Current Sustainable/Renewable Energy Reports (2025) 12:26
https://doi.org/10.1007/s40518-025-00274-9

REVIEW

Ten challenges for mathematical modeling of the green-energy transition

Edward Anderson[1] · Michael Ferris[2] · Andrew Philpott[3] · Mihai Anitescu[4] · Peter Cramton[5] · Sijia Geng[6] · Richard Green[1] · Tito Homem-de-Mello[7] · Olivier Huber[2] · Vincent Leclère[8] · Ramteen Sioshansi[9,10]

Received: 25 July 2025 / Accepted: 20 August 2025

Abstract

Purpose of Review The global transition from fossil fuels to renewable energy creates a wide array of challenges that call for new models and analytical methods. This review identifies ten mathematical modeling challenges that are central to supporting the energy transition across operational, planning, market, and policy dimensions. Our aim is to provide structured research agenda for the analytics community, focusing on areas where methodological advances can have the greatest real-world impact.

Recent Findings Drawing on the expertise of leaders in the field, we present a consensus view of current modeling needs that span temporal, spatial, and institutional scales. These include short-term operational problems, long-term infrastructure planning under uncertainty, and the formulation and solution of increasingly large and complex optimization problems. In addition to technical issues, we highlight the growing importance of modeling social and behavioral dimensions – such as procedural and distributive justice, retail-consumer participation, and the representation of diverse stakeholders. We identify also new challenges in market design, distributed energy integration, and the validation of large-scale models used for policy support.

Summary The ten challenges reflect the breadth and complexity of the energy transition and emphasize the need for models that are scalable, robust, and socially aware. Collectively, they form a roadmap for analytics researchers aiming to contribute to the energy transition through innovative and impactful modeling.

Keywords Green energy · Energy transition · Mathematical modeling

This article is part of the Topical Collection on *Energy Markets*.

✉ Edward Anderson
e.anderson@imperial.ac.uk

1 Imperial College London, London SW7 2AZ, UK

2 University of Wisconsin-Madison, Madison, WI 53706, USA

3 University of Auckland, Auckland, New Zealand

4 University of Chicago, Chicago, IL 60637, USA

5 University of Maryland, College Park, MD 20742, USA

6 Johns Hopkins University, Baltimore, MD, USA

7 Universidad Adolfo Ibáñez, Santiago, Chile

8 ENPC, Institut Polytechnique de Paris, Marne-la-Vallée, France

9 Carnegie Mellon University, Pittsburgh, PA 15213, USA

10 The Ohio State University, Columbus, OH 43210, USA

Introduction

In an effort to limit global warming, the world has committed to a transition from using energy generated by fossil fuels to renewable energy. The scale of this transition is enormous, and it will be costly. A wide range of models and analytical tools have been devised to help in planning and implementing the transition. In this paper we use the term "model" to encompass analytical approaches more generally. Examples include a machine-learning approach to find good recourse actions; a computational tool that enables equilibria of markets to be found; analysis that predicts instabilities in energy systems; or a description of a policy choice under uncertainty for which an optimal solution can be found.

We outline a set of ten significant challenges that need to be addressed, as a guide to where new research could be

Published online: 08 September 2025

pursued profitably. Rather than a single concrete problem, each of these challenges refers to an area in which a set of related problems needs to be resolved. Experience convinces us that in many areas of the energy transition, we do not yet have the right mathematical models to capture important aspects of the energy transition, or the right methods to provide useful analysis. In identifying these challenges, we want to provide directions for research in this area. We have focused our attention on analytical challenges arising in the energy transition, rather than considering related technological challenges, such as carbon-capture technology or battery design.

The literature on modeling the energy transition is extensive, and this paper is not intended to survey it. Rather, we focus on the remaining modeling challenges that we regard as key to the transition.

In assessing models for the transition, we place a high value on their practicality. We want the models to be realistic, understandable and trusted, so that decision makers find them useful. Large complex models do not always satisfy these criteria. Validation on real data builds trust, but this can be difficult for long-term models, even if historical data sets enable back-testing. Ideally, models should yield new insights.

By collecting a set of ten challenges in one document we aim to provide a helpful summary of the many opportunities for future research analyzing the green-energy transition. In distilling the perspectives of a number of researchers from different disciplines, this paper reflects a consensus on the most important analytical challenges in the transition. We have aimed to be broad in scope, since this will be helpful in suggesting research possibilities that may otherwise be overlooked. This breadth is what makes our paper distinctive in comparison with other papers that have discussed modelling challenges [22, 33]. On the other hand, to keep the scope of the paper within reasonable bounds we have restricted attention almost entirely to the electricity sector that is at the heart of the green-energy transition. For example, we do not discuss gas, biofuels or hydrogen.

Figure 1 shows how the challenges relate to the components of the energy transition. We summarize the individual challenges as follows.

We begin by considering the decisions that are needed to build infrastructure for the energy transition (Challenge 1). The green-energy transition is a matter of urgency. Thus, the transformation needs to occur at speed, which introduces constraints on the way that infrastructure is built that must be accounted for in models (Challenge 2). But revamping infrastructure alone is insufficient. There are also changes that are needed in the way that the electricity industry operates at both a market level, where price mechanisms may need to be redesigned (Challenge 3), and at the physical level, where mechanisms for stability and control are impacted by the switch to renewable-energy sources (Challenge 4).

Understanding the behavior of the energy system as a whole implies an understanding of how interdependent participants that interact with the system behave. At the wholesale level, this requires the use of game theory to represent independent suppliers making strategic choices (Challenge 5). At the consumer level, customers' trade-offs in making energy-usage decisions requires new models (Challenge 6).

Energy systems require us to make decisions in an uncertain environment. Uncertainties occur at the macro level, when we consider investments that are made now and will be used for decades into the future in an environment that we cannot predict accurately (Challenge 7). Uncertainties occur also at short time horizons: our goal is to build systems that are robust to uncertain extreme events of various kinds (Challenge 8).

With large changes in the energy system, there is potential for injustice and inequity, for which one must account alongside other considerations (Challenge 9). Finally, we need to recognize that modeling the transition in an energy system which is large and complex brings its own challenges in the scale and complexity of the models built and their validation and use (Challenge 10).

In some cases, we have good versions of the models that we need but fall short of being able to analyze them, or compute solutions. In other instances, the structure of the model may be clear, but we do not have the data that we need. In other cases, we do not yet know the best way to model the problem that we are interested to study.

The Ten Challenges

Challenge 1: Policy Choices for Infrastructure Planning

> Infrastructure-investment decisions are made by multiple actors under deep uncertainty and misaligned incentives, with complex interdependencies between generation, transmission, and storage. An effective model must capture the dynamic, sequential nature of these decisions and the policy mechanisms that shape them.

Policy mechanisms that support major infrastructure investments must incentivize robust long-term capacity decisions, while accounting for the substantial uncertainty regarding what will happen during the lifetime of the assets (e.g., 10 or 20 years). Costs are likely to change substantially, there is inherent policy uncertainty and volatility, and consumer demand is difficult to forecast, e.g., owing to the rate of electrification (see Challenge 7).

Infrastructure-investment decisions involve interactions between many different actors, including government at var-

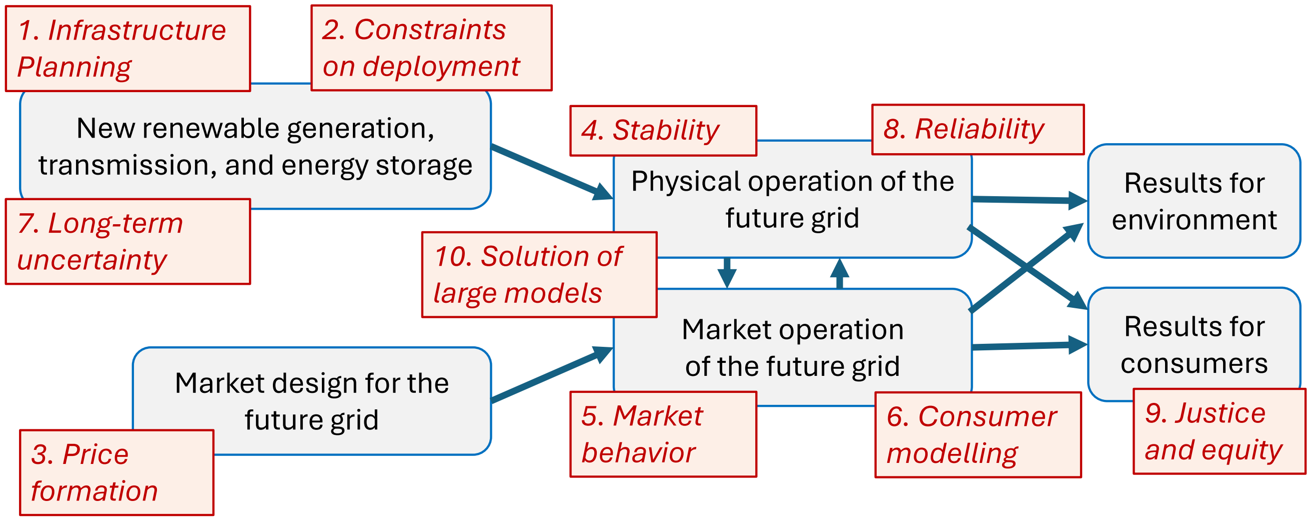

Fig. 1 Overview of the challenges and where they occur within the energy-transition framework

ious levels, market operators, transmission-network owners, and individual investors. Each of these entities makes decisions within its own regulatory and market environment, with complex connections between different decisions. A simple model of the way that this occurs may involve government determining the aggregate amount of new generation to be procured, which is followed by an auction to determine the exact mix of generation and energy storage that is built and decisions made by transmission owners regarding reinforcement of the transmission network.

Infrastructure decisions are not made once but repeatedly. For instance, generation investments are made throughout the time horizon of a planning model, and transmission capacity can be built reactively (in response to generation investments) or proactively (based on anticipated locations for generation investments) [52, 55]. As the penetration of variable renewable energy increases, the value of dispatchable resources, including energy storage, increases. Thus, the timing of investment decisions is critically important.

Determining the appropriate levels of transmission or energy storage involves a trade-off between curtailing generation during periods of local surplus and incurring higher capital costs for expanded transmission or energy storage capacity [54]. An optimal capacity decision depends also on the variation of generation supply and electricity demand and details of the market design that provides price signals.

Contracting for procurement of generation capacity can take many different forms. Examples include contracts for differences, payments for curtailment, and availability payments and penalties. In addition, implementation details, e.g., the length of the contract term, must be determined.

The choice of objective function for planning models is not straightforward. Due to misaligned incentives, a good outcome for one agent may not be so for another. Moreover, the relationship between outcomes may be complex. As an example, a transmission planner that preserves real options, e.g., by delaying investment until demand grows, might increase risk for generation-capacity planners and produce an outcome that reduces social welfare.

Infrastructure-planning models give different results depending on the order in which decisions are made and when information becomes available, and this may be difficult to determine. For example, it is unclear whether transmission-investment decisions lead generation-investment decisions or vice versa. Regardless, the sequential and autonomous nature of these decisions can lead to complex investment dynamics, including signaling games and information asymmetries, which may result in socially undesirable outcomes.

Challenge 2: Constraints on Deployment

> Rapid deployment of clean energy technologies is limited by supply-chain bottlenecks, skilled-labor shortages, and institutional delays such as electricity-system connection and permitting. Models must account for these dynamic constraints to identify feasible, low-regret strategies and prioritize actions under uncertainty.

The urgency of decarbonization implies that changes to the energy system need to occur very rapidly, with a large scale deployment of renewable generation and other sustainable technologies. The need to move fast creates bottlenecks across multiple domains: supply chains, skilled labor, permitting, and electricity-system interconnection.

Given the constraints on the availability of various resources, the timing of our deployment actions becomes important. We need models that reflect these constraints to answer questions regarding what is feasible, what actions should be given priority, and which low-regret strategies are robust under uncertainty.

Supply-chain constraints are especially significant. Scaling up wind and solar generation depends on sufficient manufacturing capacity, access to raw materials, and logistics for transporting and installing equipment. For instance, shortages in key inputs to photovoltaic production have emerged already [41]. Building renewable generation involves the use of energy that is associated with carbon emissions [16]. Different policies for the sequence and the speed of manufacture of the products that are needed for the energy transition will give different results in terms of total emissions. The problem of finding the right trajectory here is reminiscent of the classical bottleneck problem that is formulated by Bellman [4]. Incorporating learning effects and endogenous cost dynamics adds further modeling complexity (see Challenge 7).

Labor shortages represent another critical constraint. These are seen acutely in large-scale roll-outs of new technologies at the consumer level. An example occurs in the shortage of heat-pump engineers to conduct home installations. A global shortfall in electrical engineers and skilled trades threatens to slow progress [34], and must be accounted for in workforce-constrained deployment models.

Institutional processes present further obstacles. This is seen most clearly in the ballooning of interconnection queues around the world [35]. The queues consist of new renewable-generation projects that are waiting to be connected to electricity systems, due to capacity constraints in conducting the required impact studies. There is a related difficulty in going through the necessary processes to obtain planning permissions for new renewable generation and the increased transmission that is also needed. In many countries these constraints are sufficiently severe that they can rule out reaching some of the short-term intermediate emissions targets that are proposed.

The appropriate modeling approach depends on the time horizon. Short-term deployment problems resemble scheduling challenges, where the sequence of actions is critical. Longer-term problems are likely to involve considerations of optionality, because there is uncertainty of what will happen. Decisions made early will influence future possibilities, both through resource consumption and by affecting cost trajectories (e.g., via material price shifts).

Challenge 3: Price Formation in Wholesale Markets

> Efficient electricity price formation is essential to coordinate short-term operations and long-term investment, but current market designs struggle with non-convexities, uncertainty, and integration of energy storage and demand-side resources. Models are needed to improve dispatch, enable robust forward markets, and support risk management under growing variability and volatility.

Wholesale electricity markets use price as a means to guide behavior. Price formation is essential to support efficient decision making. If the prices are wrong, then production, consumption and investment decisions also will be wrong. Inefficient prices can arise from non-convexities in production, the exercise of market power, or missing or illiquid markets for hedging risk.

Existing wholesale markets can come close to the ideal of prices reflecting marginal social utility. For example, US day-ahead and real-time markets provide granular time and location signals that support efficient dispatch and scheduling of traditional generators [14]. However, today's markets often fail to accommodate energy-storage and demand-side resources. As the share of wind and solar rises, inelastic demand can lead to increasingly volatile wholesale prices, ranging from negative prices [53] to scarcity pricing near the value of lost load. Improved dispatch and pricing mechanisms are needed to enable participation of flexible demand and energy storage in both operational and investment timescales.

Short-term price formation relies on multi-period economic-dispatch models, that are solved in a rolling-horizon fashion. These models deal with non-convexities from unit commitment through forms of convex-hull pricing or other approaches. Even in the convex case, dispatch and prices can be inconsistent with agents' preferences, or time-inconsistent, when viewed *ex post*.

At shorter time horizons, real-time dispatch models can be improved with some form of look-ahead that recognizes resource constraints or future opportunities that arise during short periods. When the future is uncertain, flexibility has a value that should be rewarded and using stochastic dispatch models is one approach to such valuation (though other approaches are possible [11]). However, agents must agree on this stochastic model and, as with multi-period models, they may not yield time-consistent dispatch and prices. Spot markets, day-ahead to real-time, enable efficient operation of existing resources. Longer-term price signals are needed to motivate investment and let participants establish positions to manage needs and risks. Forward markets play a crucial role in enhancing the efficiency and stability of electricity markets by addressing issues such as risk, market power, and investment coordination [15]. Liquid forward markets enable price risks to be hedged and reduce volatility in the cash flows that are needed to support investment. By allowing new entrants to compete before entering the market, forward markets foster competition and reduce uncertainty. Moreover, by shifting a significant share of transactions to forward contracts, these markets also reduce the incentive for suppliers to exercise market power during periods of scarcity.

New models are needed to inform the design of forward markets that maintain liquidity across many interrelated products and are sufficiently granular across space and time to be (close to) complete. Integrating forward-market design with retail tariffs, insurance-style contracts, and other risk-management tools can enhance welfare for both suppliers and consumers [5].

Challenge 4: Stability and Control of Systems with High Renewables

> As inverter-based renewables replace conventional generators, electricity systems lose inertia and face new forms of instability across multiple time scales. Modeling is needed to capture the complex dynamics of inverter-based resources and design controls that ensure stability under large disturbances.

The rapid growth in renewable energy introduces increased variability in electricity systems at multiple time scales: how can such variability be controlled?. The variability poses significant challenges, including the need for backup power when wind or solar output is low, and a decline in system inertia due to the retirement of conventional plants. Moreover inverter-based resources can introduce new stability concerns as their control dynamics differ fundamentally from those of synchronous machines.

Renewable generation is converted to AC using power electronics [44]. The dynamic behavior of power electronic converters is dominated by the enforced control law [26]. If inverters are set to match the observed frequency, then fluctuations in the latter can cause inverters to follow a dropping frequency with risk of system collapse. For example, during the 2021 Winter Storm Uri [13], a fault at a Texas combined-cycle generator resulted in power reduction from solar plants totaling 1 GW of capacity (a quarter of those operating during the time). This power reduction was not due to the fault itself, but due to inverter-level or feeder-level tripping or control-system behavior within the resources.

New developments in so-called grid-forming inverters endow these devices with software that responds to system disturbances more intelligently [38]. Grid-forming inverters have been deployed successfully in small-scale systems. Although the small-disturbance behavior of inverter-based systems can be made to match synchronous-generator dynamics, their large-disturbance behavior displays hybrid dynamics due to inherent limit-induced events which is quite different from synchronous generators [32]. A key modeling challenge is to develop generalized dynamic models that capture the hybrid, nonlinear behavior of diverse inverter-based systems under large disturbances—moving beyond case-by-case analysis.

The integration of variable renewable energy (VRE) into high-voltage transmission networks is associated with rising system costs and operational complexity [31]. Backup supply, via energy storage, peaking generators, or hybrid systems, is required when renewable generation falls short. These resources may be aggregated with wind or solar so that a firm supply can be offered to the market, though this is less efficient than dispatching through the grid. Dispatch decisions require multi-period models that are solved in a rolling-horizon fashion using forecasts, such as CAISO's 65-minute horizon with five-minute increments used to compute locational marginal prices. This can lead to pricing inconsistencies, as we discuss in Challenge 3.

Conventional generators produce electricity from heavy rotors that spin at a nominal frequency. The angular momentum due to the inertia of these spinning devices serves to dampen frequency deviations. As these units retire, maintaining frequency becomes more difficult. Stability requirements are typically addressed through ancillary services markets. In many cases, these services, such as spinning reserves, are procured from market offers and co-optimized with energy in the security-constrained dispatch. As the cost of providing stability services grows with renewable-energy penetration, there is growing interest in incorporating such services directly into market settlements. This is a challenge that will become more pressing as distributed renewable-energy resources are aggregated into virtual power plants [36].

Challenge 5: Predicting the Behavior of Wholesale Energy Market Participants

> The growing complexity of wholesale electricity markets – driven by diverse technologies, strategic bidding, and repeated interactions – makes it increasingly difficult to predict participant behavior. Modeling must address market power, learning dynamics, and information asymmetries to understand how real-world decisions deviate from idealized equilibrium assumptions.

As a result of the energy transition, wholesale electricity markets are undergoing structural and behavioral shifts that make participant behavior more difficult to predict. There are a greater number and variety of generation participants including an increased role for non-dispatchable generators; an increased amount of demand-side response; a greater geographical spread of generation (including imports from different countries); and increased short-term uncertainty in supply. Existing ancillary services, such as reserve and fast-acting response, will become more important, alongside new services, such as the provision of inertia (Challenge 4).

The decarbonization imperative makes it important to model how energy-market participants respond to incentives. Real markets will have imperfections. We should use models to understand and avoid the impacts of these imperfections. In studying wholesale markets, we typically assume rational agents who make decisions to maximize profits (or utility). We assume then that market participants follow an equilibrium strategy, which is computed using the best model of these profits that we have available.

Equilibrium behavior for wholesale-market participants involves bids and offers that may take different forms depending on the jurisdiction. Trade can occur during different times, with forward contracting, day-ahead auctions, the possibility of during-the-day adjustments, and a market to balance generation (as well as demand) during real time. Different participants will have different information.

Any proposed market design should maximize welfare in the setting of perfect competition and complete markets [20] as a minimal requirement. In reality, large generators often will be aware that they have market power to affect prices [28], while facing risks that cannot be hedged [1]. Indeed the exercise of market power may become an increasing problem with high renewable penetration.

The starting point for comparison is a full-information (Nash-)equilibrium set of bids and offers. But this can be difficult to find: there may be no equilibrium in pure strategies and there may be multiple possible equilibria (e.g., in many supply-function models there is a continuum of equilibria). To enable predictions in real situations these models typically have to be large scale, which poses a computational challenge. Finding one equilibrium may not be enough, and there are no current effective methods for computing all possible equilibria.

There is a tension between the relative simplicity in, e.g., cost structures of many game-theoretic models and the complexity of electricity systems. As the number of empirically important markets grows, generators need to consider how to allocate their capacity across multiple products, such as energy and reserve, or submit multi-part bids to the system operator to signal separate start-up and energy costs [18]. In systems with locational prices, the quantity that is offered in one place will also affect prices elsewhere, so that the best response function becomes a high dimensional object [28].

Because the market operates repeatedly with the same set of participants, we can expect learning to occur, so that behaviors vary over time. The result will be behavior that diverges from static equilibrium predictions, and consequently actions may seem irrational or inconsistent from a static perspective. We can consider also the possibility of implicitly collusive behavior, where there is a non-competitive outcome, but market participants have no incentive to change this.

Both types of outcomes can distort market efficiency, but collusion is particularly hard to model. "Folk Theorems" [24] imply that there will be many different possible collusive outcomes. The use of reinforcement learning in bidding processes [59] may well increase the likelihood of collusive outcomes, without this being a deliberate choice of participants.

The overall aim of modeling is to develop tools to enable better prediction of actual outcomes. However, comparing predicted with actual bids is not straightforward, because the information behind the actual decision may not be available. It is a challenge to model the information available to the different participants and their individual circumstances (e.g., their beliefs about other players, the financial contracts they hold, and their risk attitudes).

Challenge 6: The Impact of Consumer Decisions on the Energy System

> The rise of distributed energy resources and electrified demand is shifting operational and investment decisions toward the distribution grid and individual consumers. New models must capture heterogeneous household behavior, automation, retail price responsiveness, and the role of aggregators, while addressing challenges of privacy, coordination, and system-level impacts.

Some key components of the energy transition, especially distributed photovolatic solar and widespread electric-vehicle adoption (with or without vehicle-to-grid operations) are pushing the electricity system toward more decentralized operation. As energy flows and decision-making shift closer to end-users, the distribution network becomes a critical bottleneck, requiring increased attention relative to the traditional focus on transmission. For example, a transformer that currently is adequate for a residential area may be short of what is required if 50% or more of the houses choose to charge their electric vehicles simultaneously. Thus, the design of the distribution network (e.g., transformer sizes, line capacities, and topology), as well as its operation, must be optimized to accommodate these potential future requirements.

If centralized, electric-vehicle charging can be sequenced so as to limit peak consumption. However, charging is a consumer's choice that can only be incentivized, with finer control attainable through automation. It is possible also that automated charging in a way that over-responds to wholesale prices will give rise to problems with new demand peaks [39]. Therefore, one might ask what is the right way to model the household decisions on the demand side (e.g., vehicle charging) and the way that these decisions interact with the rest of the market through aggregators? More broadly, tools that model options at the "grid edge" (i.e., the distributed hardware, software, and business innovations that exist in proximity to the end user) are needed.

Understanding consumer choices requires modeling retail markets and consumer behavior [23]. The gap between retail and wholesale markets is being closed with increasing granularity of pricing options for businesses and individual consumers. Retail market design varies from simple time-of-use pricing to incentive-based schemes and demand response through automatic control mechanisms. At the extreme, consumers may opt for real-time pricing [29]. The use of home automation offers many possibilities for demand to respond to prices, or for control to be exercised without the use of prices. For example control may be delegated to a third-party in charge of satisfying the consumer's needs for an agreed-upon price. It is necessary, however, to understand the barriers to implementing such mechanisms at the household level [17, 47]. The absence of demand response has long been recognized as a significant cause of inefficiencies in energy systems.

Households can reduce or shift demand through both automated systems (e.g., smart appliances that respond to electricity-system signals) and discretionary actions (e.g., delaying a washing cycle or adjusting heating schedules). We require models that capture household behavior, and this may involve identifying different types of household with different characteristics [56]. Accurate modeling of household demand may require the use of data-science methods [60], but these raise important concerns around consumer privacy and data protection [43].

Challenge 7: Dealing with Long-Term Uncertainty and the Associated Risks

> The energy transition involves deep uncertainties in climate impacts, technology costs, demand growth, and policy evolution. Modeling these uncertainties requires going beyond fixed scenarios to incorporate decision-dependent uncertainty, investor behavior, and the risks of model mis-specification.

The energy transition must be planned under multiple sources of long-term uncertainty, including: (i) uncertainty about the long-term effects of climate change on energy systems, e.g., extreme temperatures or droughts; (ii) uncertain increasing electricity demand as the residential, transportation, and industrial sectors become more electrified, and as data-center capacity grows significantly; (iii) uncertain future costs, not only because of unforeseen technological advances but also because of the learning process in manufacturing that typically leads to cost decreases over time; and (iv) uncertainty about future regulatory and policy environments (e.g., carbon pricing).

The system-optimization models that are used by policy makers and stakeholders do not represent the long-term uncertainties and associated risks faithfully. If modeled at all, uncertainties are nearly always represented using finite sample spaces, yielding a set of "scenarios" [19], each of which is a possible realization of a sequence of random events that occur independently of any actions or policies. The choice of scenarios and estimation of probabilities for them in these long-term models is a challenge [37]. Computational challenges also arise when solving multistage optimization problems where uncertainty is represented by large scenario trees, as complexity typically grows exponentially with the number of stages.

Policy makers (and many in the energy modeling community) often define "scenarios" differently: they are a possible narrative of future events and decisions under some broad assumptions about the future. These make sense when used to simulate fixed policies, but it is commonplace to see different policies adopted in different scenarios. Since allowing decisions obtained with deterministic optimization to vary with future realizations of uncertain parameters will give a clairvoyance bias, it is important to communicate to policy makers this limitation of the use of narrative scenarios.

Optimization under uncertainty becomes more difficult when uncertain parameters are affected by decisions. Typical examples arise in optimizing the tradeoff between exploiting actions known to give satisfactory results and those that riskily explore for potentially better outcomes (as occur in bandit algorithms [40]). Optimizing subsidies for technologies (e.g., solar panels) to improve learning is another example [27]. Such models often can be solved using mixed-integer programming [30], but they are limited to small-scale problems.

Investors choose technologies that they perceive to be promising. Uncertainty over these choices will affect decisions that are made by other investors. While some of these issues are identified in the economics literature [48], existing models often fail to include such uncertainties appropriately in optimization models that are used for planning. Investors will have different risk attitudes and time-based preferences (discount rates) [42]. Models must integrate the selfish decisions of investors to maximize their own risk-adjusted welfare subject to any government policy objectives. Integrating such ideas with long-term optimization constitutes an important challenge.

Finally, model mis-specification poses a fundamental risk. This includes not only errors in estimating probability distributions, but also mis-specification of the model itself. For instance, ignoring the dependence of the uncertainty on the decisions can have disastrous consequences; Cooper et al. [12] present simple models to demonstrate this effect, albeit in a different context.

Challenge 8: Reliability and Resilience to Extreme Events

> Electricity systems must be designed to withstand rare but severe disruptions, including climate-related events that are increasing in frequency and intensity. Models are needed to represent rare-event dynamics and cascading failures, and enable resilience in the face of high-impact, low-probability disruptions.

Power system engineers balance the risk of system failures against the cost of everyday performance. Climate change has led to an apparent increase in the frequency of once-in-a-century events, which creates a need to account more for such extreme events in planning, thereby affecting this balance.

We can distinguish different types of extreme events. Some, such as earthquakes, are unpredictable and the focus will be on the efficient physical recovery of the system to a good operating state. While the green-energy transition may lead to new options, due to a more distributed supply or movable electrical storage, existing modeling techniques can be used to find appropriate sizing, staging, and operation during this recovery.

In contrast, predictable extreme events – especially those driven by weather systems – pose a distinct challenge, as proactive strategies are feasible and necessary. Understanding the frequency, scale, and impact of the event is critical to address these questions. There is potential for severe consequences from such events, such as the widespread power outages caused by Winter Storm Uri in Texas during February 2021 [8]. Many events are highly correlated due to their dependence on weather, especially temperature. Storms, hurricanes, destructive wildfires, heatwaves, drought, torrential rains, and flooding can have severe impacts on both electricity supply and demand. Extreme temperatures simultaneously increase electricity demand (e.g., for cooling) and reduce supply (e.g., via thermal derating), amplifying electricity-system stress [45] and have contributed to major power outages and near-shortage events during recent years. Data-driven approaches that form better predictions, coupled with approaches that incorporate learning [25], are needed to optimize effectively under such settings. In both settings, it is also important that useful forensics are generated for future planning and response, to determine what could have been done better. Capacity-expansion models (Challenge 1) have a key role to play, providing redundant generation to guard against the risk, specifically adapted to systems that are impacted by high-impact, low-frequency events.

Cascading failures, in which a localized fault propagates through the network, are a common mode of large-scale power system collapse [58]. Modeling resilience therefore requires understanding the mechanisms and conditions under which such cascades occur.

Extreme events can lead to very high prices. There are difficult questions to address regarding whether these are an appropriate part of the market functioning, or whether there should be additional caps and safeguards in place. A related set of questions are what new instruments, or forms of reserve or ancillary services, would be valuable to help counter extreme events and how these can be validated.

Sampling approaches are difficult in these rare-event settings. Various approaches exist to address sampling issues of severe tail events [51]. One approach is importance sampling, where different weights are applied to such events. Another is to split the main model from the extreme-event model, and validate rare-event outcomes using the extreme-event model [50]. Methods such as importance sampling or hybrid frameworks that separate baseline and extreme-event dynamics [50, 51] can improve estimation of low-probability, high-impact risks.

Challenge 9: Justice and Equity

> The costs and benefits of the energy transition are distributed unequally across households, regions, and communities, raising critical questions of fairness, inclusion, and political legitimacy. Modeling frameworks must move beyond efficiency alone to incorporate equity as a core objective or constraint, using data-driven metrics to evaluate and inform just outcomes.

The green-energy transition affects individuals differently according to where they live, what capital resources they may have, their family circumstances, and their lifestyle choices. For example, significant changes in employment will occur as legacy fossil-fuel industries are replaced with renewable-energy alternatives [9]. Changes of this magnitude should not be conducted without regard to equity and justice. Perceived or actual inequities can erode public trust. Thus, there are also political consequences, that may threaten the stability and continuity of climate policy. The challenge is to design energy markets and systems that actively promote justice and minimize inequities, or at the very least to ensure that injustices are not created through lack of attention to these issues.

Concepts of equity and justice are multi-faceted and there are many aspects of equity which might be considered within an electricity-market design [2]. The most attention has been paid to distributive justice, relating to benefits or dis-benefits that arise for different groups of people. If a minimum amount of energy (e.g., for heating) is viewed as a human right, then policies that moderate the price of retail contracts should reflect this. Disconnection of customers in times of shortage should not affect the vulnerable.

Distributive justice also arises in the structure of retail tariffs, particularly in the allocation of fixed cost, which is often absorbed into an energy charge. This means that large energy users pay a higher proportion of the fixed cost of connection. In the past, large users were typically wealthier families in larger houses, although some people, particularly the elderly, may have high consumption despite living on low incomes. The advent of rooftop solar has allowed many households with the resources to install solar panels to reduce consumption and pay a much lower share of the fixed costs. Furthermore, it is often the wealthy who are among the first to adopt green technologies (e.g., solar panels and electric vehicles) and benefit from incentives that are funded by taxpayers [6, 7].

Another aspect is procedural justice, which relates to the transparency of decision-making processes and whether they represent the interests of affected parties. For example, what steps must be followed before some communities are required to host intrusive new infrastructure such as transmission lines?

Changes to the energy system will have different implications for consumers living in different regions. An example occurred in the U.S. Department of Energy's Justice40 initiative [57], where disadvantaged communities were identified from census data, with the goal that 40% of the benefits from a range of federal investments should flow to these disadvantaged communities. A related approach is described by Chapman et al. [10] who give an example of equity considerations in decisions on the closure of different coal-fired generation plants.

Equity considerations should be built into models from the start. Models are useful for exploring trade-offs, so if equity can be measured appropriately, one can include this in a multi-objective optimization and look for trade-offs between different objectives (e.g., reducing emissions and avoiding fuel poverty) to find a Pareto frontier.

On the other hand, equity can be considered a constraint. Model outputs can be used to determine metrics needed to assess the equity of the resulting decisions. These could include environmental and health impacts; access to energy services and their affordability; and community engagement and participation. Unacceptable outcomes can lead to a revision of the policy, or the use of other interventions to offset the distributional consequences that are discovered. Equity metrics can also be used to measure how outcomes for different groups change over time and between scenarios.

Challenge 10: Computation and Validation for Solution of Large Models

> As electricity systems grow in scale and complexity, energy models must capture high-resolution dynamics across space and time, as well as dealing with uncertainty, while remaining computationally feasible. Improvements in model formulation, solution algorithms, and validation methods are needed to ensure that models remain tractable, credible, and relevant for policy decisions under uncertainty.

Modern electricity systems, often described as the world's largest machines, involve many interconnected producers and consumers. The scale of the models that are required for their planning and operation has always posed challenges in analyzing their behavior [46]. The green-energy transition has magnified these difficulties [21]. Increased temporal and spatial interdependence through variable renewable generation and elevated use of inter-connectors between regions has raised the scale of the models that are required. These models need to support policy choices that reflect decarbonization goals over longer time periods.

Challenges occur in the following three areas: the collection of high-quality and realistic input data, the formulation and resolution of the model, and the validation and interpretation of the solution.

Building, solving, and validating large-scale models is time-consuming and data-intensive. It is important to find ways to generate representative datasets to tame the size of the instance, while still faithfully capturing the underlying phenomena. This is particularly important when we wish to represent uncertainty: multi-period models scale linearly with time when they are deterministic, but increase exponentially when uncertainty is taken into account (so that fine temporal resolution becomes impossible). The uncertainty may relate to wind and solar output [49] as well as longer-term issues (Challenge 7). The use of very large models that are based on enormous data sets makes this a potentially interesting area for the application of machine learning.

In addition to high-quality data, faster algorithms and implementations are needed to compute solutions within time frames that are appropriate for the underlying decision problem. Exploiting mathematical structure is a key aspect of algorithmic design. Hence, modeling frameworks that can provide such information to solvers are essential in tackling larger and larger instances. Parallel computation and advances in optimization and machine-learning software will have an impact here, along with the use of specialized computational hardware for solutions.

There are different types of models that relate to energy systems of the future. For instance, integrated assessment models are used to explore different pathways that meet energy and climate targets over periods of many years. These have a wider scope than our focus here, being concerned with emissions; land and resource usage; climate impacts; and technology choices (e.g., in carbon capture). We need more models that are concerned with the economic impacts of different policy choices for the transition to green energy [3].

Diagnostic tools are needed to validate the solutions and test the models. This can take various forms: for example, a model might be "back-tested" on historical data to determine if its forecasts made 10 or 20 years ago have transpired. Different models of the same region can be compared: what drives any differences in model solutions to similar problems?

To support effective policy analysis, models must represent the diversity of actors and stakeholders with potentially competing objectives. This requires explicitly modeling

Table 1 Summary of modeling challenges for the energy transition and associated research directions

Challenge	Core Issue	Potential Research Directions
1. Policy choices for infrastructure planning	Coordinating investment decisions under uncertainty and multiple objectives	- Dynamic multi-agent models for investment under policy uncertainty - Mechanism design for co-optimizing public and private objectives - Game-theoretic treatment of government, transmission planner and generator interaction
2. Constraints on deployment	Time-dependent constraints on build-out rates and system integration	- Spatiotemporal deployment optimization models - Dynamic constraints in capacity planning - Deployment priorities with permitting processes and supply chain limitations
3. Price formation	Ensuring efficient and stable price signals in evolving market designs	- Coupled physical-economic dispatch models - Integration of flexibility markets with energy and capacity pricing - Evaluation of forward and real-time market interactions under volatility
4. Stability	Maintaining voltage, frequency, and system control with low inertia	- Control-theoretic models for low-inertia grids - Dynamic models for inverter-based systems under large disturbances - Probabilistic stability analysis with high renewable penetration
5. Market behavior	Strategic bidding, market power, and competition in mixed-asset environments	- Equilibrium modeling with renewables and energy storage - Game-theoretic models with learning and bounded rationality - Empirical validation of strategic behavior
6. Consumer modeling	Electrification, demand-side flexibility, and response to new tariffs	- Behavioral models of flexible demand and automation - Aggregator optimization with household-level constraints and preferences - Models linking consumer heterogeneity to pricing and adoption
7. Long-term uncertainty	Structural uncertainty in policy, technology, and demand	- Distributionally robust and adaptive optimization in energy systems - Stochastic modeling with scenario discovery - Learning models in multi-decade planning models
8. Reliability	System resilience to extreme events, correlated failures, and weather-driven variability	- Probabilistic reliability modeling with climate-informed risk - Cascading-failure simulation and mitigation strategies - Planning models with resilience constraints
9. Justice and equity	Distributional impacts of energy policies and transition pathways	- Multi-objective modeling with equity constraints - Quantitative metrics for fairness in cost/benefit allocation - Spatially resolved impact assessments across demographic groups
10. Solution of large models	Scalability and tractability of complex, multi-sector, multi-scale models	- Decomposition and parallel-computing techniques for scalable multi-stage optimization - Machine-learning surrogates for simulation - Validation, benchmarking, and stakeholder trust

distributional trade-offs and institutional settings to generate insights that are both technically robust and politically relevant.

Conclusion

This paper presents ten modeling challenges that arise from the transition to green energy. The broad themes are infrastructure (Challenges 1–3), short-term models of electricity (Challenges 4–6), long- and short-term uncertainty (Challenges 7 and 8), justice (Challenge 9), and computation (Challenge 10). A summary of these challenges is given in Table 1, where we give also a number of potential research directions.

Because the focus is on the green energy transition, systems for electricity generation and transmission receive most emphasis, which perhaps also reflects the backgrounds of the authors. We do not discuss green fuels (e.g., hydrogen) or reducing emissions from agriculture and transport, and we hardly touch on general integrated models, as these have a much broader modeling scope (dealing with emissions, land use, *etc.*) than the energy transition alone. Our hope is that the paper will provoke discussion among modelers and policy makers, and provide a starting point for applied mathematicians, engineers, and economists who are looking for research areas that will contribute to reaching decarbonization targets.

Key References

- E. Baker, A.P. Goldstein, and I.M.L. Azevedo. A perspective on equity implications of net zero energy systems. *Energy and Climate Change*, 2:100047, 2021.

  Discusses how a net-zero energy system requires the development of tools to assess equity outcomes, and to address existing inequities, such as energy burden, health impacts, and decision-making power.

- M.C. Ferris and A.B. Philpott. Optimizing green energy systems. *INFORMS Journal on Optimization*, 2025.

  Reviews the contributions that mathematical optimization and equilibrium models can make to the green-energy transition, looking at a range of physical scales and timescales.

- B. Guo and M. Weeks. Dynamic tariffs, demand response, and regulation in retail electricity markets. *Energy Economics*, 106:105774, 2022.

  Considers the use of demand response via dynamic tariffs so consumers have appropriate incentives to shift or reduce peak load and analyses this through a two-stage dynamic game.

- P.J. Heptonstall and R.J.K. Gross. A systematic review of the costs and impacts of integrating variable renewables into power grids. *Nature Energy*, 6(1):72–83, 2021.

  Provides a wide-ranging review of the international evidence on the cost and impact of integrating wind and solar generation showing that costs depend on the penetration of renewable energy.

- L. Hofbauer, W. McDowall, and S. Pye. Challenges and opportunities for energy system modelling to foster multi-level governance of energy transitions. *Renewable and Sustainable Energy Reviews*, 161:112330, 2022.

  Reviews energy-modelling studies and shows how these typically focus on a single governance level, and argues for the need for models taking into account multi-level governance systems.

Acknowledgements This paper has emerged from discussions of participants at the Architecture of Green Energy Systems (AGES) program held at Institute of Mathematical and Statistical Innovation at University of Chicago. The authors acknowledge gratefully the contributions to this document of Miguel Anjos, Ari Ball Burak, John Birge, Benjamin Hobbs, Jesse Holzer, Liz Moyer, Richard O'Neill, Shmuel Oren, Line Roald, Adam Wierman, Golbon Zakeri, and other attendees of the AGES closing workshop.

Author Contributions E.A. and A.P. wrote the Introduction and Conclusion. Material for individual challenges was written by the following authors R.S. (Challenge 1), E.A. (Challenge 2), P.C. (Challenge 3), M.A. and S.G. (Challenge 4), R.G. (Challenge 5), V.L. (Challenge 6), T.H-d-M. (Challenge 7), M.F. (Challenge 8), E.A. and R.G. (Challenge 9), O.H. (Challenge 10). All authors were involved in editing the text.

Funding Open Access funding provided by Imperial College London. The Architecture of Green Energy Program was supported by the National Science Foundation (Grant No. DMS-1929348). V.L. was supported by the Bézout Labex, funded by ANR (grant ANR-10-LABX-58). T. H-d-M. was supported by grant FONDECYT 1221770, ANID, Chile. R.S. was supported by Electric Power Research Institute grant DKT230520, Carnegie Mellon Electricity Industry Center, and Wilton E. Scott Institute for Energy Innovation.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

References

1. Abada I, de Maere d'Aertrycke G, Smeers Y. On the multiplicity of solutions in generation capacity investment models with incomplete markets: a risk-averse stochastic equilibrium approach. Math Prog. 2017;165(1).
2. Baker E, Goldstein AP, Azevedo IML. A perspective on equity implications of net zero energy systems. Energy Climate Change. 2021;2:100047.
3. Barbrook-Johnson P, Mercure J-F, Sharpe S, Peñasco C, Hepburn C, Anadon LD, et al. Economic modelling fit for the demands of energy decision makers. Nat Energy. 2024;9(3):229–31.
4. Bellman R. Bottleneck problems, functional equations, and dynamic programming. Econometrica. 1955;73–87.
5. Bobbio E, Brandkamp S, Chan S, Cramton P, Malec D, Ockenfels A, Yu L. Resilient electricity requires consumer engagement Technical report, University of Maryland, 2024.
6. Borenstein S. Private net benefits of residential solar pv: the role of electricity tariffs, tax incentives, and rebates. J Assoc Environ Resour Econ. 2017;4(S1):S85–122.
7. Borenstein S, Davis LW. The distributional effects of US clean energy tax credits. Tax Policy Econ. 2016;30(1):191–234.
8. Busby JW, Baker K, Bazilian MD, Gilbert AQ, Grubert E, Rai V, et al. Cascading risks: understanding the 2021 winter blackout in Texas. Energy Res Soc Sci. 2021;77:102106.
9. Carley S, Konisky DM. The justice and equity implications of the clean energy transition. Nat Energy. 2020;5(8):569–77.
10. Chapman AJ, McLellan BC, Tezuka T. Prioritizing mitigation efforts considering co-benefits, equity and energy justice: Fossil fuel to renewable energy transition pathways. Appl Energy. 2018;219:187–98.
11. Cho J, Papavasiliou A. Pricing under uncertainty in multi-interval real-time markets. Oper Res. 2023;71(6):1928–42.
12. Cooper WL, Homem-de-Mello T, Kleywegt AJ. Models of the spiral down effect in revenue management. Oper Res. 2006;54(5):968–87.
13. North American Electricity Reliability Corporation and Texas Reliability Entity. Odessa Disturbance: https://www.naes.com/odessa-disturbance-nerc-report-of-key-findings/.
14. Cramton P. Electricity market design. Oxf Rev Econ Policy. 2017;33(4):589–612.
15. Cramton P, Brandkamp S, Chao H-P, Dark J, Hoy D, Kyle AS, Malec D, Ockenfels A. A forward energy market to improve reliability and resiliency. Technical report, University of Maryland, 2024.
16. Davidsson S, Grandell L, Wachtmeister H, Höök M. Growth curves and sustained commissioning modelling of renewable energy: investigating resource constraints for wind energy. Energy Policy. 2014;73:767–76.
17. D'Ettorre F, Banaei M, Ebrahimy R, Ali Pourmousavi S, Blomgren EMV, Kowalski J, et al. Exploiting demand-side flexibility: state-of-the-art, open issues and social perspective. Renew Sustainable Energy Rev. 2022;165:112605.
18. Duggan JE Jr, Sioshansi R. Another step towards equilibrium offers in unit commitment auctions with nonconvex costs: multi-firm oligopolies. Energy J. 2019;40(6):249–82.
19. Dupačová J, Consigli G, Wallace SW. Scenarios for multistage stochastic programs. Annals Oper Res. 2000;100:25–53.
20. Ferris MC, Philpott AB. Dynamic risked equilibrium. Oper Res. 2022;70(3):1933–52.
21. Ferris MC, Philpott AB. Optimizing green energy systems. INFORMS J Optim. 2025.
22. Fodstad M, del Granado PC, 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.
23. Frederiks ER, Stenner EV, Hobman K. Household energy use: applying behavioural economics to understand consumer decision-making and behaviour. Renew Sustain Energy Rev. 2015;41:1385–94.
24. Fudenberg D, Maskin E. The folk theorem in repeated games with discounting or with incomplete information. In: A long-run collaboration on long-run games, p. 209–230. World Scientific, 2009.
25. Garcia JD, Street A, Homem de Mello T, Muñoz FD. Application-driven learning: a closed-loop prediction and optimization approach applied to dynamic reserves and demand forecasting. Oper Res. 2025;73(1):22–39.
26. Geng S, Hiskens IA. Unified grid-forming/following inverter control. IEEE Open Access J Power Energy. 2022;9:489–500.
27. Gerarden TD. Demanding innovation: the impact of consumer subsidies on solar panel production costs. Manage Sci. 2023;69(12):7799–820.
28. Graf C, Wolak FA. Measuring the ability to exercise unilateral market power in locational-pricing markets: an application to the Italian electricity market. Conditionally accepted at RAND J Econ.
29. Guo B, Weeks M. Dynamic tariffs, demand response, and regulation in retail electricity markets. Energy Econ. 2022;106:105774.
30. Hellemo L, Barton PI, Tomasgard A. Decision-dependent probabilities in stochastic programs with recourse. CMS. 2018;15(3–4):369–95.
31. Heptonstall PJ, Gross RJK. A systematic review of the costs and impacts of integrating variable renewables into power grids. Nat Energy. 2021;6(1):72–83.
32. Hiskens IA, Pai MA. Trajectory sensitivity analysis of hybrid systems. IEEE Trans Circuits Syst I Fundamental Theory Appl. 2000;47(2):204–20.
33. Hofbauer L, McDowall W, Pye S. Challenges and opportunities for energy system modelling to foster multi-level governance of energy transitions. Renew Sustain Energy Rev. 2022;161:112330.
34. Jagger N, Foxon T, Gouldson A. Skills constraints and the low carbon transition. Climate policy. 2013;13(1):43–57.
35. Johnston S, Liu Y, Yang C. An empirical analysis of the interconnection queue. National Bureau of Economic Research: Technical report; 2023.
36. Kaiss M, Wan Y, Gebbran D, Vila CU, Dragičević T. Review on virtual power plants/virtual aggregators: concepts, applications, prospects and operation strategies. Renew Sustain Energy Rev. 2025;211:115242.
37. Keutchayan J, Ortmann J, Rei W. Problem-driven scenario clustering in stochastic optimization. CMS. 2023;20(1):13.
38. Kroposki B, Hoke A. A path to 100 percent renewable energy: grid-forming inverters will give us the grid we need now. IEEE Spectr. 2024;61(5):50–7.
39. Kühnbach M, Stute J, Klingler A-L. Impacts of avalanche effects of price-optimized electric vehicle charging-does demand response make it worse? Energ Strat Rev. 2021;34:100608.
40. Lattimore T, Szepesvári C. Bandit Algorithms. Cambridge University Press, 2020.

41. Liang Y, Kleijn R, Tukker A, van der Voet E. Material requirements for low-carbon energy technologies: a quantitative review. Renew Sustain Energy Rev. 2022;161:112334.
42. Lind RC, Arrow KJ, Corey GR, Dasgupta P, Sen AK, Stauffer T, Stiglitz JE, Stockfisch JA. Discounting for Time and Risk in Energy Policy. RFF Press, 2013.
43. Liu J, Xiao Y, Li S, Liang W, Chen CP. Cyber security and privacy issues in smart grids. IEEE Commun Surveys Tutorials. 2012;14(4):981–97.
44. Milano F, Dörfler F, Hug G, Hill DJ, Verbič G. Foundations and challenges of low-inertia systems. In: 2018 Power Systems Computation Conference (PSCC), p. 1–25. IEEE, 2018.
45. Murphy S, Sowell F, Apt J. A time-dependent model of generator failures and recoveries captures correlated events and quantifies temperature dependence. Appl Energy. 2019;253.
46. Papavasiliou A. Optimization Models in Electricity Markets. Cambridge University Press, 2024.
47. Parrish B, Heptonstall P, Gross R, Sovacool BK. A systematic review of motivations, enablers and barriers for consumer engagement with residential demand response. Energy Policy. 2020;138:111221.
48. Popp D, Newell RG, Jaffe AB. Energy, the environment, and technological change. Handbook Econ Innov. 2010;2:873–937.
49. Ringkjøb H-K, Haugan PM, Seljom P, Lind A, Wagner F, Mesfun S. Short-term solar and wind variability in long-term energy system models - a European case study. Energy. 2020;209:118377.
50. Rossmann R, Anitescu M, Bessac J, Ferris M, Krock M, Luedtke J, Roald L. A framework for balancing power grid resiliency and efficiency with bi-objective stochastic integer optimization. Technical report, University of Wisconsin, 2024.
51. Ruszczyński A, Shapiro A. Optimization of convex risk functions. Math Oper Res. 2006;31(3):433–52.
52. Sauma EE, Oren SS. Proactive planning and valuation of transmission investments in restructured electricity markets. J Regul Econ. 2006;30:261–90.
53. Seel J, Millstein D, Mills M, Bolinger A, Wiser R. Plentiful electricity turns wholesale prices negative. Advan Appl Energy. 2021;4:100073.
54. Sioshansi R, Denholm P. Benefits of colocating concentrating solar power and wind. IEEE Trans Sustain Energy. 2013;4:877–85.
55. Sioshansi R, Hurlbut D. Market protocols in ERCOT and their effect on wind generation. Energy Policy. 2010;38:3192–7.
56. Sridhar A, Honkapuro S, Ruiz F, Stoklasa J, Annala S, Wolff A, et al. Residential consumer preferences to demand response: analysis of different motivators to enroll in direct load control demand response. Energy Policy. 2023;173:113420.
57. USDOE. Justice40 initiative fact sheet: https://www.energy.gov/sites/default/files/2022-08/J40FactSheet8_25_22v3.pdf. Technical report, US Department of Energy, 2022.
58. Vaiman M, Bell K, Chen Y, Chowdhury B, Dobson I, Hines P, et al. Risk assessment of cascading outages: methodologies and challenges. IEEE Trans Power Syst. 2012;27(2):631–41.
59. Ye Y, Qiu D, Sun M, Papadaskalopoulos D, Strbac G. Deep reinforcement learning for strategic bidding in electricity markets. IEEE Trans Smart Grid. 2020;11(2):1343–55.
60. Zhou K, Yang S. Understanding household energy consumption behavior: the contribution of energy big data analytics. Renew Sustain Energy Rev. 2016;56:810–9.