nature energy

Review article

https://doi.org/10.1038/s41560-023-01340-6

Energy storage solutions to decarbonize electricity through enhanced capacity expansion modelling

Received: 9 November 2022

Accepted: 14 July 2023

Published online: 14 September 2023

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To meet ambitious global decarbonization goals, electricity system planning and operations will change fundamentally. With increasing reliance on variable renewable energy resources, energy storage is likely to play a critical accompanying role to help balance generation and consumption patterns. As grid planners, non-profit organizations, non-governmental organizations, policy makers, regulators and other key stakeholders commonly use capacity expansion modelling to inform energy policy and investment decisions, it is crucial that these processes capture the value of energy storage in energy-system decarbonization. Here we conduct an extensive review of literature on the representation of energy storage in capacity expansion modelling. We identify challenges related to enhancing modelling capabilities to inform decarbonization policies and electricity system investments, and to improve societal outcomes throughout the clean energy transition. We further identify corresponding research activities that can help overcome these challenges and conclude by highlighting tangible real-world outcomes that will result from pursuing these research activities.

Many countries, regional governments and companies are committed to achieving net-zero greenhouse gas emissions by mid century to mitigate climate change, improve air quality and achieve other goals associated with decarbonization, such as the provision of affordable and reliable energy. Although targets are often framed in terms of economy-wide decarbonization, there has been an emphasis on strategies for achieving net-zero emissions in the electricity sector. So far, this sector has demonstrated a set of cost-effective technologies that

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https://doi.org/10.1038/s41560-023-01340-6

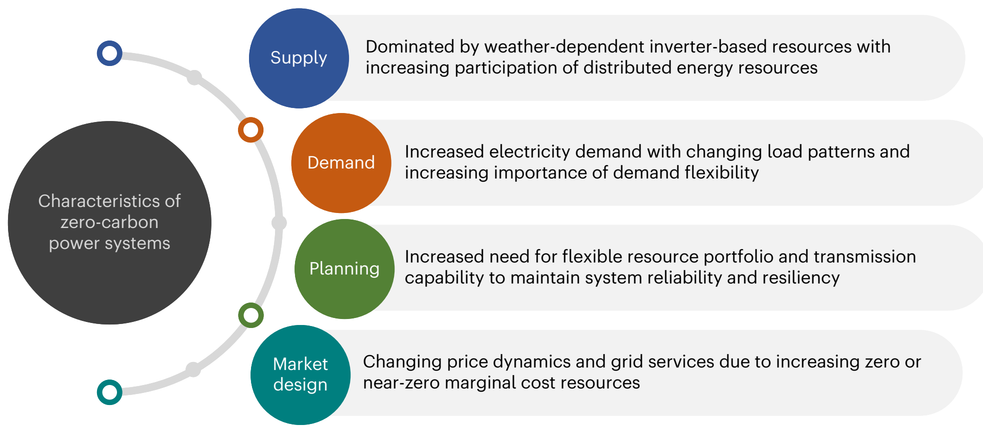

Fig. 1 | Characteristics of zero-carbon power systems. A fully decarbonized power system will exhibit several new characteristics and dynamics that must be represented accurately in CEM to capture the value of different technologies and identify socially optimal capacity expansion pathways.

enable deep reductions in carbon emissions. Moreover, electricity sector decarbonization offers compound benefits due to the important role of electrification in decarbonizing other sectors.

Capacity expansion modelling (CEM) is often used by system planners, resource developers, policy makers and researchers to evaluate different electricity system pathways and to balance the trade-offs in satisfying several objectives, including (1) eliminating carbon emissions, (2) ensuring affordability and (3) maintaining system reliability. There is a large body of literature that has established the development of best practices in CEM over the past decades[1–8]. However, in recent years, the rapidly evolving clean energy transition has introduced a host of new challenges to electricity system planning. As a result, corresponding new approaches to CEM are required to ensure that the crucial dynamics of this transition are captured and reflected in CEM[9–13]. Given the high stakes that are associated with reaching net-zero emissions in a cost-effective, reliable, just and expedient manner, it is important to take a critical look at CEM and its ability to identify and assess decarbonization pathways.

Chief among the new considerations that are driving changes in CEM are a rapid growth in both variable renewable energy (VRE) technologies, that is, wind and solar, and the technologies that are being developed in parallel to integrate them reliably and cost-effectively into the grid. In particular, capturing the value and contributions of energy storage (ES) in supporting the clean energy transition poses a host of new challenges for CEM due to the complex technical dynamics and novel operating paradigms introduced by these resources.

This Review contributes to the literature by providing a detailed review of the challenges that are associated with improving CEM to better reflect the role of ES in future low-carbon electricity systems. Our objective is to communicate these challenges to practitioners of CEM and the broader energy community, while also highlighting the important role that addressing these research needs will play in guiding the energy transition. The remainder of the Review is organized as follows. First, we briefly review the current literature that is related to CEM before introducing new challenges presented by the clean energy transition and discussing the role of ES in this transition. We then introduce three crucial areas of research that are relevant for enhancing the representation of ES in CEM: (1) technology representation; (2) system representation; and (3) markets, policy and societal considerations. Within each of these areas we provide a detailed accounting of specific challenges and research needs. We conclude by summarizing the tangible benefits of pursuing these research goals to capture the complex dynamics of ES in CEM and inform pathways, solutions and policies for electricity sector decarbonization.

Planning low-carbon electricity systems

Capacity expansion modelling

CEM is a quantitative approach to analyse configurations of future power systems that may result from given assumptions about technology performance and cost, system reliability requirements, markets and policy drivers. CEM is utilized commonly to simulate future power systems and optimize the time, location, size and type of new investments over one or more planning years in support of investment planning and policy design (Fig. 1).

Traditionally, CEM was used by regulated electric utilities to identify the least-cost mix of generation and transmission resources to meet expected future electricity demand[14]. Over time, new mathematical programming methods were developed to solve increasingly complex optimization problems, allowing for more details to be considered in the analysis[6,7]. Following the introduction of competitive electricity markets in many regions during the 1990s, the scope of CEM expanded to also consider competition between market participations, the role of demand response[1,8], and energy storage[15]. Moreover, the importance of considering multiple criteria, including environmental impacts, was increasingly recognized[1,16]. More recently, the rapid increase in VRE has given rise to a number of challenges for CEM, as it becomes more important to capture operational details and system needs in planning decisions[2,4,10,17].

Today, analysts typically conduct CEM by utilizing advanced computer models and tools to represent the physical characteristics of the electricity system, simulate complex decision-making across all its elements, and analyse interactions with markets and policy. CEM is commonly utilized by (1) electric utilities and energy companies to inform their resource planning and strategic investments; (2) governments and regulators to inform and evaluate existing and new energy or environmental policies; (3) electricity market operators to analyse the impacts of different rules and regulations governing electricity markets; (4) consultants to support industry stakeholders with the aforementioned activities; and (5) researchers at universities, national laboratories and other research institutions to conduct forward-looking analyses and identify future system needs and opportunities for methodological enhancements.

One important consideration is that CEM is a process intended to inform decision-making, but it will not answer every conceivable question. As modelling cannot capture every detail of a power system, each application of CEM must be designed to provide information that is useful and actionable for decision-makers. This may require making compromises across the range of detailed inputs required by CEM, including (1) the geographic representation of the power system; (2) the physical and financial characteristics of different components of

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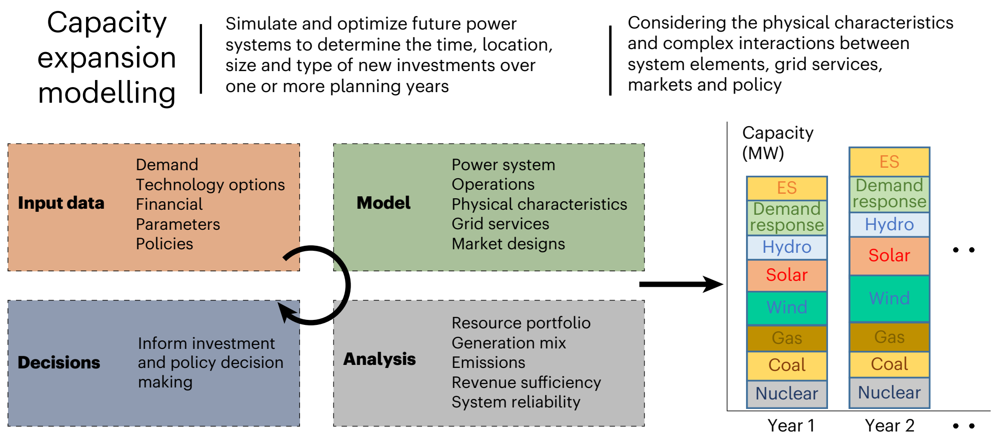

Fig. 2 | Key components of CEM. CEM is a complex process that includes several key components, including collecting data, running models, analysing outputs and interpreting results to inform decision-making. These steps are typically executed successively to determine an optimal future generation mix under a given set of assumptions and system parameters.

the system, including new and emerging technologies; (3) time-series forecasts for electricity demand and the weather-dependent availability of VRE resources; and (4) the projected evolution of policies and regulations that may impact investment and operational decisions. This complex set of input data is typically fed into a large-scale mathematical optimization model that determines future system configurations that minimize total system cost subject to reliability, resource, engineering and policy constraints.

As CEM is being used increasingly to inform electricity decarbonization pathways and the design of efficient energy and environmental policies and regulations, many new objectives, risks and variables must be considered. In particular, CEM is becoming more complex, with the adoption of new technologies, such as ES, which offer new characteristics, for example, net energy loss and degradation, high operational flexibility, and SOC management. In recent years, the literature on decarbonization analysis with CEM has grown rapidly, with numerous studies in the United States[18–20], Europe[21,22] and other parts of the world[23–26]. It is therefore important for policy makers, industry and other stakeholders to become familiar with the capabilities, limitations and challenges associated with CEM to inform the policy and planning decisions that will govern the energy transition[27].

The role of energy storage in decarbonization

VRE resources, such as wind and solar, are likely to constitute a large share of electricity generation in a decarbonized future due to their cost competitiveness and technical maturity[28,29]. The unique characteristics of electricity systems dominated by zero-carbon generation resources (Fig. 2) will require a number of fundamental changes in how they are planned and operated[27,30–32]. As outlined below, ES technologies are particularly well suited to address many of these challenges. Thus, ES will be crucially important under most decarbonization scenarios[33,34].

The weather-driven nature of VRE creates operational and planning challenges in the power grid, which needs more flexibility to manage the associated weather-dependent uncertainty and variability[35,36]. Power systems will therefore require an increasingly flexible resource portfolio to balance supply and demand and to maintain system reliability, a challenge that may be magnified as the carbon-emitting resources that today typically provide a substantial part of system flexibility retire. Many ES technologies can provide much of the flexibility that is needed to move energy through time to improve alignment between electricity generation and consumption patterns. These technologies can also provide many of the grid services that are needed to maintain operational reliability with increasingly volatile and uncertain system conditions.

Future decarbonized electricity systems also are likely to be dominated by generation resources with zero or near-zero marginal costs. This will change price dynamics in competitive wholesale markets, potentially leading to higher frequency of low or even negative electricity prices during periods of surplus VRE supply in the system[32]. ES can charge during periods of low or negative prices and discharge at times when prices are higher. Ultimately, such price arbitrage will help to mitigate price volatility and reduce financial risks for market participants.

Electrifying sectors that currently rely on the direct consumption of carbon-emitting fuels, such as transportation or industrial processes, will play an important role in economy-wide decarbonization efforts. As additional sectors electrify, total electricity demand is likely to increase and load patterns will shift in ways that may motivate new approaches to planning and operations. ES can play a major role in this transition by moving energy through time to help the power system adapt to changing demand profiles, increasing grid-scale resilience as the economy becomes more dependent on the electricity system, and supporting local reliability through the adoption of distributed ES resources.

As some VRE resources are located far from demand centres, are deployed in geographically correlated clusters, and have lower capacity factors than dispatchable generation, electricity system planners will need to improve transmission planning to account for the changing usage patterns of the transmission system. As a result, requirements for planning and operating the transmission system will change under a high VRE future. Properly sited ES technologies can provide transmission services, thereby allowing for the deferral of investments in new transmission infrastructure[37,38]. This is particularly important, as it can take many years to deploy new transmission infrastructure. Therefore, ES can be an important enabler of near-term climate goals that are dependent on transmission service expansion.

From a technological perspective, electrochemical, chemical, thermal and mechanical ES methods are all important for electricity sector decarbonization. Electrochemical (for example, lithium-ion and other batteries) and mechanical storage (for example, pumped storage hydropower or fly wheels) can help to stabilize a VRE-dominated system against variations in VRE availability, increase the utilization of transmission and distribution networks, and support seasonal energy shifting. Chemical ES (for example, hydrogen or ammonia) can help decarbonize industry and heavy-duty transportation. Chemical and thermal ES (for example, molten salt and ice storage) can help to meet weekly and seasonal ES needs for heating, cooling and power. All types of ES solution can contribute to capture synergies between different parts of the energy system, which will move towards tighter coupling

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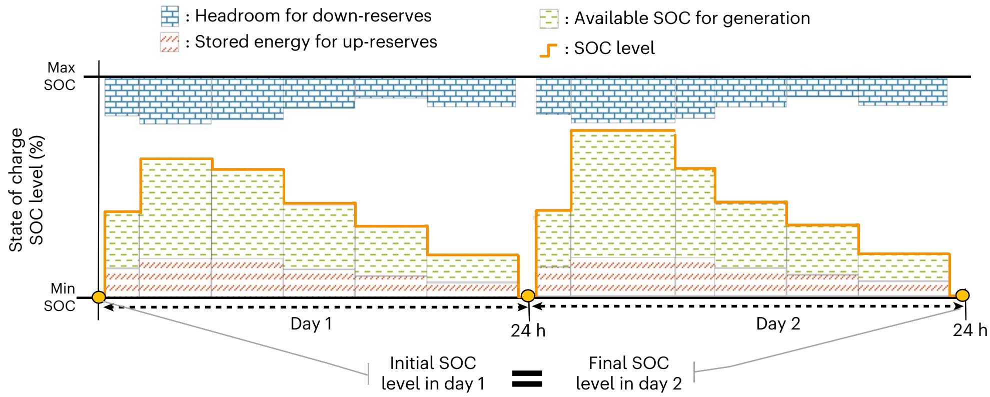

Fig. 3 | Sample SOC management profile. The SOC must be tracked for ES resources in each considered time period as it dictates their ability to charge, discharge and provide other grid services. As SOC depends on actions during previous time periods, capturing chronological continuity becomes much more important in CEM with ES.

to enable efficient decarbonization[39]. However, the specific role of any one ES technology will depend on the ultimate composition of the decarbonized system. For this reason, a range of ES technologies are under development, with differing performance characteristics and attributes, from short-duration ES to handle sub-hourly fluctuations and transients to long-duration ES for multi-day and seasonal balancing needs[40]. Given the wide range of ES technologies and their potential to provide numerous electricity system services, it is becoming critical to assess the roles, costs and benefits of these technologies when planning future power systems. Hence, it is increasingly important to improve the representation of ES in CEM to ensure robust and reliable inputs to planning, market and policy decisions.

Challenges and opportunities for modelling energy storage

Technology representation

Often, ES is represented in CEM as a single homogeneous asset, but in truth there are many ES technologies. These technologies offer different characteristics that must be represented accurately to reflect their respective nuances, for example, charge/discharge capacity, duration, losses, capacity degradation and lifetime[41]. ES can be sited behind the same grid interconnection as a generation resource (for example, solar) and operated as a hybrid resource. Such arrangements may be based on contractual obligations that differ from system least-cost outcomes and are challenging to incorporate into CEM. ES also may substitute for network capacity at both transmission and distribution levels, factors that contribute to the full system value of ES[42].

A key differentiating physical feature of ES is the need to represent the amount of energy that is stored in a device at all times, or its state of charge (SOC). SOC management may also involve maintaining sufficient headroom and energy reserve to provide operating reserves and standby flexibility, as shown in Fig. 3. Because the energy available during one time period is a function of the charge and discharge decisions of all prior time periods, a dynamic SOC constraint is needed to link the time periods of the planning problem. As a result, chronological modelling of operational decisions is crucial for capturing ES dynamics. ES can also have SOC-dependent losses and power limits that add to model complexity. Similarly, it is important to model the SOC of multi-day and seasonal ES technologies over their full charge and discharge cycles.

Moreover, the storage capacity of chemical ES technologies degrades over time in a manner that depends on how they are operated. This creates a complex dynamic between planning and operational decisions that typically is not captured in CEM[43]. ES, like many power system assets, can provide a range of services over different timescales, which makes optimizing its operations in the context of a broader resource portfolio challenging. Assumptions regarding service contributions can have a large impact on investment decisions. For example, it is typically assumed that ES must maintain certain SOC levels to provide ancillary services reliably for an extended duration (Fig. 3).

For many ES technologies, energy and power capacities can be sized independently. These independent decisions should be captured and constrained appropriately in CEM[20,44]. The operating costs of ES also differ in important ways from other traditional generation resources. First, ES operation incurs no direct fuel costs but rather opportunity costs that are driven by expectations of future system conditions and prices. Second, some ES assets incur degradation costs as their storage capacity and lifetime are reduced by frequent and deep drawdowns[45]. These costs can be uncertain and may differ between assets based on their techno-economic characteristics, how they are operated and their owner's risk tolerance. Accurately capturing ES opportunity and degradation costs is also important from a system perspective, as these costs are potentially a key driver of dispatch decisions and price formation in zero-carbon electricity markets[46]. These costs also need to be understood to monitor the exercise of market power by ES, which is much more challenging to monitor for assets with high opportunity costs and zero fuel costs. Finally, because ES can provide many grid services, it is important to accurately capture the cost of providing these services.

The value of ES in a power system depends on the other technologies that are in the system. ES can deliver value by deferring or substituting poorly utilized generation or network capacity, via energy arbitrage and the provision of ancillary services in the form of operating reserves and standby flexibility[47]. ES may compete with many different technologies to provide these services, including nascent technologies. For example, the success of low-carbon technologies, such as carbon capture and sequestration or hydrogen for power generation might reduce the value of long-duration ES systems. Similarly, innovations in long-duration ES may reduce the value of other forms of dispatchable, low- or zero-carbon generation. Furthermore, history suggests that new technologies will emerge and impact planning outcomes in unforeseen ways. For example, it is easy to see in retrospect that failing to account for solar photovoltaics or lithium-ion batteries in CEM a decade ago would have yielded suboptimal investments. It is also important to note that many of the aforementioned challenges that are associated commonly with novel ES technologies also impact more traditional resources such as pumped storage hydropower and conventional hydropower with reservoirs[48,49].

Several other existing and emerging technologies can influence ES investment and operation. Price-responsive loads, distributed energy resources (DERs), hydropower, flexible nuclear power, technologies with multiple energy products (for example, heat, hydrogen, synfuels and water), multistage (combined-cycle) generators, significant zero-carbon hydrogen availability and negative-emissions technologies could all impact the role of ES in the power system.

System representation

There are two primary dimensions to the geographical representation of a power system—the number of considered nodes or zones (resolution) and the size of the study area (scope). Increasing complexity across either dimension also increases computational requirements. Therefore, the modeller must assess these trade-offs based on the specific questions posed[50]. Due to the complex operational dynamics and varying sizes of ES systems, rich detail across both dimensions may be necessary to reveal their optimal locations and capacities. Energy storage also can provide multiple transmission services, possibly reducing the need for grid investments[37]. Such transmission services constitute a substantial part of ES value[51]. Therefore, it is important to represent transmission with sufficient detail in CEM, particularly given the trend of increasing congestion in some systems[52]. However, the limited availability of distribution network data poses challenges for determining optimal siting strategies for distributed ES.

With the growth of VRE, weather data are increasingly important for CEM. As ES consumes power and then resupplies that power to the grid, it is doubly sensitive to weather-driven impacts on electricity demand patterns, weather-dependent VRE output, commodity prices (for example, natural gas) and the resultant electricity prices, making high-quality, synchronized weather data critical. Specifically, it is important to capture the full distribution of future weather outcomes, including extreme events, and joint distributions of time-series variables to evaluate the economic competitiveness of ES and other assets in the electricity system[53]. These analyses may reveal that ES can deliver substantial value during relatively infrequent periods with high net load or unplanned generation outages, as has been observed with transmission infrastructure during the past ten years[54]. In principle, ES can provide 'fuel security' and 'firm fuel supply' products that are being considered by some grid operators, such as ISO New England[55] and the Electricity Reliability Council of Texas[56], to ensure fuel and energy availability during periods of extreme weather conditions.

It is important to consider multiple weather years to capture year-to-year variability in weather-driven resources[57] so as to improve the valuation of long-duration, multi-day and seasonal ES technologies[58,59]. Yet, outside a few studies[60,61], the reliability impacts of extreme weather currently are characterized poorly in CEM. Additionally, CEM commonly employs time-sampling methods to reduce dimensionality and improve computational tractability. These methods struggle to simultaneously capture the full covariance between weather-dependent time series and the patterns of variation within each time series. This limitation may substantially impact valuation and modelled outcomes for ES. Moreover, it is rare for CEM studies to capture changes in future climatological conditions, despite the potentially large impact on decisions[62,63].

Uncertainty in power systems can be categorized into long-run planning uncertainties[64] (for example, variations in demand, fuel prices, technology cost and availability, and policies) and short-term operational uncertainties[65] (for example, generator outages or demand and VRE forecast errors). Traditionally, these two dimensions are modelled largely independently; that is, CEM is used to model long-run uncertainties, whereas dispatch models capture operational uncertainties. However, with the transition towards more variable and uncertain supply resources, operational uncertainty becomes a bigger driver for investment needs, which intersect with planning decisions and long-run uncertainty. Uncertainty particularly impacts ES, which can address uncertainty across multiple time frames. The need to capture both uncertainty dimensions simultaneously within CEM creates computational challenges that may require new modelling approaches.

Because many ES technologies are either relatively new or not yet commercialized, there is tremendous uncertainty around the future cost and performance of these technologies. Care must be taken when combining emerging and established technologies in CEM, as both are typically represented with the same types of cost and performance parameters, although there may be a large variation in the level of uncertainty in the specific parameter values. Moreover, other uncertain factors, such as fuel costs and policy decisions, can impact planning decisions in at least two ways. First, uncertainty increases the value of diversified resource portfolios. Second, uncertainty creates an option value associated with delaying large investments until more is known about future developments.

Such long-run uncertainties can be captured endogenously in CEM using stochastic or robust models[66]. Sensitivity analysis is also commonly used to capture uncertainty in CEM, although there are important limitations in using this approach to value flexibility and optionality in decision-making[67]. Importantly, key long-run uncertainties, from future policy conditions to the pace of technology development and climate-related changes in weather, exhibit deep uncertainty[68]. The probability distributions for these uncertain parameters are either unknowable or entirely subjective. Modellers must be clear and transparent when imposing their own subjective beliefs about these future distributions via the construction of scenarios, sensitivities or weightings for the scenario trees used in stochastic optimization[69]. Alternatively, studies and scenarios should be designed to empower decision-makers to interpret the results in the context of their own subjective beliefs regarding highly impactful future distributions.

The resource adequacy contributions of ES and other emerging resources depend on several uncertain factors, including operating strategies and the make-up of the broader system resource portfolio[70–73]. This will require moving beyond traditional CEM metrics such as planning reserve margins and towards metrics that better reflect the marginal reliability contribution of individual resources, such as effective load-carrying capability. However, determining the reliability contribution of resource additions can be challenging in the context of a dramatically changing resource portfolio and potential extreme weather conditions[74]. Therefore, improving the methods and metrics to assess resource adequacy will be of paramount importance for CEM as the grid decarbonizes[75–77].

Meanwhile, many short-run aspects of power system operations are truly stochastic in nature, including load, wind and solar-forecasting errors, and unforced outages of system assets. Energy storage can mitigate the detrimental impacts of these short-term uncertainties. Within CEM, operational uncertainty has traditionally been addressed by imposing requirements for operating reserves and planning reserve margins. More recently, it has been more common to address operational uncertainty through scenario-based two-stage stochastic or robust optimization. These approaches ensure that investment and retirement decisions made during the first stage consider system operating conditions during the second stage. Modelling scenario-based stochastic problems can improve insights and help CEM correct the biases of deterministic models that fail to recognize the significant impact of forecast uncertainty upon the operations and value of ES. Still, even with advanced modelling and solution algorithms, the scalability of stochastic models is limited due to computational challenges, and one model cannot capture every relevant uncertainty. Therefore, the modeller plays a key role in designing the uncertainty representation and in analysing the uncertain parameters that are most important to the questions at hand.

The rise of VRE has made increasing temporal granularity a critical feature of CEMs[78,79]. Properly valuing ES requires representing inter-temporal operational constraints due to the chronological impact of charging and discharging events on SOC management. These inter-temporal constraints make models more challenging to solve as temporal subsets cannot be modelled independently.

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Therefore, historically it has been necessary to select a limited or reduced number of representative periods for consideration in the model[80,81] while retaining inter-temporal linkages over longer periods[82,83]. However, due to the emergence of longer-duration storage it is increasingly necessary either to forgo time-sampling methods in CEMs altogether (for example, by considering system states instead[84]), model one or more full years at a fine (for example, hourly) resolution, or to dramatically extend the sampled periods from days to multiple weeks[85–87].

The appropriate choice of temporal representation also depends on the duration of ES considered. Diurnal storage (capacity of 2–12 h) can be dispatched near-optimally with a relatively short look-ahead (~1–3 days). Longer-duration and seasonal ES need longer chronological periods to properly value their contribution to meeting power system needs, particularly when there are extended periods with high net load or unplanned outages. Capturing seasonal or interannual ES also makes it hard to apply temporal decomposition methods to solve the full-scale CEM optimization problem. Experience with modelling large hydroelectric reservoirs in CEM can be applied to address some of these challenges. It is also important to increase temporal granularity to capture the value of ES assets that can respond to real-time price signals over sub-hourly intervals as models with hourly time steps typically will undervalue ES assets with this capability[88].

There are trade-offs in the choice of modelling details. More detail in one dimension (for example, geographic) requires reduced detail in another dimension (for example, temporal) if the computational requirements are to remain the same. Some of the associated computational challenges can be addressed by implementing improved decomposition methods across the temporal and geographic dimensions[89]. An optimal choice along these two dimensions depends on the goals of the study and the questions that are being asked. It is important to understand how these different assumptions and relaxations impact results.

Securing a resilient supply of the materials and devices that are needed to enable a zero-carbon grid is an increasingly important challenge as the rapid deployment of new technologies continues. As ES is a key enabler for zero-carbon grids, and lithium-ion batteries remain a primary choice among developers at the global scale, supply chain and manufacturing constraints may slow the energy transition. Adding to growing demand for lithium-ion batteries in the grid is the rapid increase in the adoption of electric vehicles, which has caused significant constraints in the supply of critical materials such as nickel and cobalt and on developing new manufacturing facilities to make devices at scale[90]. Commercializing new ES concepts that can diversify the supply chain while reducing costs remains a critical challenge. In particular, it will be important to address the need for longer-duration ES, which is likely to become more acute at high VRE penetration levels. New electrochemical, thermal and chemical ES materials are needed for these applications[91,92]. Materials and manufacturing challenges are usually ignored in CEM, but these aspects will play an important role in identifying viable decarbonization pathways at national and global scales and warrant increasing consideration.

Policy, market and societal considerations

Nearly 75% of Americans are served by an electric utility with a target to decarbonize fully. Given the increasing stringency of these targets over time, it is critical that CEM accounts for future decarbonization targets and the complex details of new policies that are being implemented to support the energy transition. The specific details of regulations and policies can affect investment decisions greatly, but are not always captured in CEM. For example, models may overlook requirements that hybrid ES assets be charged only by power produced by a coupled generation facility to obtain certain policy benefits. The recently passed Inflation Reduction Act in the United States provides incentives for siting some resources in energy communities and low-income areas[93]. Therefore, it is important that CEMs can distinguish regions that fall under these classifications and identify investment opportunities at this level of geographic resolution. Capturing policy interactions also requires using multi-year look-ahead models, in which investment decisions are made with foresight, rather than myopically. Many policies, such as carbon pricing and tax credits, can be incorporated directly into a least-cost optimization framework[94]. Others, such as air-quality standards, may require linkage with other models[95].

Competitive wholesale electricity markets are replacing or supplementing centralized power system planning in many parts of the world. Traditional least-cost CEM does not attempt to replicate strategic behaviour in such markets. Rather CEM presumes to capture outcomes under the assumption of fully efficient and competitive markets with risk-neutral decision-makers. The discrepancy between these outcomes may widen in deeply decarbonized electricity systems wherein price formation will be increasingly driven by VRE, scarcity or ES opportunity costs[46,96,97]. This will have substantial impacts on price dynamics, making it more challenging to accurately model ES value streams in several ways. First, a large fraction of the value of an ES resource may be realized during a relatively small number of periods with atypical operating conditions, making it crucial to capture those periods[98]. However, accurately representing system behaviour during infrequent periods of extreme operating conditions is typically not a priority for CEMs. Second, market rules for different grid services are evolving, which makes it difficult to model future value streams for ES and other resources and raises questions about the balance between normative and descriptive elements in modelling. Moreover, with the phase-out of synchronous generators, it is becoming more important to consider additional system services, such as inertia, within CEM[99]. Third, as discussed previously, it will be important to enhance uncertainty representations and temporal granularity to capture market interactions, opportunity costs and value streams accurately[77]. This challenge extends to capturing interannual variability in expected revenues, which will change substantially with heterogeneous impacts for different resources and investors with differing risk tolerance[100]. Fourth, CEM will not capture all important market details, for example, the impact of limited look-ahead in real-time markets that can result in inefficient SOC management[101]. Finally, most CEM omits a representation of market power or other market failures[102–104], leading to potential CEM biases that could over- or undervalue ES.

Traditional power system modelling centres around system cost minimization. With increasing awareness of the importance of energy equity and justice considerations[105], it is important to extend CEM analysis beyond total system costs. This can include objectives that are related to the distribution of benefits and impacts from energy-system transitions, which introduce new modelling challenges.

ES can support energy justice objectives by improving community reliability and resilience, reducing costs, building wealth for underserved populations, empowering energy independence and supporting critical services such as water supply[106]. However, these benefits may go largely unrecognized until energy justice objectives are incorporated into CEM. In particular, it has been demonstrated that the distribution of air benefits from decarbonization varies depending on the pathway that is pursued[107], and that relying strictly on least-cost decarbonization pathways may increase disparities in health impacts across vulnerable populations[108].

Capturing societal objectives in CEM will require innovative methods, tools and algorithms for solving energy planning problems, such as multi-objective optimization, trade-off analysis, or modelling to generate alternatives to quantify trade-offs across multiple objectives[109–111]. Traditional planning criteria should be expanded to include distributions of costs and benefits across different population groups, as well as new metrics that quantitatively reflect the core dimensions of energy equity across different modelled outcomes[112,113]. Capturing the distribution of costs and benefits rather than aggregate systemwide outcomes may require greater spatiotemporal granularity. Furthermore, supplemental post-processing methods may be needed to analyse and interpret the data generated by CEM and ensure that modelling results are informative and actionable. Initially, energy equity concerns could be captured in CEM by soft-linking to other models for equity assessment. An ideal goal would be to develop a new class of cohesive equity-informed CEM frameworks to supplant current approaches.

Outlook

Investors, policy makers and other stakeholders rely on CEM to inform key decisions for the energy transition. Therefore, the evolution of CEM tools will substantially impact how investments are allocated to achieve decarbonization goals, while meeting reliability requirements and societal objectives to ensure a just and equitable energy-system transformation. The growing role of ES in low-carbon power systems presents a plethora of new challenges for CEM. These challenges are prompting the search for advanced methods capable of accurately valuing ES in all its forms and applications and capturing its interactions with other energy systems assets. We conclude by summarizing how enhancing CEM to address the challenges outlined in the previous section will impact real-world energy-system decarbonization outcomes.

Improving the physical and cost representation of ES in CEM will ensure that ES is valued properly in planning decisions, considering the full range of grid services provided by ES and corresponding value streams. Similarly, improving the representation of other technologies in CEM will ensure that the synergistic ability of ES to support and integrate these technologies is captured and valued. As CEM is used to inform policy and drive investment decisions, such improvements will lead to tangible changes in how systems evolve and decarbonization pathways unfold. Improving the representation of weather-driven system impacts in CEM will help to ensure that future weather-dependent grids are planned in a weather-informed manner and that CEM accounts for the value of ES in mitigating these characteristics. More specifically, improving spatiotemporal representation in CEM will help to ensure that the operational flexibility and locational value of ES is captured appropriately. Parallel enhancements in CEM formulations, computational performance and data availability will ensure that CEM can be conducted with sufficient spatiotemporal resolution to capture the factors that influence system evolution, while enabling improved representation of long- and short-term system uncertainties to identify more robust expansion plans. Moreover, computationally scalable models will enable improved impact assessment of decarbonization pathways down to the regional and local scales. Expanding CEM to consider materials and manufacturing constraints will help to identify synergies as well as points of potential conflict across sectors, while developing solutions to overcome supply bottlenecks that are of crucial importance for many emerging technologies but are not considered in traditional CEM. This will help to identify energy infrastructure solutions that provide reliable service across sectors under future climate conditions and as supply chains for critical materials become more strained. It will also be important to enhance CEM to capture the impacts and the requirements of new policies and regulations that are being implemented to support local, state and national decarbonization targets and have implications for both resource costs and siting. Meanwhile, competitive wholesale electricity markets are used increasingly to provide economic incentives for operations and investments while also balancing electricity supply and demand. Such markets will continue to evolve to accommodate technologies with characteristics that have not been traditionally accounted for in market design. Thus, it will be important to capture evolving market operations in CEM, particularly in the context of representing market participation models for resources that are energy-limited and exhibit opportunity costs, have rapid response times, or the ability to meet growing demands for new grid services. Such model developments will help inform the changes in market design that are needed to maintain incentives for efficient market entry and exit, establish new types of grid service, determine system needs for existing and new services, and enhance price formation mechanisms. Contemporaneous efforts to capture societal objectives in CEM will help ensure that the benefits of the energy transition are shared across all population segments, that vulnerable groups do not bear the bulk of the associated costs and burdens, and that the technologies needed to support equitable energy systems are procured efficiently.

Finally, to achieve the aforementioned advances, it will be critical to strengthen collaboration across industry, government and academia to ensure that information is shared efficiently between stakeholders, model developers and analysts. This will be particularly important as the electricity sector expands to support more sectors, directly impacts more distributed consumers, and incorporates new and novel technologies, including ES. Such information sharing will help to ensure that CEM is able to inform complex real-world decision-making processes and that all key stakeholder perspectives are considered throughout the energy transition. Enhanced collaboration across stakeholders also will facilitate cogent dissemination of results to non-technical audiences, while also improving communication of their implications and limitations. Furthermore, leveraging diverse perspectives across multiple stakeholders will support evaluation of a wider range of near-optimal solutions that may be easier to implement in practice than the theoretical optimum. Ultimately, enhancing CEM to better capture the valuable role that ES can play throughout the clean energy transition will contribute to developing new and more reliable policy insights, resolving critical interdependencies, and establishing a common understanding of optimal decarbonization pathways, trade-offs and objectives.

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Acknowledgements

This Review emerged from a workshop organized by Argonne National Laboratory on 'Informing Storage Solutions to Decarbonize Electricity' 2–3 November 2021 (https://www.anl.gov/esia/informing-storage-solutions-to-decarbonize-electricity). We acknowledge all participants and organizers of the workshop. This material is based, in part, on work supported by Laboratory Directed Research and Development (LDRD) funding from Argonne National Laboratory, provided by the Director, Office of Science, of the US Department of Energy under contract no. DE-AC02-06CH11357. Finally, we wish to recognize our co-author, George W. Crabtree, an energy trailblazer and true renaissance scientist, who passed away in January 2023. During his six-decade career at Argonne National Laboratory, George advanced several scientific disciplines and inspired colleagues and friends, here and around the world. His work and dedication to the global scientific community will not be forgotten.

Competing interests

J.D.J. is part owner of DeSolve, LLC, which provides techno-economic analysis and decision support for clean energy technology ventures and investors. He serves on the advisory board of Eavor Technologies Inc. and Rondo Energy and has an equity interest in each company. He also provides policy advisory services to Clean Air Task Force and serves as a technical advisor to MUUS Climate Partners and Energy Impact Partners. The remaining authors declare no competing interests.

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Peer review information *Nature Energy* thanks Rolf Golombek, Eric S. Hittinger, and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.