hourly operational resolution as they can utilize their fast response time to stabilize the grid and take advantage of price fluctuations in intraday and real-time markets with high time resolution [123]. At the same time, it is essential to consider inter-temporal constraints, like ramping and unit commitment constraints, to capture the actual price volatility in markets and to ensure that models consider how storage operation in one period affects its dispatch in another [10]. This is particularly important for long-duration storage technologies, as their storage capacities may exceed the study horizon. As for hydropower reservoirs, proper calculation of opportunity cost (i.e., also called water values for hydropower [142]) is necessary for efficient scheduling and pricing of energy storage in the power market.

4.5. Hydropower representation

Hydropower resources are critical to future low-carbon power markets as they provide dispatchable power, short- to long-term flexibility, and storage with zero carbon emissions. However, hydropower and other energy storage resources are often over-simplified in power market models and, in turn, end up being under-valued because the model either lacks sufficient time resolution or has an inadequate representation of all the grid services that storage provides [10,11,141]. In power market models, hydropower resources are impacted by each of the model design features in Fig. 4, and their representation provides an excellent example of how model design features influence power market model outcomes. For example, the temporal structure of a model influences a hydropower resource's dispatch as well as its connection to long-term watershed conditions and ability to provide long-duration energy storage. Moreover, the fast ramping and storage capabilities of hydro resources allow them to provide many grid services, and the choice of uncertainty representation for water inflows/outflows greatly influences operating behavior. The representation of PSH and its associated opportunity costs influences the dispatch of other resources and the overall market model outcome. Lastly, hydropower resources also impact energy price formation as studied in the traditional hydrothermal coordination problem, i.e., determining how to schedule and dispatch a portfolio of hydropower and thermal power generation resources within an area with minimum costs. As the model design choices affect the operation and flexibility provided by hydropower resources, tailoring the model design toward a specific problem will allow for a more accurate representation and assessment of these resources. Key challenges for modeling hydropower flexibility are summarized in Fig. 7 and further discussed below.

4.5.1. Hydropower constraints

Modeling individual hydropower plants accurately within a broader power system context is challenging. The main reason for this is the computational burden of representing all technical, watershed, and environmental constraints, as well as managing uncertainty in inflows, the multi-purpose use of water, and the future value of water. An accurate description of the hydropower production function, i.e., the relationship between electricity production for each plant or unit and discharge, head, and turbine efficiency, is challenging due to nonlinearities and state dependency [111]. This is usually represented in detail in short-term decision tools but is often simplified in long-term power market models. Operational practices for different hydropower plant types are site-specific, and acquiring accurate site-specific data is challenging [12,143,144]. In addition, environmental and regulatory constraints can be hard to describe mathematically and can greatly increase model complexity [12]. While the main technical constraints that directly influence the power generation of hydropower resources are typically considered in power market models, watershed and environmental constraints are often largely ignored or greatly simplified. These constraints limit hydropower flexibility, affect operations, and are important in assessing the ability of hydropower to participate in different markets and, therefore, determining its true value [12,144,145]. Since the ability of a hydropower plant to provide different grid services is directly linked to how its constraints are represented, the choice of hydropower resource representation directly influences model results.

4.5.2. Hydropower plant types and topology

Hydropower systems vary widely in terms of topology and plant types. The three main types of hydropower plants include reservoir, PSH, and run-of-river. These are often modeled as dispatchable generation units, storage resources, and non-dispatchable resources, respectively, and the constraints outlined in the previous section may be implemented differently for each type. Since each resource behaves differently in a power market, the tradeoff between design features, computational tractability, and accuracy of results may differ based on the mix of hydropower plant types and their configuration in a given study.

PSH has traditionally been utilized to shave demand peaks and provide black-start capability in power systems, supplementing baseload assets that are costly to stop or inefficient to operate at part load. Peak-shaving PSH, which is the most common type of PSH, is less complicated to manage compared to seasonal PSH, which can transfer energy over several months and from season to season. These same seasonal challenges also face reservoir hydropower.

Run-of-river hydropower plants are less flexible than reservoir plants because they have very limited storage capabilities and are often modeled as non-dispatchable resources, similar to VRE. Run-of-river hydropower plants will often bid fixed energy quantities into the market [143,146,147]. However, the need for flexibility makes it important for run-of-river plants to consider an operational strategy that enables them to contribute to the power system with inertia and short-term reserves. In general, PSH and run-of-river hydropower can be modeled with good approximation in short-term dispatch studies without considering watershed constraints. However, time delays can complicate the planning of run-of-river assets, particularly exemplified in situations with long rivers where water can take weeks to travel between plants.

Reservoir hydropower is commonly modeled similar to a dispatchable thermal unit with unit commitment constraints in short-term models [10,119]. For these plants, modelers should be aware that poor quality boundary conditions can lead to overestimates of resource flexibility and inaccuracies in dispatch. Such boundary conditions can include a target reservoir level or an end-valuation of the stored water. In short-term frameworks where exogenously determined periodic water allotments are used to decide production volumes, dispatch strategies can become sub-optimal [144,148]. Considering the future value of water in the dispatch increases the possibility of finding flexible and optimal solutions. The future value of water can be represented by a cost function that describes the opportunity cost of water use beyond the planning horizon. Determining future cost functions requires dedicated models due to the many associated dependencies, including the long planning horizons required for reservoirs containing multiple years of inflow, future avoided fuel costs, and uncertain future inflows and power prices [12,144,149].

In longer rivers, hydropower plants are often cascaded, meaning the outflows of an upstream plant directly impact the inflows of one further downstream. Lack of consideration of the topology when scheduling resources in the same river may lead to sub-optimal resource planning, unit commitment, and overestimation of short- and long-term resource flexibility [112].

Detailed hydropower representation includes a description of watercourse topologies, each individual hydropower reservoir and power plant, and the associated production functions, constraints, and inflow. In practice, hydropower resources are often aggregated into hydropower equivalents to reduce model complexity and computation time, e.g., by using clustering [150] or bi-level optimization [151]. Currently, applied aggregation techniques may not be adequate for future grids, and appropriate techniques must be developed to avoid overestimating the flexibility and to properly account for PSH [152].

The uniqueness of hydro assets and watercourses increases the complexity of power market models, and it is common for some models, like hydrothermal coordination models, to be tailored to hydropower-dominant areas, allowing for greater hydropower detail and enhanced uncertainty representation.

4.5.3. Hydrothermal coordination

The optimal coordination of hydropower resources and thermal power plants over a given time horizon, hydrothermal coordination, is a good example of how power market models can be tailored to solve a type of problem. These models are typically applied to hydro-dominated systems, where detailed hydropower representation is critical to replicate real-world system operations. The problem easily becomes computationally intractable as it is a large-scale stochastic multi-stage problem and is often solved by a combination of optimization and simulation. Both the model methodology and a range of model design choices significantly impact model results. First, the most important technical and limiting constraints for both the thermal system and hydropower system must be considered in the problem formulation. Second, the temporal resolution of the model must be sufficient to capture important thermal constraints, and the study horizon must be long enough to capture the long-term dynamics of reservoir hydropower storage. Finally, it is important to capture uncertainty in hydro inflows, fuel costs and constraints, emission constraints, and representation of co-generation of heat and power when finding the joint least-cost strategy for both thermal, nuclear, and hydropower units.

Long-term and short-term hydrothermal coordination also each present distinct challenges. Short-term coordination problems are often treated as deterministic and solved by unit commitment and economic dispatch models considering more operational details [153]. In the long-term coordination problem where uncertainty representation plays a key role, the model is typically solved by stochastic dynamic programming (SDP) [154,155] or stochastic dual dynamic programming (SDDP) [156,157]. Long-term models typically calculate the future value of water to use as boundary conditions in short-term models. Methods based on linear programming (LP) and dynamic programming (DP) are classical approaches for solving such hydrothermal coordination problems. Other mathematical programming variants exist (e.g., successive, integer, mixed integer) and are sometimes used to represent non-linearities and non-convexities. The dimensionality issues of DP oftentimes require the use of aggregation techniques when modeling complicated hydropower systems or the unit commitment of many thermal units to make the problem tractable. Decomposition methods based on Lagrange relaxation and Benders' decomposition are used to divide large-scale optimization problems into smaller sub-problems and to incorporate uncertainty represented by scenarios. Heuristic methods such as evolutionary algorithms, fuzzy set theory, and artificial neural networks are promising techniques that can be combined with traditional optimization techniques to overcome different complexities and computational challenges in hydrothermal coordination [153,158]. Current trends in hydrothermal coordination involve enhancing uncertainty representation [159], increasing temporal and spatial resolution, and including representation of multiple market products [160]. Work to improve the solution algorithms and thereby reduce computation time is also a continual focus in literature [161,162].

Flexibility is also a critical consideration in hydrothermal coordination [163]. The cost of short-term flexibility is typically high in thermal systems and low in hydropower systems. This is one of the reasons why thermal and hydropower systems traditionally were designed to complement each other, but it also simultaneously complicates joint optimization and coordination as many technical constraints must be included to capture the synergies between these technologies. In the context of the clean energy transition, several studies have demonstrated the benefit of utilizing hydropower flexibility to facilitate the integration of large shares of VRE and highlight the shortcomings in existing hydrothermal coordination tools. Graabak et al. emphasize that utilizing simplified aggregation and heuristics in SDP-based models instead of optimizing each individual reservoir underestimates the short-term flexibility of hydropower resources [164]. Tveten et al. apply a deterministic partial equilibrium model with fine temporal resolution to capture realistic thermal ramping constraints and demonstrate that VRE integration benefits from coordination between thermal and hydro systems [165]. As always, there is a tradeoff between model detail and computation times.

4.6. Energy price formation

Price formation in power market models involves determining the price for energy or other grid services, such as flexibility products and reserves, in a given time period. These prices are the key driver for both operational strategies and investment decisions. It is therefore critical that markets prices provide sufficient revenues to support investments in the resources that are required to support the clean energy transition. Market models must therefore be able to capture these price dynamics with high fidelity. For instance, an increasing share of VRE resources may increase short-term price volatility which may in turn impact perceived investor risks and therefore influence investment decisions related to flexible resources like batteries and PSH. At the same time, there are concerns about the merit order effect from increased levels of VRE, which would lower energy prices and possibly reduce incentives to invest.

The prices that a power market model produces will be affected by modeling details and choices made regarding all design features discussed above, but also by the market clearing mechanism that is represented by the model, e.g., marginal-cost based pricing or pay-as-bid. Markets may be cleared with either nodal or zonal spatial resolution, depending on how the physical grid is represented [166]. The spatial resolution of a market is established by the number of nodes or zones where distinct prices are determined, and power market models should be designed to reflect the resolution and associated constraints of the system being assessed.

Nodal market clearing is based on a detailed representation of the grid and is common for competitive short-term markets in the U.S., where price formation involves determining locational marginal prices (LMPs) [167]. The mathematical foundation for determining LMPs is well-developed, but the difficulty in predicting costs associated with losses and congestion and determining appropriate prices for other grid services can be challenging [168]. The LMP is made up of three components: energy, congestion, and losses. The energy component is found by taking the shadow price (dual variable) of the power balance constraint, while the congestion component is found by summing the shadow prices of the transmission constraints connecting the node of interest. Losses are more challenging to quantify because accurate modeling of transmission losses requires the use of AC power flow equations that are nonlinear and non-convex. Because of the computation challenges introduced by nonlinearities, transmission networks are typically approximated by linear DC power flow equations, a simplified zonal representation of the transmission network, or a transport model, all with a simplified representation of losses, e.g., a fraction of the flow or zero losses. Zonal market clearing is implemented in Europe and does not reflect congestion and losses within each market zone in price formation. In either case it is important to properly represent transmission constraints between coupled zones or nodes in order to ensure market efficiency. To calculate the available transmission capacity between market zones, Europe is currently moving away from a simplified Available Transfer Capacity method toward a Flow-Based Market Coupling where the physical transmission constraints are better accounted for in the market clearing [166]. Power market models should reflect the coupling method that has been implemented in practice in order to accurately capture price formation in these markets.

In addition, the choice of mathematical formulation and solution technique used to establish and solve the corresponding market clearing problem also has a great impact on price formation. For example, in an agent-based simulation, all agents act strategically to maximize their profit, and the resultant prices can differ greatly from those generated by a centralized cost-minimization model that assumes a market with perfect competition. The electricity market clearing problem also has many non-convexities due to economic (e.g., startup and shutdown cost) and physical (e.g., minimum output requirements and run times) constraints. There are many ways of formulating these aspects of the problem, and similarly many different methods to determine approximate solutions, e.g., by relaxing the non-convex solution space. These include Lagrangian relaxation [169], integer relaxation [170], and convex hull relaxation [171–173]. Furthermore, some power market models represent other market products, as discussed in Section 4.2, and can thus consider price formation for capacity, operating reserves, and ramp products in addition to energy. Lastly, more complicated formulations for determining LMPs may also be implemented, e.g., to account for look-ahead schedules and additional system and asset constraints. These formulations require a deeper technical treatment, which is omitted herein [5,167,174].

5. Power market trends and model needs

Power market models are utilized to study future power markets, which are evolving due to multiple factors, including the influence of high VRE penetrations, increasing use and deployment of energy storage, the growth of demand response, and the coupling of the power sector to other industries such as heating, transport, and industry. In the next sub-sections, we review how power market models have been applied to analyze these emerging issues and identify current market modeling trends in each of these four key areas of development. We also highlight the importance of different model design features in accurately representing the evolving dynamics of future power systems.

5.1. High VRE penetrations

In recent years, a number of different studies have analyzed the impact of increasing VRE penetrations on wholesale electricity market outcomes. These have generally found that price volatility increases with increasing VRE penetration [6,175–179]. As a result, market participants are exposed to increased price risk, which may exacerbate the difficulty in incentivizing new capacity investment [180]. Higher price volatility, along with the possibility of lower average energy prices due to the merit order effect of VRE, has motivated an ongoing discussion around the need for revised resource adequacy mechanisms, such as capacity markets [6,180]. Hence, there is a need to improve the representation of these mechanisms in power market models, as they may play an increasingly important role in determining revenues and incentivizing firm and flexible generation capacity investments and retirements [50,52,53].

Increasing VRE penetrations are also driving the restructuring of reserve markets [181,182]. For example, in some European markets such as Belgium and the Netherlands, there is a trend of overcapacity procurement by system operators who procure operating reserves well in advance (up to months or a year) of day-ahead market clearing and hence deal with large uncertainties in future demand and VRE availability at the time of the market clearing [182,183]. Recent studies show significant market efficiency improvements, quantified in terms of system cost reduction and resource allocation, when reserve markets are cleared simultaneously with or after day-ahead energy markets, similar to what is typically done in U.S. electricity markets [181,182]. Overall, markets for reserves and flexibility may play a more important role in future low-carbon systems, and it is therefore increasingly important to develop tools that can co-optimize service provision across multiple markets in a computationally efficient fashion.

Lastly, high VRE penetrations introduce greater levels of generation uncertainty and market price volatility, which collectively increase revenue uncertainty for market participants [3,4,182]. This demands enhanced uncertainty modeling and improved representation of bidding behaviors across a wide range of different operating conditions [6]. Importantly, VRE generation uncertainties also occur on sub-hourly time scales, highlighting the need for enhanced uncertainty representation at finer temporal resolutions.

5.2. The role of energy storage

Energy storage is a technology class that brings multiple challenges to power market models, as discussed in Section 4.4. As energy storage penetrations in power systems increase, there is a need to improve the representation of storage resource opportunity costs in power market models to ensure that their operational strategies are properly captured, and their value is adequately recognized [184]. Similarly, finer temporal resolutions may be needed to capture the value that storage resources can provide in terms of balancing the system over short time scales [11,123,141]. Specifically, power market models need to evolve to consider the key characteristics that distinguish different energy storage technologies, including interactions between operational strategies and resource degradation, appropriate representation of operating costs, consideration of sequential time steps, and dispatch logic that properly optimizes the operation of storage resources within their technical constraints across hours, days, weeks or months depending on the duration of the respective storage assets [10,11,47,140,185]. In addition to improving traditional market models that simulate the system as a whole, alternative models may be developed and specifically tailored to address these key storage considerations. We identify three types of tailored models that will assist in properly quantifying the value of storage in power markets throughout the clean energy transition:

- **Price-taker models:** focused solely on storage valuation and participation in markets, properly accounting for opportunity costs and including all appropriate revenue streams.
- **Short-term system-level market models:** focused on the dynamics of resource scheduling, dispatch, and pricing, considering opportunity costs of short- and long-duration storage and the interplay with various supply and demand resources at different levels in the grid.
- **Sector-coupled models**: tailored to study the change in operational dynamics and revenues of storage resources in a power system coupled to other energy demand sectors (e.g., transportation, heating).

5.3. Increasing demand response

Demand response (DR) describes the group of mechanisms that allow for electricity demand to be adjusted to better match supply, thereby creating demand flexibility. DR will be an important source of grid flexibility in future low-carbon power grids with high VRE penetrations and may also become a more dominant factor in future price formation. Power market models have already been used to study many market trends surrounding DR. Some applications include analyzing the optimal design and structure of DR participation programs, managing uncertainty associated with DR, understanding the effect DR has on wholesale market prices, modeling the participation of DR in ancillary services markets, analyzing how DR impacts the market value of renewables, and determining the cost-efficiency, cost-allocation, and remuneration of DR [65,66,124,186–191]. However, to better understand DR in future power markets, models need to evolve by 1) developing a better understanding of costs and risk, willingness to pay, participant size and type, and potential strategic behavior of DR participants, and 2) improving the representation of technical DR constraints, opportunity costs, and price coupling with other resources and sectors [66].

Several types of DR mechanisms and technologies exist, each requiring unique modeling treatment depending on their respective participation strategies, costs, and related uncertainties. These mechanisms include utility and wholesale market DR programs, which may be based on prices or other incentives and vary for different consumer types, demand aggregators that cluster consumers demand, Load Serving Entities (LSEs) that facilitate DR participation in wholesale markets on behalf of consumers, and integrated DR which utilizes the electrification of technologies in adjacent sectors to provide flexible demand through load-shifting [64]. Power market models are most commonly applied to assess wholesale market participation of aggregators and LSEs, DR in microgrids, integrated DR in sector-coupling, optimizing utility management of consumer demand, smart building management, and retail pricing program structures [66]. In the context of power market modeling, the most relevant of these is the participation of LSEs and aggregators in wholesale markets since the demand bids from these entities have an influence on grid flexibility and power prices [187,191,192]. Such market participation is commonly modeled as some combination of price-responsive demand, shiftable load, or virtual generation with an associated cost function. It is difficult to model the bulk effect of individual consumer participation on wholesale markets because consumer needs and risk preferences vary [66,192].

The main challenges with modeling DR include properly

Table 1
Summary of key considerations in power market model design features and selected technology features for applications to analyze important trends, including VRE integration, energy storage, demand response, and sector-coupling.

		5.1 Variable Renewable Energy	5.2 Energy Storage	5.3 Demand Response	5.4 Sector-Coupling
Model Design Features	Temporal Resolution	Wind and solar generation profiles vary across all timescales, including sub-hourly	Opportunity costs and flexibility benefits occur across multiple timescales, including sub-hourly	Increased scope of models challenges their ability to capture adequate temporal resolution	Increased scope of models challenges their ability to capture adequate temporal resolution
	Grid Services	Variability and uncertainty, as well as impacts from transmission bottlenecks, may increase the need for local grid services	A substantial share of storage revenues may come from capacity and ancillary service markets	DR is allowed to participate in energy and ancillary markets, and revenue/cost savings contribute to system efficiency	Some coupled sectors can provide price-responsive demand and ancillary services provision
	Uncertainty Representation	Wind and solar generation profiles are inherently uncertain	Important for planning and operation of energy storage; impacts its opportunity cost	Multiple uncertainties in DR, including costs, participation, and response levels, consumer preference, willingness to pay	Inclusion of multiple markets adds new dimensions of uncertainty
	Price Formation	Low marginal cost VRE changes the supply curve (merit order effect)	Price impacts driven by opportunity costs may have a stabilizing effect on prices	DR shifts load away from peak periods, thereby reducing peak prices. Prices are influenced by willingness to pay and energy purchased in forward markets	Closely coupled sectors can influence power prices
Model Technology Features	Storage Representation	Hybrid solutions combining VRE and storage contractually or physically can be important for system operation	Important to capture opportunity costs, operational strategies, revenue streams, intertemporal constraints, technology distinction	Facilitates DR participation – needs accurate technical, network, and market constraints and opportunity cost	Electrolyzers, EVs, district heating, and other technologies can provide short- and long-duration energy storage for multiple markets
	Hydropower Representation	Importance grows with VRE penetrations for the ability to provide clean firm capacity	Energy storage problems can learn from hydropower modeling	The role of hydropower will increase as DR shifts dispatch away from high marginal cost resources	Hydropower has an impact on water availability, storing water, and mitigating floods

understanding and representing related costs, uncertainties, and technical constraints. Furthermore, DR modeling requires an understanding of how cost allocation shifts both benefits and risks and thereby impact the consumers' willingness to pay as well as their participation in spot and forward markets [192]. Consumer costs include their initial investment in enabling DR technologies and any rescheduling or discomfort costs, while the utility/LSE experiences costs associated with metering, system upgrades, administrative procedures, and incentive payments [66]. Energy generation costs are allocated differently depending on the wholesale entity and the program. Understanding these costs and incorporating them into power market models is not straightforward since participation programs vary, the cost of energy purchased in the spot market varies based on forward contracts, and because enabling technologies vary in size, scope, and cost [64,192]. The amount of risk exposure in markets also varies with costs and contracts, which affects the willingness to pay and benefit of consumers, which is uncertain. Participation also requires estimates of consumers' baseline consumption patterns, which introduces significant uncertainty to aggregators and LSEs [193]. Lastly, the types of technologies used for distributed generation and load-shifting vary in type and size, and their technical constraints associated with consumer network operation, supply limits, or market participation are not always transparent [64,66,192,193]. A better understanding of all these effects is needed to fully capture the impacts of DR in power market models as participation grows in future systems.

As DR participation grows to appreciable levels, its ability to influence price formation in wholesale markets will increase. DR tends to decrease the average power prices in wholesale markets since it shifts generation scheduling away from high marginal cost resources that are called upon in times of peak demand [64,66,192]. The extent to which DR will impact the spot price and create system flexibility will vary based on the type of remuneration mechanism that is provided to DR participants. Market prices and system efficiency are also tied to the behavior of DR in forward markets. LSEs and aggregators participating in wholesale markets use a mix of bilateral forward contracts with generators and purchases on the spot market to facilitate DR, inherently coupling the amount of energy purchased in each market. To properly understand the effect that DR has on price formation, these coupled market dynamics need to be captured alongside endogenous wholesale price formation. This represents a major challenge in developing power market models for future grids with more active demand-side participation.

5.4. Sector-coupling

The ability to electrify adjacent energy demand sectors such as transport and heating represents a cornerstone of the clean energy transition that will impact the power sector resource mix, its operational dynamics, and electricity prices. Sector-coupling arises when the consumption profiles of electrified technologies like heat pumps, electric broilers, hydrogen electrolyzers, and electric vehicles, among others, are adjusted in coordination with power system operations in order to shift electricity demand and, in some cases, provide energy storage [67]. These mechanisms allow sector-coupling to unlock significant system flexibility and reduce emissions [2,67].

Some common trends emerge from studies that have analyzed the impacts of enhanced sector-coupling, including decreased CO_2 emissions, increased system flexibility, decreased renewable curtailment, and increased value of energy storage technologies [186,194–203]. Other studies have shown that the coupling of sectors influences thermal plant operation and retirement, that internalizing the cost of CO_2 promotes sector-coupling and decreases emissions without necessarily increasing system costs, that power-to-gas conversion can increase the provision of ancillary services, and that coupled sectors can influence average power prices and price distributions, though these results are heavily system dependent [186,195,197,198,201,202].

In general, the results from sector-coupling studies are highly dependent on geography, the sectors included in the study, their respective representation, system resource mix, resource constraints, dispatch logic, system uncertainties, and time and space resolution. This makes it difficult to generalize results and properly identify trends from existing studies and is consequence of the sheer magnitude of dependencies caused by the large number of configurations a sector-coupled system can have. For this reason, market models should

Table 2
Future power market model trends and an associated prioritization of their respective power market modeling needs.

	Future Power Market Modeling Needs					
Future Power Market Trends	Improved co-optimization methods	Better uncertainty representation	Sub-hourly time steps	Improved representation of resource adequacy mechanisms	Opportunity cost functions	Improved representation of value streams
Increased integration of markets/sectors	High	Low				Medium
Evolving markets for grid services	Medium		Low	Medium		Medium
Increasing VRE penetrations		High	Medium	Low		
More storage		Medium	High		High	Medium
Greater price volatility		High	Low		Medium	
Increased flexibility requirements		Low		High		Medium
Shift in hydro and thermal resource utilization	Low	Medium		Medium		Low

evolve so they can be tailored to specific problems in sector-coupling, such as assessing the effects of price coupling between sectors or the ability of a coupled sector to provide ancillary services. For example, some models could evolve to specifically focus on the representation of ancillary service markets and cross-sectoral price formation. This contrasts with current general sector-coupled models that utilize coarse geographic resolution to try to analyze a myriad of different system behaviors across multiple sectors. With a more tailored approach, sector-coupled market models can reveal trends in niche areas, such as the operational strategies of energy storage in power-heat markets. Moreover, these tailored sector-coupled market models can complement one another to identify broader trends. The value of such model specificity stems from the core need to properly balance model design features against data needs and computational requirements, i.e., making sure that the most important and impactful features related to the target application are accurately represented with sufficient detail. For instance, the operating rules and time resolution of markets differ between sectors (e.g., electricity markets typically operate at a higher time resolution than natural gas markets), and information flow between markets may be limited. These characteristics need to be reflected in the corresponding model formulations. Moreover, it is particularly important that future models accurately represent resource constraints in the context of coupled markets. This can improve model accuracy and robustness and help to better understand implications for market prices and resource valuation across multiple sectors. Lastly, multi-stage formulations, such as bi-level formulations of capacity expansion and production cost models that incorporate complimentary in sector-coupling structures may provide new directions for future market models [204,205].

Current models, if they consider sector-coupling at all, typically struggle to capture the full network, resource, and market details of all coupled sectors, and largely ignore significant resource constraints, uncertainties, and coupled price dependencies between markets. Future models will benefit from enhancing these network details and from improved techniques to co-optimize the coupled markets.

5.5. Key needs for future power market models

The discussion above illustrates the importance of model design features in analyzing different challenges in future power markets. Table 1 summarizes considerations for each of the six critical model design and technology features introduced in Section 4 and each of the four key emerging issues discussed above. Table 2 summarizes a set of future power market trends and prioritizes the different power market modeling needs associated with each.

6. Conclusion and future research needs

In this paper, we reviewed power market models and their readiness to support analysis of the clean energy transition and future low-carbon electricity markets. We identified a set of model design features critical to the energy transition and analyzed how current models are typically applied to market analysis and the challenges they face to stay relevant for the energy transition. We conducted our review with an emphasis on the various approaches for representing flexibility in power markets, as flexibility needs are increasingly important with the emergence of low-carbon systems dominated by VRE. Particular attention was paid to accurately representing the largest flexible low-carbon resource available today, hydropower, but our findings will apply to other energy storage technologies as well. We discussed how energy storage representation affects a power market model's ability to adequately capture system flexibility and the importance of including different grid service markets for calculating optimal operational strategies for storage technologies. We also elaborate on how a changing resource mix and new power market dynamics influence price formation and the complicating role of uncertainty in power market models. Through our review, we identified tradeoffs between different model design features and their importance for modeling future clean power markets dominated by VRE. Our review reveals several research needs to improve power market models, including:

- Enhanced models to consider sub-hourly operational resolution to adequately represent short-term VRE variability and corresponding constraints on flexibility in supply, demand, and storage resources.
- Improved representation of long-term markets for capacity, operating reserves, and other ancillary services alongside day-ahead and real-time energy markets.
- Improved co-optimization methods to coordinate market clearing across products (e.g., energy and reserve products) and interactions between sectors (e.g., electricity, heating, transportation).
- Enhanced representation of uncertainty in supply, demand, and technology cost and characteristics.
- Improved representation of operational constraints, opportunity costs, and intertemporal dynamics for hydropower and storage resources.
- Representation of the full range of revenue streams for flexible hydropower and energy storage.
- Improved representation of transmission networks and their impact on price formation in different market nodes or zones.
- Implementation of advanced approaches for solving large-scale optimization problems to enable tractable power market models with improved granularity and resolution.

One thing is clear, throughout the clean energy transition, a variety of dedicated power market models will be needed to address the full range of future power system challenges. It is, therefore, critical that the research and modeling community work diligently on these challenges to ensure improved guidance to the electric power industry, electricity market operators, regulatory agencies, and other stakeholders in the clean energy transition.

CRediT authorship contribution statement

Mari Haugen: Writing – original draft, Methodology, Investigation, Conceptualization. **Paris L. Blaisdell-Pijuan:** Writing – original draft, Methodology, Investigation, Conceptualization. **Audun Botterud:** Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Todd Levin:** Writing – original draft, Methodology, Investigation, Conceptualization. **Zhi Zhou:** Writing – original draft, Methodology, Investigation, Conceptualization. **Michael Belsnes:** Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Magnus Korpås:** Writing – original draft, Methodology, Investigation, Conceptualization. **Abhishek Somani:** Writing – original draft, Methodology, Investigation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

The submitted manuscript has been created, in part, by UChicago Argonne, LLC, Operator of Argonne National Laboratory ("Argonne"). Argonne, a U.S. Department of Energy (DOE) Office of Science Laboratory, is operated under Contract No. DE AC02-06CH11357. The authors acknowledge financial support for this work from the U.S. Dept. of Energy's Water Power Technology's Office and the Research Council of Norway (PNO 257588) through HydroCen (Norwegian Research Centre for Hydropower Technology).

References

[1] Net Zero by 2050 - A Roadmap for the Global Energy Sector. IEA; 2021. p. 224.
[2] Babatunde OM, Munda JL, Hamam Y. Power system flexibility: a review. Energy Rep 2020;6:101–6. https://doi.org/10.1016/j.egyr.2019.11.048.
[3] Lund PD, Lindgren J, Mikkola J, Salpakari J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renew Sustain Energy Rev 2015;45:785–807. https://doi.org/10.1016/j.rser.2015.01.057.
[4] Aien M, Hajebrahimi A, Fotuhi-Firuzabad M. A comprehensive review on uncertainty modeling techniques in power system studies. Renew Sustain Energy Rev 2016;57:1077–89. https://doi.org/10.1016/j.rser.2015.12.070.
[5] Denholm P, Sun Y, Mai T. An introduction to grid services: concepts, technical requirements, and provision from wind. Renew Energy 2019;52.
[6] Mills AD, Levin T, Wiser R, Seel J, Botterud A. Impacts of variable renewable energy on wholesale markets and generating assets in the United States: a review of expectations and evidence. 2020. https://doi.org/10.1016/j.rser.2019.109670.
[7] Zhou Z, Botterud A, Levin T. Price formation in zero-carbon electricity markets: the role of hydropower. Argonne, IL (United States): Argonne National Lab. (ANL); 2022. https://doi.org/10.2172/1877029.
[8] Ringkjøb H-K, Haugan PM, Solbrekke IM. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renew Sustain Energy Rev 2018;96:440–59. https://doi.org/10.1016/j.rser.2018.08.002.
[9] Ringler P, Keles D, Fichtner W. Agent-based modelling and simulation of smart electricity grids and markets – a literature review. Renew Sustain Energy Rev 2016;57:205–15. https://doi.org/10.1016/j.rser.2015.12.169.
[10] Xu B, Korpås M, Botterud A. Operational valuation of energy storage under multi-stage price uncertainties. In: 2020 59th IEEE Conference on Decision and Control (CDC); 2020. p. 55–60. https://doi.org/10.1109/CDC42340.2020.9304081.
[11] Haas J, Cebulla F, Cao K, Nowak W, Palma-Behnke R, Rahmann C, et al. Challenges and trends of energy storage expansion planning for flexibility provision in low-carbon power systems – a review. Renew Sustain Energy Rev 2017;80:603–19. https://doi.org/10.1016/j.rser.2017.05.201.
[12] Stoll B, Andrade J, Cohen S, Brinkman G, Brancucci Martinez-Anido C. Hydropower Modeling Challenges. 2017. https://doi.org/10.2172/1353003.
[13] Uria-Martinez R, Johnson M, O'Connor P, Samu NM, Witt AM, Battey H, et al. 2017 Hydropower market report. Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States). Oak Ridge National Laboratory Hydropower (ORNLHYDRO); 2018. https://doi.org/10.2172/1513459.
[14] IRENA. Planning for the renewable future: long-term modelling and tools to expand variable renewable power in emerging economies. International Renewable Energy Agency; 2017.
[15] Chang M, Thellufsen JZ, Zakeri B, Pickering B, Pfenninger S, Lund H, et al. Trends in tools and approaches for modelling the energy transition. Appl Energy 2021; 290:116731. https://doi.org/10.1016/j.apenergy.2021.116731.
[16] Savvidis G, Siala K, Weissbart C, Schmidt L, Borggrefe F, Kumar S, et al. The gap between energy policy challenges and model capabilities. Energy Policy 2019; 125:503–20. https://doi.org/10.1016/j.enpol.2018.10.033.
[17] Crespo del Granado P, van Nieuwkoop RH, Kardakos EG, Schaffner C. Modelling the energy transition: a nexus of energy system and economic models. Energ Strat Rev 2018;20:229–35. https://doi.org/10.1016/j.esr.2018.03.004.
[18] Fodstad M, Crespo del Granado P, Hellemo L, Knudsen BR, Pisciella P, Silvast A, et al. Next frontiers in energy system modelling: a review on challenges and the state of the art. Renew Sustain Energy Rev 2022;160:112246. https://doi.org/10.1016/j.rser.2022.112246.
[19] Fattahi A, Sijm J, Faaij A. A systemic approach to analyze integrated energy system modeling tools: a review of national models. Renew Sustain Energy Rev 2020;133:110195. https://doi.org/10.1016/j.rser.2020.110195.

[20] Prina MG, Manzolini G, Moser D, Nastasi B, Sparber W. Classification and challenges of bottom-up energy system models - a review. Renew Sustain Energy Rev 2020;129:109917. https://doi.org/10.1016/j.rser.2020.109917.
[21] Ridha E, Nolting L, Praktiknjo A. Complexity profiles: a large-scale review of energy system models in terms of complexity. Energ Strat Rev 2020;30:100515. https://doi.org/10.1016/j.esr.2020.100515.
[22] Lonergan KE, Suter N, Sansavini G. Energy systems modelling for just transitions. Energy Policy 2023;183:113791. https://doi.org/10.1016/j.enpol.2023.113791.
[23] Vågerö O, Zeyringer M. Can we optimise for justice? Reviewing the inclusion of energy justice in energy system optimisation models. Energy Res Soc Sci 2023;95:102913. https://doi.org/10.1016/j.erss.2022.102913.
[24] Oberle S, Elsland R. Are open access models able to assess today's energy scenarios? Energ Strat Rev 2019;26:100396. https://doi.org/10.1016/j.esr.2019.100396.
[25] Groissböck M. Are open source energy system optimization tools mature enough for serious use? Renew Sustain Energy Rev 2019;102:234–48. https://doi.org/10.1016/j.rser.2018.11.020.
[26] Bistline J, Bragg-Sitton S, Cole W, Dixon B, Eschmann E, Ho J, et al. Modeling nuclear energy's future role in decarbonized energy systems. IScience 2023;26:105952. https://doi.org/10.1016/j.isci.2023.105952.
[27] Blanco H, Leaver J, Dodds PE, Dickinson R, García-Gusano D, Iribarren D, et al. A taxonomy of models for investigating hydrogen energy systems. Renew Sustain Energy Rev 2022;167:112698. https://doi.org/10.1016/j.rser.2022.112698.
[28] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. Renew Sustain Energy Rev 2014;33:74–86. https://doi.org/10.1016/j.rser.2014.02.003.
[29] Yoro KO, Daramola MO, Sekoai PT, Wilson UN, Eterigho-Ikelegbe O. Update on current approaches, challenges, and prospects of modeling and simulation in renewable and sustainable energy systems. Renew Sustain Energy Rev 2021;150:111506. https://doi.org/10.1016/j.rser.2021.111506.
[30] Després J, Hadjsaid N, Criqui P, Noirot I. Modelling the impacts of variable renewable sources on the power sector: reconsidering the typology of energy modelling tools. Energy 2015;80:486–95. https://doi.org/10.1016/j.energy.2014.12.005.
[31] Foley AM, Gallachóir Ó, Hur J, Baldick R, McKeogh EJ. A strategic review of electricity systems models. Energy 2010;35:4522–30. https://doi.org/10.1016/j.energy.2010.03.057.
[32] Koppelaar RHEM, Keirstead J, Shah N, Woods J. A review of policy analysis purpose and capabilities of electricity system models. Renew Sustain Energy Rev 2016;59:1531–44. https://doi.org/10.1016/j.rser.2016.01.090.
[33] Deng X, Lv T. Power system planning with increasing variable renewable energy: a review of optimization models. J Clean Prod 2020;246:118962. https://doi.org/10.1016/j.jclepro.2019.118962.
[34] Oikonomou K, Tarroja B, Kern J, Voisin N. Core process representation in power system operational models: gaps, challenges, and opportunities for multisector dynamics research. Energy 2022;238:122049. https://doi.org/10.1016/j.energy.2021.122049.
[35] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Appl Energy 2010;87:1059–82. https://doi.org/10.1016/j.apenergy.2009.09.026.
[36] Ventosa M, Baillo Á, Ramos A, Rivier M. Electricity market modeling trends Energy Policy33; 2005. p. 897–913. https://doi.org/10.1016/j.enpol.2003.10.013.
[37] Lopes JAP, Madureira AG, Matos M, Bessa RJ, Monteiro V, Afonso JL, et al. The future of power systems: challenges, trends, and upcoming paradigms. WIREs Energy Environ 2020:9. https://doi.org/10.1002/wene.368.
[38] Koltsaklis NE, Dagoumas AS. State-of-the-art generation expansion planning: a review. Appl Energy 2018;230:563–89. https://doi.org/10.1016/j.apenergy.2018.08.087.
[39] Hu J, Harmsen R, Crijns-Graus W, Worrell E, van den Broek M. Identifying barriers to large-scale integration of variable renewable electricity into the electricity market: a literature review of market design. Renew Sustain Energy Rev 2018;81:2181–95. https://doi.org/10.1016/j.rser.2017.06.028.
[40] Sequeira TN, Santos MS. Renewable energy and politics: a systematic review and new evidence. J Clean Prod 2018;192:553–68. https://doi.org/10.1016/j.jclepro.2018.04.190.
[41] Johnathon C, Agalgaonkar AP, Kennedy J, Planiden C. Analyzing electricity markets with increasing penetration of large-scale renewable power generation. Energies 2021;14:7618. https://doi.org/10.3390/en14227618.
[42] Honkapuro S, Jaanto J, Annala S. A systematic review of European electricity market design options. Energies 2023;16:3704. https://doi.org/10.3390/en16093704.
[43] Menegaki A. Valuation for renewable energy: a comparative review. Renew Sustain Energy Rev 2008;12:2422–37. https://doi.org/10.1016/j.rser.2007.06.003.
[44] Dagoumas AS, Koltsaklis NE. Review of models for integrating renewable energy in the generation expansion planning. Appl Energy 2019;242:1573–87. https://doi.org/10.1016/j.apenergy.2019.03.194.
[45] Oree V, Sayed Hassen SZ, Fleming PJ. Generation expansion planning optimisation with renewable energy integration: a review. Renew Sustain Energy Rev 2017;69:790–803. https://doi.org/10.1016/j.rser.2016.11.120.
[46] Bistline J, Blanford G, Mai T, Merrick J. Modeling variable renewable energy and storage in the power sector. Energy Policy 2021;156:112424. https://doi.org/10.1016/j.enpol.2021.112424.
[47] Levin T, Bistline J, Sioshansi R, Cole WJ, Kwon J, Burger SP, et al. Energy storage solutions to decarbonize electricity through enhanced capacity expansion modelling. Nat Energy 2023:1–10. https://doi.org/10.1038/s41560-023-01340-6.
[48] Ballireddy TRKR, Modi PK. Generation expansion planning considering reliability of the system: A review on various optimization techniques. In: 2017 international conference of electronics, communication and aerospace technology (ICECA). Coimbatore: IEEE; 2017. p. 137–42. https://doi.org/10.1109/ICECA.2017.8212780.
[49] Siala K, Mier M, Schmidt L, Torralba-Díaz L, Sheykhha S, Savvidis G. Which model features matter? An experimental approach to evaluate power market modeling choices. Energy 2022:123301. https://doi.org/10.1016/j.energy.2022.123301.
[50] Gacitua L, Gallegos P, Henriquez-Auba R, Lorca Á, Negrete-Pincetic M, Olivares D, et al. A comprehensive review on expansion planning: models and tools for energy policy analysis. Renew Sustain Energy Rev 2018;98:346–60. https://doi.org/10.1016/j.rser.2018.08.043.
[51] Guerci E, Rastegar MA, Cincotti S. Agent-based modeling and simulation of competitive wholesale electricity markets. In: Rebennack S, Pardalos PM, Pereira MVF, Iliadis NA, editors. Handbook of power systems II. Berlin, Heidelberg: Springer; 2010. p. 241–86. https://doi.org/10.1007/978-3-642-12686-4_9.
[52] Zhou Z, Chan WK Victor, Chow JH. Agent-based simulation of electricity markets: a survey of tools. Artif Intell Rev 2007;28:305–42. https://doi.org/10.1007/s10462-009-9105-x.
[53] Shinde P, Amelin M. Agent-based models in electricity markets: a literature review. IEEE Innovat Smart Grid Technol Asia (ISGT Asia) 2019;2019:3026–31. https://doi.org/10.1109/ISGT-Asia.2019.8880889.
[54] Kell AJM, Stephen McGough A, Forshaw M. A systematic literature review on machine learning for electricity market agent-based models. 2022 IEEE Int Conf Big Data (Big Data) 2022:4503–12. https://doi.org/10.1109/BigData55660.2022.10020902.
[55] Möst D, Keles D. A survey of stochastic modelling approaches for liberalised electricity markets. Europ J Operation Res 2010;207:543–56. https://doi.org/10.1016/j.ejor.2009.11.007.
[56] Haugen M, Farahmand H, Jaehnert S, Fleten S-E. Representation of uncertainty in market models for operational planning and forecasting in renewable power systems: a review. Energy Syst 2023. https://doi.org/10.1007/s12667-023-00600-4.
[57] Villar J, Bessa R, Matos M. Flexibility products and markets: literature review. Electr Pow Syst Res 2018;154:329–40. https://doi.org/10.1016/j.epsr.2017.09.005.
[58] Sioshansi R, Denholm P, Arteaga J, Awara S, Bhattacharjee S, Botterud A, et al. Energy-storage modeling: state-of-the-art and future research directions. IEEE Trans Power Syst 2022;37(2):860–75. https://doi.org/10.1109/TPWRS.2021.3104768.
[59] Rahman MM, Oni AO, Gemechu E, Kumar A. Assessment of energy storage technologies: a review. Energ Conver Manage 2020;223:113295. https://doi.org/10.1016/j.enconman.2020.113295.
[60] Calero F, Cañizares CA, Bhattacharya K, Anierobi C, Calero I, de Souza MFZ, et al. A review of modeling and applications of Energy storage systems in power grids. Proc IEEE 2023;111:806–31. https://doi.org/10.1109/JPROC.2022.3158607.
[61] Toufani P, Karakoyun EC, Nadar E, Fosso OB, Kocaman AS. Optimization of pumped hydro energy storage systems under uncertainty: a review. J Energy Stor 2023;73:109306. https://doi.org/10.1016/j.est.2023.109306.
[62] Zhang Y, Ma H, Zhao S. Assessment of hydropower sustainability: review and modeling. J Clean Prod 2021;321:128898. https://doi.org/10.1016/j.jclepro.2021.128898.
[63] Singh VK, Singal SK. Operation of hydro power plants-a review. Renew Sustain Energy Rev 2017;69:610–9. https://doi.org/10.1016/j.rser.2016.11.169.
[64] O'Connell N, Pinson P, Madsen H, O'Malley M. Benefits and challenges of electrical demand response: a critical review. Renew Sustain Energy Rev 2014;39:686–99. https://doi.org/10.1016/j.rser.2014.07.098.
[65] Boßmann T, Eser EJ. Model-based assessment of demand-response measures—a comprehensive literature review. Renew Sustain Energy Rev 2016;57:1637–56. https://doi.org/10.1016/j.rser.2015.12.031.
[66] Jordehi AR. Optimisation of demand response in electric power systems, a review. Renew Sustain Energy Rev 2019;103:308–19. https://doi.org/10.1016/j.rser.2018.12.054.
[67] Verbeeten MKD. The state-of-art of sector coupling in Europe: A literature review. Tilstandsrapport for Sektorkobling i Europa: Et Litteraturstudie; 2020.
[68] Silva WN, Henrique LF, da Silva AFPC, Dias BH, Soares TA. Market models and optimization techniques to support the decision-making on demand response for prosumers. Electr Pow Syst Res 2022;210:108059. https://doi.org/10.1016/j.epsr.2022.108059.
[69] Shariatzadeh F, Mandal P, Srivastava AK. Demand response for sustainable energy systems: a review, application and implementation strategy. Renew Sustain Energy Rev 2015;45:343–50. https://doi.org/10.1016/j.rser.2015.01.062.
[70] Wang Q, Hou Z, Guo Y, Huang L, Fang Y, Sun W, et al. Enhancing Energy transition through sector coupling: a review of technologies and models. Energies 2023;16:5226. https://doi.org/10.3390/en16135226.
[71] Rajan D, Takriti S. Minimum up/down polytopes of the unit commitment problem with start-up costs. Yorktown Heights, NY: IBM Research Division; 2005.
[72] Carrion M, Arroyo JM. A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem. IEEE Trans Power Syst 2006;21:1371–8. https://doi.org/10.1109/TPWRS.2006.876672.

[73] Bouffard F, Galiana FD, Conejo AJ. Market-clearing with stochastic security-part I: formulation. IEEE Trans Power Syst 2005;20:1818–26. https://doi.org/10.1109/TPWRS.2005.857016.

[74] Chen Y, Wang Q, Wang X, Guan Y. Applying robust optimization to MISO Look-Ahead commitment. In: 2014 IEEE PES General Meeting | Conference & Exposition; 2014. p. 1–5. https://doi.org/10.1109/PESGM.2014.6939258.

[75] Kuang X, Dvorkin Y, Lamadrid AJ, Ortega-Vazquez MA, Zuluaga LF. Pricing chance constraints in electricity markets. IEEE Trans Power Syst 2018;33:4634–6. https://doi.org/10.1109/TEC.2018.2821922.

[76] Yıldıran U. Robust multi-stage economic dispatch with renewable generation and storage. Europ J Operation Res 2023. https://doi.org/10.1016/j.ejor.2023.01.042.

[77] Lopion P, Markewitz P, Robinius M, Stolten D. A review of current challenges and trends in energy systems modeling. Renew Sustain Energy Rev 2018;96:156–66. https://doi.org/10.1016/j.rser.2018.07.045.

[78] Day CJ. Divestiture of generation assets in the electricity pool of England and Wales: a computational approach to analyzing market power. 2023. p. 19.

[79] Dai H, Zhang N, Su W. A literature review of stochastic programming and unit commitment. J Power Energy Eng 2015;3:206–14. https://doi.org/10.4236/jpee.2015.34029.

[80] Ramos A, Ventosa M, Rivier M. Modeling competition in electric energy markets by equilibrium constraints. Utilities Pol 1999;7:233–42. https://doi.org/10.1016/S0957-1787(98)00016-2.

[81] Luo Z-Q, Pang J-S, Ralph D. Mathematical programs with equilibrium constraints. Cambridge: Cambridge University Press; 1996. https://doi.org/10.1017/CBO9780511983658.

[82] Motto AL, Galiana FD. Coordination in markets with nonconvexities as a mathematical program with equilibrium constraints-Part I: a solution procedure. IEEE Trans Power Syst 2004;19:308–16. https://doi.org/10.1109/TPWRS.2003.820711.

[83] Aalami HA, Parsa Moghaddam M, Yousefi GR. Evaluation of nonlinear models for time-based rates demand response programs. Int J Electric Power Energy Syst 2015;65:282–90. https://doi.org/10.1016/j.ijepes.2014.10.021.

[84] Rahmani-andebili M. Modeling nonlinear incentive-based and price-based demand response programs and implementing on real power markets. Electr Pow Syst Res 2016;132:115–24. https://doi.org/10.1016/j.epsr.2015.11.006.

[85] Aalami HA, Pashaei-Didani H, Nojavan S. Deriving nonlinear models for incentive-based demand response programs. Int J Electric Power Energy Syst 2019;106:223–31. https://doi.org/10.1016/j.ijepes.2018.10.003.

[86] Zakaria A, Ismail FB, Lipu MSH, Hannan MA. Uncertainty models for stochastic optimization in renewable energy applications. Renew Energy 2020;145:1543–71. https://doi.org/10.1016/j.renene.2019.07.081.

[87] Ioannou A, Fuzuli G, Brennan F, Yudha SW, Angus A. Multi-stage stochastic optimization framework for power generation system planning integrating hybrid uncertainty modelling. Energy Econ 2019;80:760–76. https://doi.org/10.1016/j.eneco.2019.02.013.

[88] Zheng QP, Wang J, Liu AL. Stochastic optimization for unit commitment—a review. IEEE Trans Power Syst 2015;30:1913–24. https://doi.org/10.1109/TPWRS.2014.2355204.

[89] Zugno M, Conejo AJ. A robust optimization approach to energy and reserve dispatch in electricity markets. Europ J Operation Res 2015;247:659–71. https://doi.org/10.1016/j.ejor.2015.05.081.

[90] Nazari-Heris M, Mohammadi-Ivatloo B. Chapter 2 - application of robust optimization method to power system problems. In: Zobaa AF, Abdel Aleem SHE, Abdelaziz AY, editors. Classical and recent aspects of power system optimization. Academic Press; 2018. p. 19–32. https://doi.org/10.1016/B978-0-12-812441-3.00002-1.

[91] Dvorkin Y. A chance-constrained stochastic electricity market. IEEE Trans Power Syst 2020;35:2993–3003. https://doi.org/10.1109/TPWRS.2019.2961231.

[92] Mieth R, Roveto M, Dvorkin Y. Risk trading in a chance-constrained stochastic electricity market. IEEE Control Syst Lett 2021;5:199–204. https://doi.org/10.1109/LCSYS.2020.3000188.

[93] Qiu D, Dong Z, Ruan G, Zhong H, Strbac G, Kang C. Strategic retail pricing and demand bidding of retailers in electricity market: a data-driven chance-constrained programming. Adv Appl Energy 2022;7:100100. https://doi.org/10.1016/j.adapen.2022.100100.

[94] Lu R, Ding T, Qin B, Ma J, Fang X, Dong Z. Multi-stage stochastic programming to joint economic dispatch for Energy and reserve with uncertain renewable energy. IEEE Trans Sustain Energy 2020;11:1140–51. https://doi.org/10.1109/TSTE.2019.2918269.

[95] Zhao C, Wang J, Watson J-P, Guan Y. Multi-stage robust unit commitment considering wind and demand response uncertainties. IEEE Trans Power Syst 2013;28:2708–17. https://doi.org/10.1109/TPWRS.2013.2244231.

[96] Ding T, Zhang X, Lu R, Qu M, Shahidehpour M, He Y, et al. Multi-stage distributionally robust stochastic dual dynamic programming to multi-period economic dispatch with virtual Energy storage. IEEE Trans Sustain Energy 2022;13:146–58. https://doi.org/10.1109/TSTE.2021.3105525.

[97] Aguila-Leon J, Vargas-Salgado C, Chiñas-Palacios C, Díaz-Bello D. Energy management model for a standalone hybrid microgrid through a particle swarm optimization and artificial neural networks approach. Energ Conver Manage 2022;267:115920. https://doi.org/10.1016/j.enconman.2022.115920.

[98] Sensoy N, Ceyhan G. A genetic algorithm to solve day-ahead energy market clearing problem under network constraints. In: 2018 15th International Conference on the European Energy Market (EEM); 2018. p. 1–6. https://doi.org/10.1109/EEM.2018.8469987.

[99] Hamian M, Darvishan A, Hosseinzadeh M, Lariche MJ, Ghadimi N, Nouri A. A framework to expedite joint energy-reserve payment cost minimization using a custom-designed method based on mixed integer genetic algorithm. Eng Appl Artif Intel 2018;72:203–12. https://doi.org/10.1016/j.engappai.2018.03.022.

[100] Ponciroli R, Stauff NE, Ramsey J, Ganda F, Vilim RB. An improved genetic algorithm approach to the unit commitment/economic dispatch problem. IEEE Trans Power Syst 2020;35:4005–13. https://doi.org/10.1109/TPWRS.2020.2986710.

[101] Yang Y, Wu L. Machine learning approaches to the unit commitment problem: current trends, emerging challenges, and new strategies. Electricity J 2021;34:106889. https://doi.org/10.1016/j.tej.2020.106889.

[102] Hasan F, Kargarian A, Mohammadi A. A survey on applications of machine learning for optimal power flow. In: 2020 IEEE Texas Power and Energy Conference (TPEC); 2020. p. 1–6. https://doi.org/10.1109/TPEC48276.2020.9042547.

[103] Fang D, Guan X, Hu B, Peng Y, Chen M, Hwang K. Deep reinforcement learning for scenario-based robust economic dispatch strategy in internet of energy. IEEE Internet Things J 2021;8:9654–63. https://doi.org/10.1109/JIOT.2020.3040294.

[104] Zhou M, Wang B, Watada J. Deep learning-based rolling horizon unit commitment under hybrid uncertainties. Energy 2019;186:115843. https://doi.org/10.1016/j.energy.2019.07.173.

[105] de Mars P, O'Sullivan A. Applying reinforcement learning and tree search to the unit commitment problem. Appl Energy 2021;302:117519. https://doi.org/10.1016/j.apenergy.2021.117519.

[106] Zhang Y, Cui H, Liu J, Qiu F, Hong T, Yao R, et al. Encoding frequency constraints in preventive unit commitment using deep learning with region-of-interest active sampling. IEEE Trans Power Syst 2022;37:1942–55. https://doi.org/10.1109/TPWRS.2021.3110881.

[107] Teichgraeber H, Brandt AR. Time-series aggregation for the optimization of energy systems: goals, challenges, approaches, and opportunities. Renew Sustain Energy Rev 2022;157:111984. https://doi.org/10.1016/j.rser.2021.111984.

[108] Brown T, Schlachtberger D, Kies A, Schramm S, Greiner M. Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable European energy system. Energy 2018;160:720–39. https://doi.org/10.1016/j.energy.2018.06.222.

[109] Wang J, Zhong H, Yang Z, Lai X, Xia Q, Kang C. Incentive mechanism for clearing energy and reserve markets in multi-area power systems. IEEE Trans Sustain Energy 2020;11:2470–82. https://doi.org/10.1109/TSTE.2019.2961780.

[110] Ming B, Liu P, Guo S, Cheng L, Zhou Y, Gao S, et al. Robust hydroelectric unit commitment considering integration of large-scale photovoltaic power: a case study in China. Appl Energy 2018;228:1341–52. https://doi.org/10.1016/j.apenergy.2018.07.019.

[111] Fredo GLM, Finardi EC, de Matos VL. Assessing solution quality and computational performance in the long-term generation scheduling problem considering different hydro production function approaches. Renew Energy 2019;131:45–54. https://doi.org/10.1016/j.renene.2018.07.026.

[112] Belsnes M, Fosso OB, Røynstrand J, Gjengedal T, Valhovd E. Unit commitment in hydro power operation scheduling. In: Hydropower in the new millennium. CRC Press; 2001.

[113] Chen X, Lv J, McElroy MB, Han X, Nielsen CP, Wen J. Power system capacity expansion under higher penetration of renewables considering flexibility constraints and low carbon policies. IEEE Trans Power Syst 2018;33:6240–53. https://doi.org/10.1109/TPWRS.2018.2827003.

[114] Ruhnau O, Bucksteeg M, Ritter D, Schmitz R, Böttger D, Koch M, et al. Why electricity market models yield different results: carbon pricing in a model-comparison experiment. Renew Sustain Energy Rev 2022;153:111701. https://doi.org/10.1016/j.rser.2021.111701.

[115] Tanaka M, Chen Y. Market power in renewable portfolio standards. Energy Econ 2013;39:187–96. https://doi.org/10.1016/j.eneco.2013.05.004.

[116] Chen Y, Wang L. A power market model with renewable portfolio standards, green pricing and GHG emissions trading programs. In: 2008 IEEE Energy 2030 Conference; 2008. p. 1–7. https://doi.org/10.1109/ENERGY.2008.4780995.

[117] Nahmmacher P, Schmid E, Hirth L, Knopf B. Carpe diem: a novel approach to select representative days for long-term power system modeling. Energy 2016;112:430–42. https://doi.org/10.1016/j.energy.2016.06.081.

[118] Schyska BU, Kies A, Schlott M, von Bremen L, Medjroubi W. The sensitivity of power system expansion models. Joule 2021;5:2606–24. https://doi.org/10.1016/j.joule.2021.07.017.

[119] Gonzato S, Bruninx K, Delarue E. Long term storage in generation expansion planning models with a reduced temporal scope. Appl Energy 2021;298:117168. https://doi.org/10.1016/j.apenergy.2021.117168.

[120] Frew BA, Jacobson MZ. Temporal and spatial tradeoffs in power system modeling with assumptions about storage: an application of the POWER model. Energy 2016;117:198–213. https://doi.org/10.1016/j.energy.2016.10.074.

[121] Reichenberg L, Siddiqui AS, Wogrin S. Policy implications of downscaling the time dimension in power system planning models to represent variability in renewable output. Energy 2018;159:870–7. https://doi.org/10.1016/j.energy.2018.06.160.

[122] Poncelet K, Hoschle H, Delarue E, D'haeseleer W. Selecting representative days for investment planning models20; 2023.

[123] Levin T, Blaisdell-Pijuan PL, Kwon J, Mann WN. High temporal resolution generation expansion planning for the clean energy transition. Renew Sustain Energy Trans 2024;5:100072. https://doi.org/10.1016/j.rset.2023.100072.

[124] Tan YT, Kirschen DS. Co-optimization of energy and reserve in electricity markets with demand-side participation in reserve services. In: 2006 IEEE PES Power

Systems Conference and Exposition; 2006. p. 1182–9. https://doi.org/10.1109/PSCE.2006.296475.
[125] Zhou Z, Botterud A, Wang J, Bessa R, Keko H, Sumaili J, et al. Application of probabilistic wind power forecasting in electricity markets. 2013. https://doi.org/10.1002/WE.1496.
[126] Administration BP. Operating reserves13. Administration; 2023.
[127] FERC, NERC, Regional Entities. The February 2021 cold weather outages in Texas and the south Central United States. In: Federal Energy Regulatory Commission, north American electric reliability corporation, Midwest reliability organization, northeast power coordinating council. ReliabilityFirst Corporation, SERC Corporation, Texas Reliability Entity and Western Electricity Coordinating Council; 2021.
[128] Kirby B, Ela E, Milligan M. Chapter 7 - analyzing the impact of variable Energy resources on power system reserves. In: Jones LE, editor. Renewable Energy integration. 2nd ed. Boston: Academic Press; 2017. p. 85–101. https://doi.org/10.1016/B978-0-12-809592-8.00007-X.
[129] Söder L, Tómasson E, Estanqueiro A, Flynn D, Hodge B-M, Kiviluoma J, et al. Review of wind generation within adequacy calculations and capacity markets for different power systems. Renew Sustain Energy Rev 2020;119:109540. https://doi.org/10.1016/j.rser.2019.109540.
[130] Mertens T, Bruninx K, Duerinck J, Delarue E. Capacity credit of storage in long-term planning models and capacity markets. Electr Pow Syst Res 2021;194:107070. https://doi.org/10.1016/j.epsr.2021.107070.
[131] Byers C, Levin T, Botterud A. Capacity market design and renewable energy: performance incentives, qualifying capacity, and demand curves. Electricity J 2018;31:65–74. https://doi.org/10.1016/j.tej.2018.01.006.
[132] Murthy Balijepalli VSK, Pradhan V, Khaparde SA, Shereef RM. Review of demand response under smart grid paradigm. ISGT2011-India 2011:236–43. https://doi.org/10.1109/ISET-India.2011.6145388.
[133] DeCarolis JF, Babaee S, Li B, Kanungo S. Modelling to generate alternatives with an energy system optimization model. Environ Model Software 2016;79:300–10. https://doi.org/10.1016/j.envsoft.2015.11.019.
[134] Papavasiliou A, Oren SS, O'Neill RP. Reserve requirements for wind power integration: a scenario-based stochastic programming framework. IEEE Trans Power Syst 2011;26:2197–206. https://doi.org/10.1109/TPWRS.2011.2121095.
[135] Hasan KN, Preece R, Milanović JV. Existing approaches and trends in uncertainty modelling and probabilistic stability analysis of power systems with renewable generation. Renew Sustain Energy Rev 2019;101:168–80. https://doi.org/10.1016/j.rser.2018.10.027.
[136] Wang Y, Zhou Z, Botterud A, Zhang K. Optimal wind power uncertainty intervals for electricity market operation. IEEE Trans Sustain Energy 2018;9:199–210. https://doi.org/10.1109/TSTE.2017.2723907.
[137] Lorca Á, Sun XA. Adaptive robust optimization with dynamic uncertainty sets for multi-period economic dispatch under significant wind. IEEE Trans Power Syst 2015;30:1702–13. https://doi.org/10.1109/TPWRS.2014.2357714.
[138] Dueñas P, Reneses J, Barquín J. Dealing with multi-factor uncertainty in electricity markets by combining Monte Carlo simulation with spatial interpolation techniques. IET Generat Transm Distribut 2011;5:323–31. https://doi.org/10.1049/iet-gtd.2010.0264.
[139] Nazari-Heris M, Mohammadi-Ivatloo B. Application of robust optimization method to power system problems. Classical and recent aspects of power system optimization. Elsevier; 2018. p. 19–32. https://doi.org/10.1016/B978-0-12-812441-3.00002-1.
[140] Lai CS, Locatelli G, Pimm A, Wu X, Lai LL. A review on long-term electrical power system modeling with energy storage. J Clean Prod 2021;280:124298. https://doi.org/10.1016/j.jclepro.2020.124298.
[141] Sheibani MR, Yousefi GR, Latify MA, Hacopian Dolatabadi S. Energy storage system expansion planning in power systems: a review. IET Renew Power Generat 2018;12:1203–21. https://doi.org/10.1049/iet-rpg.2018.0089.
[142] Stage S, Larsson Y. Incremental cost of water power. Trans Am Inst Electric Eng Part III: Power Apparat Syst 1961;80:361–4. https://doi.org/10.1109/AIEEPAS.1961.4501045.
[143] Jager HI, Smith BT. Sustainable reservoir operation: Can we generate hydropower and preserve ecosystem values? River Res Appl 2008;24:340–52. https://doi.org/10.1002/rra.1069.
[144] Sternberg R. Hydropower's future, the environment, and global electricity systems. Renew Sustain Energy Rev 2010;14:713–23. https://doi.org/10.1016/j.rser.2009.08.016.
[145] Yüksel I. Hydropower for sustainable water and energy development. Renew Sustain Energy Rev 2010;14:462–9. https://doi.org/10.1016/j.rser.2009.07.025.
[146] Blom E, Soder L. Including hydropower in large scale power system models12; 2023.
[147] Edwards BK, Flaim SJ, Howitt RE. Optimal provision of hydroelectric power under environmental and regulatory constraints. Land Econ 1999;75:267. https://doi.org/10.2307/3147010.
[148] Richter BD, Thomas GA. Restoring environmental flows by modifying dam operations. E&S 2007;12:art12. https://doi.org/10.5751/ES-02014-120112.
[149] Pérez-Díaz JI, Belsnes M, Diniz AL. Optimization of hydropower operation. Reference module in earth systems and environmental sciences. Elsevier; 2021. https://doi.org/10.1016/B978-0-12-819727-1.00092-3.
[150] Härtel P, Korpås M. Aggregation methods for modelling hydropower and its implications for a highly decarbonised energy system in Europe. Energies 2017;10:1841. https://doi.org/10.3390/en10111841.
[151] Blom E, Söder L. Comparison of different computational methods and formulations for hydropower equivalents. In: 2022 IEEE 7th International Energy Conference (ENERGYCON); 2022. p. 1–6. https://doi.org/10.1109/ENERGYCON53164.2022.9830320.
[152] Härtel P, Korpås M. Demystifying market clearing and price setting effects in low-carbon energy systems. Energy Econ 2021;93:105051. https://doi.org/10.1016/j.eneco.2020.105051.
[153] Farhat IA, El-Hawary ME. Optimization methods applied for solving the short-term hydrothermal coordination problem. Electr Pow Syst Res 2009;79:1308–20. https://doi.org/10.1016/j.epsr.2009.04.001.
[154] Fosso OB, Gjelsvik A, Haugstad A, Mo B, Wangensteen I. Generation scheduling in a deregulated system. The Norwegian case. IEEE Trans Power Syst 1999;14:75–81. https://doi.org/10.1109/59.744487.
[155] Wolfgang O, Haugstad A, Mo B, Gjelsvik A, Wangensteen I, Doorman G. Hydro reservoir handling in Norway before and after deregulation. Energy 2009;34:1642–51. https://doi.org/10.1016/j.energy.2009.07.025.
[156] Pereira MVF, Pinto LMVG. Multi-stage stochastic optimization applied to energy planning. Math Program 1991;52:359–75. https://doi.org/10.1007/BF01582895.
[157] Maceiral MEP, Penna DDJ, Diniz AL, Pinto RJ, Melo ACG, Vasconcellos CV, et al. Twenty years of application of stochastic dual dynamic programming in official and agent studies in Brazil-Main features and improvements on the NEWAVE model. Power Syst Comp Conf (PSCC) 2018;2018:1–7. https://doi.org/10.23919/PSCC.2018.8442754.
[158] Rani D, Moreira MM. Simulation–optimization modeling: a survey and potential application in reservoir systems operation. Water Resour Manage 2010;24:1107–38. https://doi.org/10.1007/s11269-009-9488-0.
[159] Maceira MEP, Melo ACG, Pessanha JFM, Cruz CB, Almeida VA, Justino TC. Wind uncertainty modeling in long-term operation planning of hydro-dominated systems. In: 2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS); 2022. p. 1–6. https://doi.org/10.1109/PMAPS53380.2022.9810576.
[160] Helseth A, Haugen M, Jaehnert S, Mo B, Farahmand H, Naversen C. Multi-market price forecasting in hydro-thermal power systems. In: 2018 15th International Conference on the European Energy Market (EEM); 2018. p. 1–5. https://doi.org/10.1109/EEM.2018.8469932.
[161] Machado FDR, Diniz AL, Borges CLT, Brandão LC. Asynchronous parallel stochastic dual dynamic programming applied to hydrothermal generation planning. Electr Pow Syst Res 2021;191:106907. https://doi.org/10.1016/j.epsr.2020.106907.
[162] Chaves Brandão dos Santos L, Luiz Diniz A, Simonetti L. Accelerating dual dynamic programming for stochastic hydrothermal coordination problems. In: 2018 Power Systems Computation Conference (PSCC); 2018. p. 1–7. https://doi.org/10.23919/PSCC.2018.8442829.
[163] Helseth A, Mo B, Lote Henden A, Warland G. Detailed long-term hydro-thermal scheduling for expansion planning in the Nordic power system. IET Generat Transm Distrib 2018;12:441–7. https://doi.org/10.1049/iet-gtd.2017.0903.
[164] Graabak I, Jaehnert S, Korpås M, Mo B. Norway as a battery for the future European power system – Comparison of two different methodological approaches. In: Helseth A, editor. Proceedings of the 6th international workshop on hydro scheduling in competitive electricity markets. Cham: Springer International Publishing; 2019. p. 76–83. https://doi.org/10.1007/978-3-030-03311-8_10.
[165] Tveten ÅG, Kirkerud JG, Bolkesjø TF. Integrating variable renewables: the benefits of interconnecting thermal and hydropower regions. Int J Energy Sector Manag 2016;10:474–506. https://doi.org/10.1108/IJESM-08-2014-0006.
[166] Van den Bergh K, Boury J, Delarue E. The flow-based market coupling in Central Western Europe: concepts and definitions. Electricity J 2016;29:24–9. https://doi.org/10.1016/j.tej.2015.12.004.
[167] Pope SL. Price formation in ISOs and RTOs. 2014. p. 72.
[168] Nappu MB. LMP-lossless for congested power system based on DC-OPF. In: 2014 Makassar International Conference on Electrical Engineering and Informatics (MICEEI). Makassar, Indonesia: IEEE; 2014. p. 194–9. https://doi.org/10.1109/MICEEI.2014.7067338.
[169] Johnson RB, Oren SS, Svoboda AJ. Equity and efficiency of unit commitment in competitive electricity markets. Utilities Pol 1997;6:9–19. https://doi.org/10.1016/S0957-1787(96)00009-4.
[170] Chao H. Incentives for efficient pricing mechanism in markets with non-convexities. J Regul Econom 2019;56:33–58.
[171] Gribik PR, Hogan WW, Pope SL. Market-clearing electricity prices and energy uplift46; 2023.
[172] Andrianesis P, Caramanis M, Hogan W. Computation of convex Hull prices in electricity markets with non-convexities using Dantzig-Wolfe decomposition. 2020.
[173] Yu Y, Guan Y, Chen Y. An extended integral unit commitment formulation and an iterative algorithm for convex hull pricing. IEEE Trans Power Syst 2020;35:4335–46. https://doi.org/10.1109/TPWRS.2020.2993027.
[174] Guo Y, Tong L. Pricing multi-period dispatch under uncertainty. In: 2018 56th Annual Allerton Conference on Communication, Control, and Computing (Allerton); 2018. p. 341–5. https://doi.org/10.1109/ALLERTON.2018.8635641.
[175] Baik E, Chawla KP, Jenkins JD, Kolster C, Patankar NS, Olson A, et al. What is different about different net-zero carbon electricity systems? Energy Clim Change 2021;2:100046. https://doi.org/10.1016/j.egycc.2021.100046.
[176] Vithayasrichareon P, Riesz J, MacGill I. Operational flexibility of future generation portfolios with high renewables. Appl Energy 2017;206:32–41. https://doi.org/10.1016/j.apenergy.2017.08.164.

[177] Kopiske J, Spieker S, Tsatsaronis G. Value of power plant flexibility in power systems with high shares of variable renewables: a scenario outlook for Germany 2035. Energy 2017;137:823–33. https://doi.org/10.1016/j.energy.2017.04.138.
[178] Eser P, Singh A, Chokani N, Abhari RS. Effect of increased renewables generation on operation of thermal power plants. Appl Energy 2016;164:723–32. https://doi.org/10.1016/j.apenergy.2015.12.017.
[179] Newbery D, Pollitt MG, Ritz RA, Strielkowski W. Market design for a high-renewables European electricity system. Renew Sustain Energy Rev 2018;91:695–707. https://doi.org/10.1016/j.rser.2018.04.025.
[180] Chattopadhyay D, Alpcan T. Capacity and energy-only markets under high renewable penetration. IEEE Trans Power Syst 2016;31:1692–702. https://doi.org/10.1109/TPWRS.2015.2461675.
[181] Van den Bergh K, Delarue E. Energy and reserve markets: interdependency in electricity systems with a high share of renewables. Electr Pow Syst Res 2020;189:106537. https://doi.org/10.1016/j.epsr.2020.106537.
[182] Domínguez R, Oggioni G, Smeers Y. Reserve procurement and flexibility services in power systems with high renewable capacity: effects of integration on different market designs. Int J Electric Power Energy Syst 2019;113:1014–34. https://doi.org/10.1016/j.ijepes.2019.05.064.
[183] Energy&Climate FSR. Seams, ancillary services and congestion management: US versus EU electricity markets. Lights on EU; 2017. https://medium.com/florence-school-of-regulation/seams-ancillary-services-and-congestion-management-us-versus-eu-electricity-markets-ab9ad53a16df [accessed January 11, 2022].
[184] Zerrahn A, Schill W-P. Long-run power storage requirements for high shares of renewables: review and a new model. Renew Sustain Energy Rev 2017;79:1518–34. https://doi.org/10.1016/j.rser.2016.11.098.
[185] Mohamad F, Teh J. Impacts of energy storage system on power system reliability: a systematic review. Energies 2018;11:1749. https://doi.org/10.3390/en11071749.
[186] Bernath C, Deac G, Sensfuß F. Impact of sector coupling on the market value of renewable energies – a model-based scenario analysis. Appl Energy 2021;281:115985. https://doi.org/10.1016/j.apenergy.2020.115985.
[187] Moghimi FH, Barforoushi T. A short-term decision-making model for a price-maker distribution company in wholesale and retail electricity markets considering demand response and real-time pricing. Int J Electric Power Energy Syst 2020;117:105701. https://doi.org/10.1016/j.ijepes.2019.105701.
[188] Patnam BSK, Pindoriya NM. Demand response in consumer-centric electricity market: mathematical models and optimization problems. Electr Pow Syst Res 2021;193:106923. https://doi.org/10.1016/j.epsr.2020.106923.
[189] Pfeifer A, Dobravec V, Pavlinek L, Krajačić G, Duić N. Integration of renewable energy and demand response technologies in interconnected energy systems. Energy 2018;161:447–55. https://doi.org/10.1016/j.energy.2018.07.134.
[190] Wang F, Ge X, Li K, Mi Z. Day-ahead market optimal bidding strategy and quantitative compensation mechanism design for load aggregator engaging demand response. IEEE Trans Industry Appl 2019;55:5564–73. https://doi.org/10.1109/TIA.2019.2936183.
[191] Li C, Liu C, Yu X, Deng K, Huang T, Liu L. Integrating demand response and renewable energy in wholesale market. In: Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence. Stockholm, Sweden: International Joint Conferences on Artificial Intelligence Organization; 2018. p. 382–8. https://doi.org/10.24963/ijcai.2018/53.
[192] King R. The debate about demand response and wholesale electricity markets. 2015.
[193] Demand Response Compensation in Organized Wholesale Energy Markets. 2011.
[194] Böttger D, Götz M, Theofilidi M, Bruckner T. Control power provision with power-to-heat plants in systems with high shares of renewable energy sources – an illustrative analysis for Germany based on the use of electric boilers in district heating grids. Energy 2015;82:157–67. https://doi.org/10.1016/j.energy.2015.01.022.
[195] Arabzadeh V, Mikkola J, Jasiūnas J, Lund PD. Deep decarbonization of urban energy systems through renewable energy and sector-coupling flexibility strategies. J Environ Manage 2020;260:110090. https://doi.org/10.1016/j.jenvman.2020.110090.
[196] Bernath C, Deac G, Sensfuß F. Influence of heat pumps on renewable electricity integration: Germany in a European context. Energ Strat Rev 2019;26:100389. https://doi.org/10.1016/j.esr.2019.100389.
[197] Boblenz K, Frank V, Meyer B. Energy system analysis for evaluation of sector coupling technologies. Fuel 2019;254:115658. https://doi.org/10.1016/j.fuel.2019.115658.
[198] Du E, Zhang N, Hodge B-M, Wang Q, Lu Z, Kang C, et al. Operation of a high renewable penetrated power system with CSP plants: a look-ahead stochastic unit commitment model. IEEE Trans Power Syst 2019;34:140–51. https://doi.org/10.1109/TPWRS.2018.2866486.
[199] Kern T, Eberl B, Boing F, von Roon S. Coupling of electricity and gas market models. In: 2017 14th International Conference on the European Energy Market (EEM), Dresden, Germany. IEEE; 2017. p. 1–5. https://doi.org/10.1109/EEM.2017.7981927.
[200] Bloess A, Schill W-P, Zerrahn A. Power-to-heat for renewable energy integration: a review of technologies, modeling approaches, and flexibility potentials. Appl Energy 2018;212:1611–26. https://doi.org/10.1016/j.apenergy.2017.12.073.
[201] Sneum DM, González MG, Gea-Bermúdez J. Increased heat-electricity sector coupling by constraining biomass use? Energy 2021;222:119986. https://doi.org/10.1016/j.energy.2021.119986.
[202] Zong Y, Wang J, You S, Su W, Ohlenschlager VF, Petersen SB, et al. Identifying the system-related conditions and consequences of power-to-X solutions for a high renewables penetration in Denmark. In: 2020 IEEE 4th conference on Energy internet and Energy system integration (EI2). Wuhan, China: IEEE; 2020. p. 955–60. https://doi.org/10.1109/EI250167.2020.9346867.
[203] Witkowski K, Haering P, Seidelt S, Pini N. Role of thermal technologies for enhancing flexibility in multi-energy systems through sector coupling: technical suitability and expected developments. IET Energy Syst Integrat 2020;2:69–79. https://doi.org/10.1049/iet-esi.2019.0061.
[204] Diakov V, Cole W, Sullivan P, Brinkman G, Margolis R. Improving power system modeling. A tool to link capacity expansion and production cost models. Golden, CO (United States): National Renewable Energy Lab (NREL); 2015. https://doi.org/10.2172/1233204.
[205] Kwon J, Levin T, Zhou Z, Botterud A, Mehrtash M, Hobbs BF. The impact of market design and clean energy incentives on strategic generation investments and resource adequacy in low-carbon electricity markets. Renew Energy Focus 2023;47:100495. https://doi.org/10.1016/j.ref.2023.100495.