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Planning for a Net-Zero Future: Evolution of Electricity System Models

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Abstract

Over the last few decades, electric power systems globally have been undergoing a rapid transition toward carbon-free energy resources, primarily driven by environmental concerns, technological innovations, economic advantages, and shifts in socioeconomic patterns. The integration of carbon-free electricity generators introduces challenges related to complexity, variability, and uncertainty of system operations. With mainstreaming and upscaling of these solutions, stranded assets, social acceptance, geopolitics of critical material security, disaster resilience, resilience to medium- to long-term variations in climate, constraints on availability of land, and end-of-life disposal issues have emerged and are inviting increasing attention. Recognition of these challenges has led to the emergence of an ensemble of electricity system models to plan and track energy transitions by accounting for these constraints. In this article, we review the coevolution of the required decision support and models. We summarize the evolution across key themes and reflect on the gaps in this evolving planning landscape of actors and networks.

Contents

1. INTRODUCTION

Electricity systems have evolved over the twentieth century from individual generators supplying demand nodes to a network of interconnected generators and storage facilities operating in synchrony to meet the demand at various nodes. The demand for electricity is the manifestation of an individual's preferences for services provisioned by electricity (e.g., heating, cooling, lighting, mechanical power), and it reflects both lifestyle choices and levels of economic activity. At an aggregate national or regional level, the demand for electricity has a temporal profile that varies across hours, days, weeks, seasons, and years and is shaped by factors such as climate, industrial activity, and social patterns of consumption. Provisioning for a variable demand through a generation mix entails construction and operation of generation and transmission assets that are not always utilized to full capacity, leading to both economic inefficiencies and technical challenges in ensuring system reliability. **Figure 1** depicts the electricity system transition journey showing hourly generation mix for four different hypothetical cases of electricity system configurations across the 24 hours of a sample day (all designed to meet the same level of demand). All surplus generation is shown below the *x*-axis and charges the battery storage. This highlights the varying possibilities of hourly supply–demand balancing from a "no solar and wind" scenario to a "no thermal" scenario, emphasizing the complexity of electricity system transition planning and thereby underscoring the importance of energy system models to be able to compare and evaluate multiple options and arrive at the optimal configurations. Its transition is progressing, with flexing of fossil fuels to renewable dispatch necessitating consideration of unit commitment, scheduling, ramping, and demand response (DR).

In this context, historically, the emphasis has been on regulating the sector to ensure sufficient capacity is available to meet the variable demand while avoiding expensive excessive build-up of infrastructure, which may eventually translate into higher prices for the consumers. The consumers could be households, industries, agriculture, and businesses. The cost considerations are relevant from the perspectives of both industrial competitiveness and affordability. Since coordination across a wide range of stakeholders is required in building and operating the electricity system, the planning approaches must integrate a variety of considerations including affordability, security, reliability, and emission intensity.

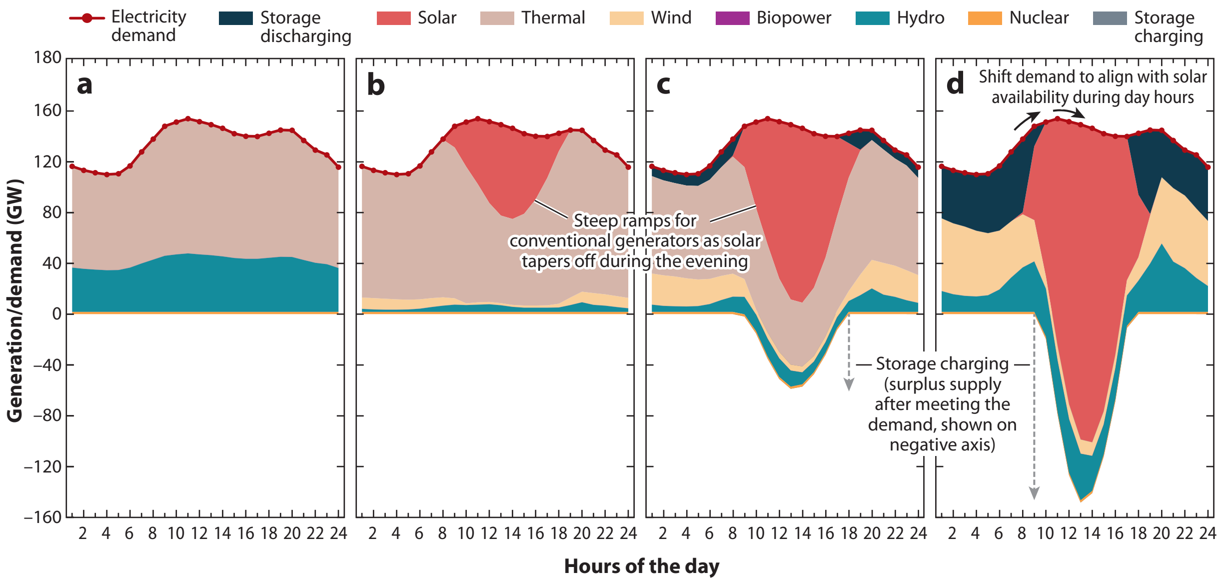

Figure 1

Energy models are inevitable to solve transition complexities. Indicative electricity system transition scenarios from (*left*) zero solar/wind to (*right*) zero thermal. The four panels represent progressive electricity transition stages, ranging from (*a*) a system with zero solar/wind generation to (*d*) one with zero thermal generation. Higher penetration of renewable energy requires steep ramping up and ramping down of generation by conventional thermal generators to maintain grid stability. A zero-thermal system might derive flexibility through demand-shifting strategies to align consumption with the availability of renewable energy. The *y*-axis shows the power output or demand in gigawatts (GW), while the *x*-axis shows the hours of the day in the four illustrative scenarios.

Such assessments have evolved (**Figure 2**) in response to the increasing needs of the stakeholders. Decision-makers, including owners of the different segments of the electricity supply chain, system operators, and regulators, increasingly need answers to a wide range of questions, which has necessitated the development of complex and sophisticated mathematical models. These models are capable of simulating electricity systems over a long time horizon, incorporating the complex technical, financial, and policy constraints.

The objectives of electricity system planning models are manifold, including determination of minimum system cost and options for long-term expansion of electricity generation, transmission, and distribution systems that can fulfill the demand requirements for a future period, subject to technical and economic constraints (1, 2) under uncertainty and socioeconomic implications. The models provide a framework to assimilate data on all these components, track transition progress, allow periodic alterations, and provide insights on alternative system designs. Such analysis is useful for policy makers and industrial energy decision-makers. What are the needs of such models and how are these needs evolving? What does it take to develop these models, what has changed in recent decades, and are there identifiable themes and trends in these evolutions? In this article, we attempt to answer these questions.

2. ELECTRICITY SYSTEM PLANNING MODELS: IN THE AGE OF CLIMATE URGENCY

In recent decades, there has been a growing recognition that countries worldwide have no option but to reduce greenhouse gas (GHG) emissions in order to limit the global temperature rise within 1.5°C, as outlined in the Paris Agreement (1). The negative consequences of climate change

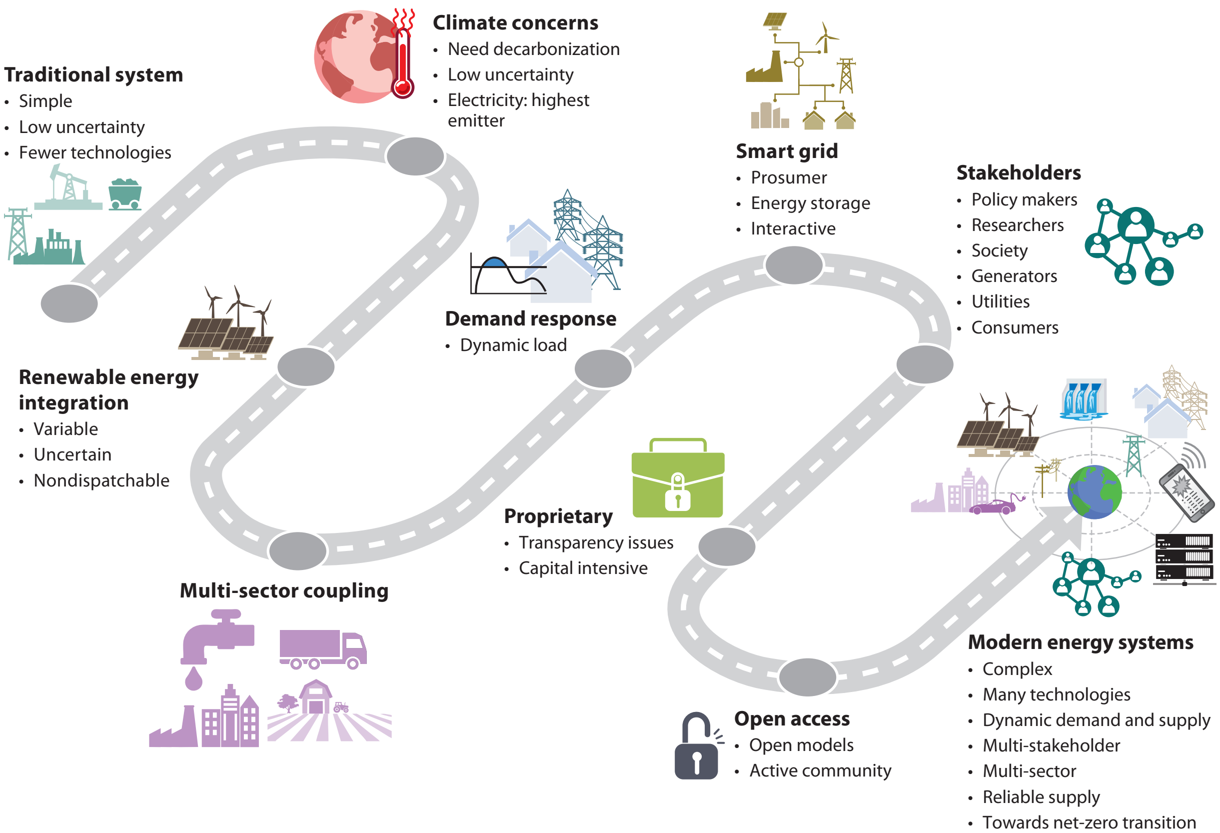

Figure 2

Evolution of energy system complexity and modeling approaches. The figure illustrates the progressive transition of energy systems from conventional, centralized architectures to more complex, multi-technology, net-zero–oriented modern energy systems. The transitions in energy systems are necessitated by climate change concerns, as the energy sector contributes a substantial share of greenhouse gas emissions globally. The transition journey is complex and capital-intensive, necessitating the importance of evidence-based policy making, for which electricity system modeling, with integration of renewable energy, multi-sectors, demand response, and smart grid, serves as an important enabling tool. Given the capital-intensive nature of the energy transition, the choice of modeling approach carries several implications. Proprietary modeling tools are costlier and may lack transparency, limiting their suitability in guiding large-scale public investments. By contrast, open-source modeling offers transparency, reproducibility, and broader stakeholder participation supported by active research communities. These models assimilate large quantities of data and require specialized software for their execution and for the analysis of results.

and the consequent expenditures toward adaptation measures are mounting. The energy sector, which is responsible for approximately three-quarters of global GHG emissions (2), is pivotal to addressing this challenge. In 2022, CO_2 emissions from the energy sector reached a record high of 37 gigatonnes (Gt), further increasing to 37.4 Gt in 2023. Emissions from coal accounted for 65% of this rise, highlighting the pressing need for a transition to sustainable energy systems (3).

Nation states across the world have announced net-zero goals with different target years set in the upcoming decades. Electrification of the energy services and supply of electricity from renewable sources is a robust feature of all such future conceptions (4). The global CO_2 emissions report (5) emphasizes the critical role of enhanced capacity additions in solar photovoltaic and wind power plants in mitigating the growth of energy-related CO_2 emissions. However, these renewable energy (RE) sources face a significant challenge: their inherent variability, uncertainty, and unpredictability. These challenges pose planning and operational challenges for system planners, investors, capacity developers, and operators tasked with balancing real-time electricity supply and demand in the short- and medium-term. Without sufficient grid flexibility, which can be provisioned at all stages of the electricity supply chain, from consumers through DR, RE intermittency can result in mismatches, threatening grid stability (6, 7). India has put in place statutory iterative planning processes with modeling at the heart of the process alongside forecasting for all load serving entities and has tied all electricity procurement decisions, including power purchase agreements and spot markets, to this process (8).

In addition to governments, industrial facilities develop and operate captive fleets of electricity generators to meet their needs. In India, the steel and aluminum industries constitute a bulk of 78.4 gigawatt of such captive capacity, including predominantly coal, diesel, gas, and increasingly solar and wind (9). Hence, understanding the optimal electricity generation mix is of interest to such industrial actors as well. Although the advances in contracting mechanisms permitted by the electricity system regulators allows such captive fleet owners to plan and deploy RE at their premises or elsewhere on the grid, both of these options require modeling assessments. Large energy-consuming organizations are increasingly exploring actions and strategies to ensure every hour of the electricity demand is met with carbon-free energy, referred to as "round-the-clock zero-carbon energy planning" (10). It entails consideration of renewables, storage, demand flexibility, procurement strategies, and regional collaboration, which is facilitated by models (11). Electricity systems worldwide are integrating solar and wind energy at a fast pace. In 2024, global electricity demand increased by 4% and solar generation grew by 29% (12). With these increasing shares, the system complexity and the planning requirements are also increasing.

These challenges necessitate robust techniques to foresee potential operational and functional modalities. As RE sources are incorporated into the grid, these concerns must be addressed to ensure smooth transitions and operations, necessitating forward-looking strategies to mitigate their impacts (13, 14). To make informed and effective decisions, policy makers require robust scientific assessments of potential long-term transition pathways that are tailored to their specific national contexts (15). In this review, we primarily focus on optimization-based bottom-up electricity planning models.

By simulating different pathways, the electricity planning models help design sustainable and resilient energy systems that align with climatic goals and developmental priorities (16). Modeling approaches offer these long-term perspectives, providing policy makers, researchers, and engineers with the tools to anticipate changes, design resilient systems, and optimize operations in dynamic scenarios. Electricity planning models thus enable informed decision-making by handling large data sets and studying systems at various scales, addressing intertemporal and spatial variabilities, and optimizing alternatives and suggesting trade-offs (13). In this article, the review of evolving planning concepts and modeling paradigms is not confined to the context of any specific country, though the practical adoption/applications in the Indian context are briefly discussed.

Energy models gained prominence through the emission scenarios developed by the Intergovernmental Panel on Climate Change (IPCC), which used six global energy models: ASF, AIM, IMAGE/TIMER, MiniCAM, MESSAGE, and MARIA. These models showcased potential pathways for GHG emissions, providing essential inputs for global climate policies (17, 18). Important system dynamics and other phenomena that increasingly find relevance in electricity system transition planning and modeling include unit commitment with cold-warm-hot start (19), short- and long-term storage (20), ramping requirement, transmission constraints (21), and energy–food–water nexus considerations. There are compelling use cases across geographies for the inclusion of many of these phenomena in the planning processes. We discuss some of these aspects in subsequent sections.

For several decades, the electricity planning models have been a necessary input to the planning processes of organizations responsible for building, procuring, and serving electricity to the consumers. The objectives of electricity system planning models are manifold, including the determination of minimum system cost and emissions. While determining the system configuration yielding the desired outcomes, the models assess a large number of candidate solutions for long-term expansion of electricity generation, transmission, and distribution systems. The resulting solution fulfills the electricity demand for a future period, subject to technical and economic constraints (22, 23) under uncertainty, considering socioeconomic implications.

Many of the early models followed neoclassical economic assumptions, including rational choice, perfect foresight, and utility maximization, as exemplified in foundational texts. These assumptions underline many top-down models, such as MERGE (24) and GEM-E3 (25), which emphasize macroeconomic equilibrium and cost-optimality. Although effective for exploring economic efficiency, these models largely ignore institutional change, actor heterogeneity, and equity considerations. Simultaneously, bottom-up models like MESSAGE (26), MARKAL (27), and TIMES (28) focus on technological detail and investment pathways but remain technocratic in scope. Their detailed treatment of technologies does not extend to sociopolitical variables, behavioral dynamics, or adaptive decision-making processes. OSeMOSYS (29), while open-source and accessible, inherits many of these limitations.

Even though a range of modeling paradigms is available for studying the broader energy transition, including optimization and agent-based, bottom-up, and top-down models, each is useful to answer pertinent energy transition–related questions (30). In this work, we primarily focus on electricity system generation expansion models.

The models provide a framework to assimilate data on all these components, track transition progress, allow periodic alterations, and provide insights into alternative system designs. A range of actors, including nation-states (31), subnational administrations, and businesses, have set net-zero targets by certain target years. Consequently, the range of actors using such models has increased and now includes planners and policy makers across governments, businesses, and system operators. Before venturing into the evolution of electricity planning modeling landscape in the next section, we briefly discuss what constitutes a model.

2.1. The Electricity System Modeling Landscape

At the back end, these models constitute a set of constraints and an objective function. The constraints are equations and inequalities with terms constituted by variables (unknowns) and parameters (knowns). The variables include capacities and dispatch from generating stations and transmission capacity, while parameters include per-unit capital and generation cost, emissions, and ramp limits. Similarly, the objective function has terms that typically represent the discounted cost and/or emissions, depending on the formulation. The number of variables and equations can run into millions.

The structure of the models has been evolving with different and more complex objective functions (e.g., inclusion of reliability, pollution, stranding costs, socioeconomic parameters, flexibility) and new types of constraints to capture spatial-temporal variability in supply dependent on weather, storage, and demand-side management. In the modeling parlance, these additions involve binary and integer variables and tightly coupled constraints. The number of variables in the model instances and the number of equations has been increasing over time. For better treatment of uncertainty, large number of these large modeling instances need to be solved (32).

Developing a model involves creation/generation of a large number of equations parameterized by the underlying data. Specialized programming languages and packages like GAMS, JuMP

(Julia), linopy (Python), Pyomo (Python), among others, offer functionality to generate these variables, terms, expressions, equations, and inequalities in a tractable manner. There is a range of specialized open source (33, 34) and proprietary software (PLEXOS, Ordena among others) that provide modeler-friendly classes to declare the objects and the pertinent attributes and automatically handle the model building. The distinction between open source and proprietary is an important one.

The variables can be binary, integer, and continuous. The terms in the constraints and/or the objective function could be linear, bilinear, and/or quadratic. These choices are driven by the underlying phenomenon that is of interest (e.g., plant start-ups) and, accordingly, the model could be a linear, binary, mixed-integer, or nonlinear program. Large-scale models are usually linear. For the other variants, the solution time is significantly higher. The model instance is passed to a solver, which is usually agnostic to the problem domain. The solvers are either proprietary (Gurobi, CPLEX, Express) or open source (HiGHS, GLPK). Some of the proprietary solvers offer free licenses for academic research and teaching. Availability of the open-source solvers is expected to improve adoption of the models across academic and policy stakeholders in developing and least-developed parts of the world.

Early development and application of the models happened after the oil crisis of 1970s at the multilateral energy bodies (International Atomic Energy Agency, International Energy Agency). With time, the landscape has evolved with developments in software life cycles. Actors and activities from academia as well as commercial entities contribute to this process by way of developing methods and investigating questions relevant to public policy and economic actors. It is useful to ask the question: How synchronized are the development cycles of the models and the analysis with their consumption in the policy and business processes? How are the actors across academia and business contributing to them? In this process, in line with wider trends of open science and accountability, distinct patterns can be observed in this landscape as well.

In the following subsections, we segment the range of actors and stakeholders in this domain into the (*a*) academic and research landscape; (*b*) proprietary, specialized, and commercial landscape; and (*c*) open access landscape. The actors and their networks in these landscapes overlap with each other, with consequent synergies and trade-offs; nonetheless, the delimitation provides useful perspectives on how the stakeholder landscape has evolved.

2.1.1. Academic and research landscape. As sampled throughout this review, academic researchers have contributed to research in electricity system generation expansion through methodological advancements as well as application of these methods to specific regional contexts. The applications address the requirements of stakeholders, including policy makers. Academics also undertake a range of consultancy projects across the development of methods, tools, and their applications in this space. In academia, there are people across the continuum of advanced developers and modelers to applied researchers. Different research groups tend to have different combinations of these capabilities. Bespoke source codes, proprietary model generators, and open-source tools are being put to use in academia. The former has low replicability, maintenance, and quality assurance. Proprietary models are becoming more sophisticated. A prominent trend is the impressive development of open-source data and models initiatives spawned from academic labs (35). They provide useful community tools by way of solver benchmarks and track the development of similar initiatives in terms of their user, GitHub stars, and other metrics. These initiatives are often backed by philanthropic grants. Sustenance of these capabilities in the long run remains to be seen. Academics in developing and least-developed regions are more likely to use open-source tools.

2.1.2. Proprietary, specialized, and commercial landscape. Energy investments are capital-intensive and long-lived. For commercial projects, a detailed modeling exercise to underpin the investment and operational decision usually constitutes a very small fraction of the project development costs. It is therefore common to see applications of sophisticated proprietary tools and data sets in such contexts. These tools also find applications in regulatory planning processes. These tools are usually expensive from the perspective of the stakeholders in developing and less-developed regions. Some providers do, however, offer free licenses for academic use. For commercial reasons, these tools are black box and licensed, which can be a point of concern especially for policy-making and planning of public electricity utilities (36), as the decisions based on these plans are capital-intensive and long-lived.

Although the commercial solutions along the value chain of data, model generator, and solver are expensive (especially from a developing and least-developed country perspectives) and opaque (though some are editable and auditable), they usually have better user support and user interfaces. For developing a generic model, such software offers a steep learning curve, and they come with paid data sets and prebuilt models, features increasingly available in open-source alternatives. Customizability, including modeling of advanced phenomena, may at times be difficult and time-consuming. Developments in the open-source space are rapidly improving, making open-source options comparable to proprietary alternatives.

The choice of how best to design such software—the relative advantages and disadvantages of using an open-source versus a proprietary software—is an ongoing debate (37). For a generation expansion modeling exercise and subsequent analysis, the attributes of whether or not open-source software and open data were used have a bearing on the utility of the analysis in terms of stakeholder engagement and acceptance.

2.1.3. Open-access landscape. The movement from closed black box to open-source models is a recent phenomenon that should be seen in the wider context of open science. Grid2050 is an open-source tool enabling users to design and evaluate low-carbon electricity generation portfolios for the United States by 2050 (38). OptGen, a long-term generation capacity expansion model, was applied to four African countries (39). OSeMOSYS is an open-source modeling platform for long-term energy planning (40). It is recognized for having a relatively lower learning curve compared to similar tools and has been widely replicated for use in several national electricity models (41). The Open-Source Electricity Model Base for Europe (OseMBE), derived from OSeMOSYS, was utilized for European Union energy planning (42).

Pfenninger (43), after several years of experience in unpacking the black box models and developing open-source data and modeling workflows, has reached the conclusion that open code and open data, though useful, are insufficient, and he calls for understandability as the design goal for energy system models. Such understandability of the building blocks of the particular model will help future modelers to adapt and apply the models for specific research questions, thereby reducing the modeling lead time. In addition to the modeling community, the model users will also greatly benefit from the qualitative understanding of what is happening in the model. There are initiatives to streamline and better organize the open-source modeling solutions by providing benchmarks for model generators and solvers (44). An active community of open-source users and developers also is emerging.

2.2. The Electricity System Modeling: Indian Context

A review of electricity system models used in the Indian context highlights several key limitations that hinder their ability to support robust RE integration. The observations in varying measures are likely to be applicable across developing countries. We use the Indian example to explain the arguments. First, these models often fail to capture short-term variabilities and uncertainties associated with RE generation, an omission repeatedly identified as a critical area for future improvement (45–47). Most India-specific models rely on the generation capacity expansion frameworks that are ill-equipped to simulate transmission network adequacy or system contingencies, both of which are vital for efficient electricity system planning (48). While operational models can address such complexities at high temporal granularity, they are rarely used for long-term or national-level planning due to their computational intensity (49). Second, the prevailing models lack sufficient spatial and temporal resolution, neglecting the dynamic impacts of RE integration on grid flow and congestion (50, 51). Their primary focus remains on resource adequacy, sidelining operational constraints such as ramping limits and flexibility requirements (52–54). This results in miscalculations of system reliability, costs, and adequacy. To address these gaps, recent efforts advocate for embedding spatial-temporal considerations (55), integrating planning and operational models (56), and employing hybrid, bidirectional modeling approaches that can handle long-horizon and high-RE scenarios more realistically (57, 58).

3. EVOLUTION OF ELECTRICITY SYSTEM PLANNING MODELS

Since the 1950s, electricity generation expansion models have guided the planning of generation facilities. Massé & Gibrat (59) employed linear programming for investment planning, while Phillips (60) introduced nonlinear programming for optimal plant mix decisions. Until the 1970s, resource planners focused on the optimal size, timing, and type of large central station plants to meet growing demand. Scherer (61) integrated environmental constraints into planning, and by 1995, models began addressing uncertainties in generation, competition among producers, and demand-side management (DSM) (62).

Balachandra (63) proposed a planning model for resource-constrained systems incorporating planned rationing, private sector participation, and capacity adjustments for costlier private sector generation. Since 2010, the integration of large-scale RE has introduced complexity due to its variability. Amrutha et al. (64) utilized mixed-integer linear modeling to align RE integration with policy mechanisms like RE obligations and certificates. Studies by Carrasco et al. (65) and Kahrl et al. (66) highlighted challenges in integrating flexible, low-carbon resources. Model size and complexity have both increased over time. This increase can be attributed to various factors including the capability and tractability of large-scale optimization models; improvement in availability and access to computing resources, both local deployments and through the web; and development of open-source tools. In the following subsections, we identify the key themes of this evolution. This delimitation is by no means exclusive or exhaustive, and the themes are often interlinked. There are multiple lenses through which to look at the evolution; what follows is but one such taxonomy.

3.1. Modeling Renewable Energy Integration in Transition Planning

As global ambitions for deep decarbonization rise, energy system models have emerged as crucial tools in planning, evaluating, and optimizing the integration of RE sources into conventional electricity systems. Modeling RE integration involves a multifaceted approach: capturing supply variability, optimizing grid operations, guiding policy formulation, and evaluating long-term system costs and benefits. A wide array of models, such as OMNI-ES, Balmorel, OPERA, urbs, LUT-ESTM, BeWhere, MyPyPSA-Ger, REMix, Calliope, TIMES, SWITCH, PLEXOS, MESSAGEix, and others, have been developed globally and applied in various regional and national contexts. The following passage outlines the evolution of RE integration modeling chronologically, through key academic and technical contributions over nearly two decades.

An early contribution was made by Muela et al. (67), who introduced a fuzzy multi-objective optimization model for hydroelectric and thermal power planning. By addressing uncertainties in annual electricity planning, their work provided a structured approach to balance cost, fuel usage, and curtailment, marking a shift toward handling variability even before intermittent renewables became mainstream. Building on this, Tuohy et al. (68) expanded the modeling framework to include wind energy and load-shedding mechanisms. Their unit commitment model integrated DSM as a key tool for mitigating intermittency, thereby laying the groundwork for the incorporation of flexible loads in renewable-heavy systems.

The recognition of spatial diversity as a potential buffer against intermittency came next. Katzenstein et al. (69) demonstrated through frequency domain analysis that interconnected wind farms in Texas could smooth out generation fluctuations. This insight is connected with the work by Tuohy et al (68) by extending flexibility from the demand side to the geographical configuration of supply. Meanwhile, in the Indian context, Joseph (70) critiqued the country's electricity reforms and urged policy makers to reframe renewables as central rather than supplementary in the long-term planning. His emphasis on institutional and political dimensions highlighted the nontechnical barriers to RE integration and connected earlier operational models with broader governance issues.

As models became increasingly computationally intensive, Baños et al. (71) synthesized various optimization methods like genetic algorithms and parallel computing. Their review emphasized the increasing complexity of renewable planning and reinforced Joseph's (70) call for systemic approaches by offering the tools necessary to handle such complexity. Complementing these computational advances, Hart et al. (72) critically evaluated how different models are addressing the intermittency problem. Their comparative analysis introduced a meta-perspective, helping modelers to select appropriate methods for matching supply variability and fluctuating demand, a concern echoing the challenges raised by Tuohy et al. (68) and Baños et al. (71).

With a more probabilistic outlook, Meibom et al. (73) introduced a stochastic mixed-integer linear programming (MILP) model for the Irish grid. Their work on operational reliability under high penetration of wind power reflected a synthesis of earlier deterministic and statistical approaches, bringing together Muela et al.'s (67) cost–curtailment balance, Tuohy et al.'s (68) flexibility, and Katzenstein et al.'s (69) spatial insights. Santos-Alamillos et al. (74) further deepened spatial considerations by applying principal component analysis to identify wind sites in southern Iberia that aligned closely with the base load patterns. Their method tied directly to the variability mitigation strategies explored by Meibom et al. (73) and Katzenstein et al. (69), confirming the importance of location in RE system planning.

The growing attention to system flexibility further gained traction in Huber et al.'s (75) work, which emphasized the ramping capabilities of thermal and hydroelectric power systems. Their findings underscored how traditional assets could still play a vital role in balancing variable renewable supply, bridging earlier planning models with real-world operational requirements. At the same time, Carrasco et al. (65) examined the technological infrastructure, particularly power electronics needed to enable RE integration. Their focus on grid-side enablers complemented Huber et al.'s (75) plant-level flexibility, together painting a comprehensive picture of the system components needed to accommodate renewables.

Parallel to these developments, Amrutha et al. (76) brought policy relevance into the modeling discourse by developing a LINGO-based MILP framework that optimized for both cost and emissions. Their inclusion of demand-side interventions echoed Tuohy et al.'s (68) work while integrating the technical and economic concerns championed by Carrasco et al. (65) and Huber et al. (75). Carrasco et al. (65) and Kahrl et al. (66) then offered a systemic perspective on electricity resource planning in the age of renewables. They argued that traditional planning paradigms were insufficient in light of the evolving technologies and variability, thus tying together the institutional concerns raised by Joseph (70) and the technical shifts championed by Amrutha et al. (77) and Carrasco et al. (65).

This systemic approach took practical shape in India through Palchak et al. (78), whose study showcased operational and cost-modeling frameworks for high RE penetration. Their case study bridged Kahrl et al.'s (66) conceptual vision with implementable policy insights, reinforcing the feasibility of RE integration in a developing economy. In the same year, Amrutha et al. (79) focused specifically on Karnataka's experience with feed-in tariffs, renewable power obligations, and renewable energy certificates. Their findings revealed that a disconnect existed between well-intentioned policy instruments and on-the-ground effectiveness, reinforcing Joseph's (70) earlier critique of policy design while providing empirical grounding to Kahrl et al.'s (66) systemic arguments.

Sharma & Balachandra (80) responded to this policy–technical gap by proposing a hierarchical model that simulated RE integration under various policy and technological conditions. Their approach operationalized Palchak et al.'s (78) scenario analysis while addressing Amrutha et al.'s (79) call for improved policy alignment. Simultaneously, Amrutha et al. (64) provided a policy-focused MILP model aligned with India's Renewable Energy Obligation framework. Their work directly complemented Sharma & Balachandra's (80) hierarchical design by detailing how obligation-based instruments can be integrated into long-term capacity expansion models.

Refining their earlier approach, Sharma & Balachandra (81) advanced an MILP model using real-world solar and wind-generation profiles. Their findings highlighted a paradox: While renewables reduced carbon emissions, they also led to system-wide capacity redundancy, thereby reconnecting with Huber et al.'s (75) flexibility challenge and Meibom et al.'s (73) concerns about underutilized infrastructure. Expanding this systems-level approach, Lugovoy et al. (82) introduced the Indian Zero Carbon Energy Pathways Optimization Model, called the IDEEA model, which explored India's potential to transition entirely to wind and solar by 2050. Their spatially resolved, multi-scenario framework directly responded to the work by Santos-Alamillos et al. (74) and Meibom et al. (73), while bringing Sharma & Balachandra's (81) national-level simulations into sharper geographic and temporal focus.

Building on the IDEEA model's regional granularity, Sambasivam & Balachandra (83) zoomed into Karnataka to evaluate wind–solar–battery combinations under current grid constraints. Their results showed that battery storage alone capped reliability at 63%, which underscored the limitations of single-technology solutions and brought Amrutha et al.'s (79) policy concerns and Carrasco et al.'s (65) technical arguments into conversation with the IDEEA model's long-term vision. Similarly, Gangopadhyay (84) conducted a detailed modeling study for Karnataka, validating Sambasivam & Balachandra's (83) findings. Her work reinforced the critical insight that battery storage is necessary but insufficient and that deeper decarbonization requires rethinking of curtailment policies, resource assessments, and demand-side strategies. This conclusion resonates with Joseph's (70) early advocacy for institutional reform, Sharma & Balachandra's (85) integrated planning approach, and Kahrl et al.'s (66) vision of evolving electricity systems.

Over the past two decades, modeling RE integration has evolved from deterministic, supply-side focused tools to probabilistic, system-wide frameworks that account for variability, policy constraints, and technological limits. From the early fuzzy and MILP-based models to modern spatially resolved, multi-scenario planning tools like the IDEEA model (86), Open Source Energy Modelling System (OSeMOSYS) (40), and Python for Power System Analysis (PyPSA) (87), the progression reflects increasing complexity and realism in how electricity systems are planned. The Indian experience illustrated through models applied at national and subnational scales shows that integrating renewables involves not only technological readiness but also institutional agility, policy coherence, and demand-side participation. Moving forward, the synthesis of modeling insights with real-world grid operation, land-use planning, and behavioral change strategies will be critical in achieving a reliable and inclusive RE transition.

3.1.1. Climate, energy, and water linkages. Solar and wind energy vary across regions. At any given location, these resources have a temporal profile. Planning, developing, and operating an RE-dominated energy system will understandably demand an assessment of these variations. For electricity system modeling, such resource profiles are available from some curated resources (88–90). The primary data sources are based on satellite-based ground observations often corrected using ground station observations. The quality and resolution of the data vary across global regions. Such data can be fairly large and require significant processing before assimilation into the models. In response, research and practitioner communities are working to bridge the gap between energy system modeling and climate modeling (91). This work has led to the development of integrated analytical approaches that capture the interdependencies across climate, land, energy, and water systems. The Water, Energy, and Food (WEF) Nexus Tool (92) and the Climate, Land, Energy, and Water systems (CLEWs) framework (93) are tools introduced to quantitatively assess the critical nexus between natural resources and climate change.

3.1.2. Sector coupling. Wind and solar generation capacity requires significant utilization of land and water resources. Land requirements are higher as compared to the conventional electricity generation alternatives. Land availability could be a constraint on the potential deployment of such generating capacity in the future. For instance, India has the lowest per capita land availability among Group of 20 (G20) nations, and land availability can put a limit on solar deployment (94)

Water–energy interactions and institutional dynamics are often ignored in modeling space, as noted by Scott et al. (95). Implications for water consumption have been explored by Srinivasan et al. (96) in the Indian context and underscore the role of technological choices in moderating the impacts. Savvidis et al. (97) underscored the disjunction between what policy makers need and what models provide. They found that models are often incapable of representing key energy policy instruments or sectoral interactions. Sokołowski & Heffron (98) argue that poorly aligned assumptions can result in policy failure, reinforcing the need for more robust model evaluation frameworks.

Electrification of an increasing range of energy end uses and provision of electricity from RE sources is a dominant trend. This trend is manifesting through integration of energy sectors that have conventionally between independent, e.g., electrification of mobility. Such intersectoral coupling is necessitating inclusion of these sectors in the electricity system planning and modeling frameworks (99). This inclusion is essential to assess how the sectors interact, including propositions for vehicle-to-grid (V2G) services, for example. Electrification is also a candidate solution for hard-to-abate sectors, including steel, cement, and aluminum (100).

3.1.3. Material supply chains. Build-out of solar and wind generation, and the required batteries at scale, have brought forth dependencies on a set of critical minerals such as lithium, cobalt, nickel, copper, and rare earths. The availability of these resources and the capabilities to process them are rather concentrated (101, 102), posing geopolitical risks and energy security challenges. These considerations must be factored into electricity system expansion models. The scarcity and likelihood of restricted access demand attention toward reusage and recycling across solar, wind, and storage supply chains. Moreau et al. (103) and Calvo & Valero (104) show that the raw material scarcity could hinder renewable deployment, a factor rarely accounted for in traditional modeling.

3.2. Demand-Side Management

DSM refers to the concept of actively managing and influencing electricity consumption patterns on the demand side to better align with the available supply of electricity. As the global power system evolves to accommodate a growing share of variable RE sources, the focus must extend beyond the supply side to include demand-side strategies. DSM as a strategic intervention took shape in the 1970s when the US electric power utility industry witnessed energy shocks (105) due to a sharp increase in fuel prices. DSM is defined as "the planning, implementing, and monitoring of utility activities designed to influence customers' use of electricity in ways that will produce desired changes in the utility's load shape, i.e., changes in the time pattern and magnitude of a utility's load" (106, p. 1468). Such changes in load shapes help improve the capacity utilization of the generation assets.

In today's context of high RE penetration, DSM plays a critical role in reshaping electricity consumption patterns to align more closely with the availability of clean, variable energy sources (107). It encompasses a range of strategies aimed at influencing when, how, and how much electricity is used, including energy efficiency measures, time-of-use pricing, DR programs, and the flexible operation of loads such as electric vehicles (EVs) and smart appliances. By shifting or reducing demand during peak periods, DSM alleviates stress on the grid, postpones the need for additional generation capacity, and empowers consumers to participate actively in grid management (108). As renewable integration deepens, DSM becomes essential for real-time balancing of intermittent supply and demand, enhancing system flexibility and stability (109).

In terms of load-shaping objectives, DSM can be classified into six broad categories: peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape. These strategies target different aspects of load demand to optimize secure operation of the electric grid (105).

Among the various DSM strategies, a particularly transformative approach lies in the harnessing of demand-side resources not only for energy efficiency or load shifting but also for providing flexibility, a capability that is essential for integrating high shares of renewables into the power grid. This evolving paradigm is captured by the concept of demand-side flexibility (DSF), which enables consumers to play an active role in real-time grid balancing and system optimization. DSF is defined as "the capability of any active customer to react to external signals and adjust their energy generation and consumption in a dynamic time-dependent way, individually as well as through aggregation" (110, p. 167). In simpler terms, DSF refers to the ability of electricity consumers—ranging from residential households to large industrial facilities—to actively modify their electricity usage or distributed generation patterns in response to various signals. These signals may include real-time electricity prices, demand-response requests, grid frequency fluctuations, or RE availability.

Rather than being passive recipients of electricity, consumers enabled with DSF technologies and mechanisms can shift, reduce, or increase their consumption depending on system needs. By enabling adjustments in demand to match available supply better, DSF can contribute significantly to balancing the grid, improving reliability, and reducing operational costs. Importantly, it offers a no- or low-cost alternative to traditional supply-side solutions, such as peaking plants or grid-scale storage, which are often capital-intensive (111).

Incorporation of DSF is found in various electricity system transition studies. Capacity expansion planning, including demand-side resources, is proposed via a two-stage optimization model by Li et al. (112) along with concentrating solar plants and battery-based energy storage. The research proposed a two-stage approach in which the first stage minimizes the investment costs of generation assets while the second stage determines the optimal power dispatch under different operation conditions (112). DSF from high-consumption industrial loads is examined within a generation expansion planning framework that adopts an energy-based modeling approach (113). The study explores the inherent operational flexibility of these localized, energy-intensive consumers and assesses their potential to act as substitutes for conventional generation capacity.

The increasing penetration of EVs introduces a new dimension to DSF through V2G capabilities. Power system expansion planning has been explored by Ramirez et al. (114) by incorporating the co-optimization of EV flexibility. The model integrates a comprehensive set of technical characteristics for various generation technologies while also capturing the ability to schedule EV charging demand and V2G injections optimally. Another study analyzed the demand flexibility from smart charging of EVs and electrolyzers in the expansion planning of dispatchable generation and energy storage (115). In a related expansion planning study, Borozan et al. (116) indicated that implementation of demand flexibility through smart charging could generate considerable economic savings and act as hedging instruments against renewable uncertainty.

DR is a tool under the broad umbrella of DSM that makes use of price or incentive schemes to shift or curtail demand (117). The effectiveness of DR in achieving supply–demand balance was investigated by Balasubramanian & Balachandra (118) through an MILP-based optimization framework. The study found that DR interventions are effective in providing flexibility through chopping peak loads and topping valleys. A study on decarbonization of the power system of China indicated that DR could bring huge savings through load-shedding, short-term load-shifting, and long-term load-shifting strategies (119).

DSM is the overarching set of strategies to influence longer-term energy use for improving efficiency and reducing peak demand through pricing schemes and programs. DR, conversely, is a signal- or event-driven intervention that encourages customers to modify their electricity consumption behavior in response to incentives, prices, or guidelines. DSF is the capability of demand centers to shift a part of their consumption temporally across different hours of the day (120–123).

3.3. Low-Carbon Electricity System Transition Planning

Globally, the installation base of RE adoption is growing; however, a complete transition away from fossil fuels requires significant time and investment (124). This transition is also driven by the slower-than-expected pace of RE capacity additions, which has not been sufficient to bridge the widening supply–demand gap especially in developing countries such as India. Another factor is the requirement of firm and dispatchable resources for the safe operation of power systems. Firm and dispatchable resources, such as coal, hydroelectric, nuclear, and gas, provide essential inertia and primary frequency response to electrical power systems (125).

Low-carbon capacity expansion planning was studied by Hjelmeland et al. (126), who considered nuclear energy as a source for baseload demand and as a firm/dispatchable resource. Carbon capture–based generation expansion studies have been extensively explored in the literature. Saboori & Hemmati (127) proposed a generation expansion planning model for the Iranian Power system making use of nuclear energy, RE, and carbon capture retrofits on the existing thermal fleet. The Low-Carbon Generation Expansion Planning (LC-GEP) model is proposed by Pourmoosavi & Amraee (128) to determine the optimal type, capacity, and installation timeline of both conventional and renewable generation technologies. The model incorporates carbon capture, utilization, and storage (CCUS) as a carbon-reduction strategy for existing coal-fired power plants.

Operational aspects of the flexible carbon capture system and Power-to-X are explored in numerous studies. The low-carbon economic dispatch model was formulated for a post-combustion flexible carbon capture system and power-to-gas facility by He et al. (129). The objective function in the model is to minimize the total cost, consisting of the operation cost, the CO_2 processing cost, and the penalty cost of wind power curtailment. By enabling such a flexible response, CCUS can act as a critical bridge between fossil fuel–based power generation and renewables, ensuring grid stability while significantly reducing carbon emissions. This adaptability enhances the economic viability of carbon capture and supports a smoother transition to a low-carbon energy system. Expansion planning of an integrated electricity–natural gas system, along with EV fast charging stations, was studied by Wu et al. (130) with CCS technology employed for the decarbonization of conventional sources. A notable study by Khaligh et al. (131) demonstrated the integration of CCU within an electricity–hydrogen system, wherein the captured CO_2 was used for methane synthesis through methanation. This synthesized methane was subsequently utilized in a downstream integrated gas plant, thereby creating a closed-loop carbon cycle that optimizes resource use while reducing emissions by 36%.

3.4. Modeling Social and Economic Facets of the Transition

The transition from fossil fuel–based systems to low-carbon and RE alternatives is not merely a technological shift but a deep structural transformation with far-reaching socioeconomic implications. These include potential job losses in traditional energy sectors, creation of new employment in RE industries, shifts in regional development, and implications for equity, affordability, and social welfare. Such multidimensional impacts necessitate informed and holistic decision-making that can anticipate trade-offs and guide just transition pathways.

3.4.1. Theoretical foundations of socio-technical modeling. As the global energy transition gathers momentum in response to climate and sustainability imperatives, increasing attention is being given to the social and economic ramifications accompanying deep decarbonization. Energy system models, whether used for capacity expansion planning, integrated assessment, or policy simulation, have become central to informing decisions around this transition. However, these models have traditionally focused on techno-economic optimization and continue to underrepresent or externalize key social and economic dimensions such as employment, spatial equity, public participation, behavioral change, and community acceptance. This subsection explores how social and economic aspects are (or are not) represented in energy models, examining the evolution of theory, practice, and innovation through a roughly chronological lens.

Historical theoretical developments provided the foundational vocabulary to understand energy transitions as inherently socio-technical. In his seminal work, Dosi (132) introduced the idea of technological paradigms and trajectories, asserting that technological change is shaped not just by engineering progress but by institutional and economic forces. Nelson & Winter (133) laid the groundwork for evolutionary economics, emphasizing how organizational routines and institutional learning shape innovation. Kemp et al. (134) advanced these ideas into sustainability science by proposing strategic niche management, which views technological transitions as requiring protected spaces (niches) in which learning, experimentation, and network building can take place. These frameworks formed the theoretical basis for later modeling paradigms that aimed to reflect energy transitions as multidimensional and socially embedded processes.

Foxon et al. (135) and Verbong & Geels (136) translated these insights into electricity systems research. By employing the multilevel perspective, they introduced a framework in which transitions are seen as interactions across three analytical levels: niches, regimes, and landscapes. These levels correspond to new innovations, existing socio-technical structures, and wider societal forces, respectively. This approach underscored the role of incumbent actors, policy environments, and cultural norms in shaping the speed and direction of energy transitions. Their work inspired a generation of socio-technical transition studies, especially in Europe, that critiqued the narrow, engineering-dominated vision in mainstream energy models.

Expanding on these conceptual innovations, scholars like Fischer-Kowalski (137), Scholz (138), and Rotmans et al. (139) introduced socio-metabolic, human-environment system, and transition management perspectives, respectively. These perspectives moved beyond policy and institutional change to include ecological boundaries, resilience, and systems complexity. The complex adaptive systems view of Miller & Page (140) further reinforced the idea that energy transitions are shaped by nonlinear dynamics, emergent behaviors, and feedback loops—elements largely absent in many techno-economic models. Together, these perspectives laid the groundwork for integrating a broader set of social and economic variables into energy transition modeling.

3.4.2. Empirical integration of social and economic metrics. Empirical efforts to include social metrics in modeling exercises have gained popularity in the last two decades. Modelers and researchers have attempted to include human aspects like employment, behavior, equity, and public opinion in energy system models, albeit at varying depths and levels of integration. Some of these aspects are summarized in the following subsections. Balachandra & Chandru (141, 142) were among the first to highlight the economic and social costs of electricity non-supply, showing that outage costs often exceeded supply costs. Their integrated linear programming frameworks and subsequent sustainable energy planning models demonstrated how economic, environmental, and social objectives could be explicitly balanced in model design. Building on these insights, Sharma & Balachandra (81) proposed a hierarchical sustainability framework and multi-attribute optimization model that evaluated trade-offs across the electricity supply chain, integrating technology-level and system-level choices to support a just and sustainable transition. These innovations signaled a move toward multi-criteria modeling that reflects broader socio-technical complexity.

3.4.3. Modeling of employment, justice, equity, and distributional issues. As employment shift and the resultant distribution issues are perhaps the most prominent effects of the RE transition, it has captured the attention of energy system modelers. One of the earliest attempts was the US National Renewable Energy Laboratory's Job and Economic Development Impact (JEDI) models (143), which have long provided job and economic impact estimates linked to the construction and operation of energy projects. These models have been connected to capacity expansion models like Regional Energy Deployment System (REDS) to evaluate direct, indirect, and induced employment. A more ambitious approach was proposed by Vanatta et al. (144), who endogenized employment into a least-cost capacity expansion model. Their model enforced constraints to ensure that employment displaced by coal plant retirements would be replaced locally by RE jobs, revealing the trade-offs between efficiency and spatial equity. Building on this, the Net-Zero America Project (145) coupled energy system modeling with employment forecasting using regression techniques to estimate job impacts across technologies and states. This integration offered insights into how labor markets might evolve under different decarbonization pathways.

The approaches to assess labor market dynamics have also been deeply influenced by advances in the knowledge of analytical, macroeconomic, and empirical tools. For example, Mayfield (146) used the Gini coefficient and income data to evaluate the labor market equity of the shale gas boom in Appalachia, offering an approach for assessing historical employment impacts from a justice lens. Nock & Baker (147) applied multi-criteria decision analysis to evaluate electricity portfolios in the New England region of the United States, integrating employment metrics, sustainability criteria, and reliability concerns. This approach offered a way to make explicit the trade-offs and preferences that stakeholders may have beyond cost minimization.

Job creation in the RE sector or job loss in the conventional generation sector are not standalone events but have upstream and downstream implications on their allied industries. While some of these sectors are formally organized, a large section also comprises the unorganized sector, making their accounting and estimation difficult. Owing to these complexities, policy reports seldom publish data on these aspects (148). Studies that have considered indirect and induced job impacts of RE transition have applied indirect approaches to estimate and account for them. A study presenting data on wind energy adoption in Spain and its impacts has quoted a secondary data source for indirect job estimates (149). Some studies have used production function multipliers to obtain an estimate of indirect and induced employment impact, but the process, being data- and assumption-intensive, generates less-reliable values (150, 151).

3.4.4. Inadequate representation of social and economic aspects of renewable energy transition. Scholars began identifying the mismatch between model capabilities and real-world transition complexity in the early 2010s. Koppelaar et al. (152) assessed the purpose and capacity of electricity system models for policy analysis, noting their failure to address institutional reform or equity. Similarly, Li et al. (153) reviewed socio-technical energy transition (STET) models and found limited integration of social behavior, political dynamics, and uncertainty. Pfenninger et al. (50) argued that while energy models are vital for climate and energy policy, they often fail to incorporate uncertainty, complexity, and sociopolitical considerations. Their critique became a foundation for calls to enhance transparency and interdisciplinary integration. Chatterjee et al. (154) found that existing demand-side models poorly address behavioral shifts and lifestyle changes. Sovacool et al. (155) emphasized the marginalization of social sciences in energy research and warned that models based solely on technical variables risk political irrelevance; they criticized energy models for their failure to incorporate cultural values, gender dynamics, and democratic governance and called for greater integration of social science in energy modeling.

Krumm et al. (156) identified five underrepresented social factors in energy models: lifestyle, actor heterogeneity, public acceptance, participation, and transformation dynamics. These gaps reduce the policy applicability and social realism of model results. Huckebrink & Bertsch (157) also highlighted the challenge of integrating behavioral aspects and organized them into categories like acceptance, adoption, and use. Martin et al. (158) conducted a meta-review for the SENTINEL project and concluded that most models remain techno-economic, failing to internalize socio-ecological drivers or local environmental limits. Integrated assessment models (IAMs), despite their scale and policy relevance, suffer from simplified assumptions on land use and emissions (159). Trutnevyte (160) and Nikas et al. (161) further critiqued these models for lacking societal desirability, values, and behavior-change mechanisms.

In this context, though energy system modeling has emerged as a powerful and indispensable tool for supporting policy and planning decisions during the energy transition, it fails to adequately integrate socioeconomic dimensions, such as employment impacts, distributional equity, and social acceptance. Modeling these aspects poses significant challenges due to data limitations, lack of standardized methodologies, and the inherent complexity of social systems. Furthermore, existing models often fall short in capturing informal economies, behavioral responses, and institutional constraints, particularly in the Global South. As energy transitions accelerate, expanded modeling paradigms are urgently needed to account for not just cost and carbon but also context and communities.

3.4.5. Outlook of socioeconomic considerations in energy models. Looking ahead, socioeconomic energy models are likely to evolve from purely techno-economic optimization frameworks toward participatory and reflexive platforms that can better capture societal complexities. Scholars such as Nikas et al. (161) have proposed demand-side modeling approaches that embed deliberative processes, stakeholder coproduction, and behaviorally realistic scenarios. Similarly, Süsser et al. (162, 163) emphasized the coevolution of policy and modeling practices, arguing that transparency, reflexivity, and closer alignment with societal priorities are essential for policy relevance. Accounting for ripple effects of RE transition on other industries and sectors is extremely tricky and challenging and should be a focus area for future researchers (164–166). Future models will need to systematically integrate employment, justice, behavioral change, and community acceptance as endogenous drivers of system outcomes, rather than as exogenous caveats.

While energy models have made progress in integrating economic indicators such as employment and investment, the inclusion of social dimensions remains uneven and often superficial. Most models continue to treat social and behavioral variables as exogenous inputs or post hoc discussion points, rather than as integral components of system behavior. To bridge this gap, a new generation of socio-technical models is needed—models that incorporate equity, justice, behavioral dynamics, and participatory inputs into the core of their analytical frameworks. Such integration will not only improve the realism of scenario outcomes but also ensure that model-based policy recommendations are inclusive, robust, and politically feasible in the real world.

4. SUMMARY OF FINDINGS AND DISCUSSION

The energy transition toward decarbonization and sustainability requires rigorous analytical tools to evaluate pathways, assess risks, and guide policy. Energy models have played a central role in enabling such analysis, but there is growing recognition that their capacity to capture the complexity of real-world transitions is limited. The evolution of electricity system models has been marked by two broad schools of thought: (*a*) Top-down models, such as MERGE and GEM-E3, are rooted in neoclassical economics and emphasize macroeconomic equilibrium, rational choice, and cost-optimality. They excel at assessing economy-wide interactions, trade, and market effects of energy policies, but they often simplify technological detail and ignore heterogeneity among actors. (*b*) Bottom-up models, such as MESSAGE, MARKAL, TIMES, and the open-source OSeMOSYS, by contrast, provide granular representation of technologies, fuel options, investment pathways, and infrastructure evolution. They are better suited for exploring detailed system configurations but often remain technocratic, with limited integration of sociopolitical factors or behavioral dynamics. While both paradigms have their limitations, their combined use has enriched energy transition research by offering complementary perspectives. Recent hybrid approaches attempt to bridge this divide, embedding technological detail within macroeconomic frameworks to capture both micro- and macrolevel system dynamics.

A review of literature and model development trajectories reveals key strengths and applications as well as the shortcomings in both the theoretical foundations and practical applications of electricity and energy system models. They help system planners, operators, and policy makers design robust energy transition pathways, balancing the technical requirements with economic and social elements. These models, built using open source or proprietary platforms, integrate complex constraints and objective functions, simulating the expansive real-world scenarios of energy generation and consumption dynamics. These scenarios have been instrumental in shaping international climate negotiations, by providing quantitative insights into feasible mitigation pathways. They highlight how different technology choices, fuel mixes, and policy interventions translate into future emissions trajectories, making long-term modeling a cornerstone of global climate governance. Beyond emissions, these models also capture energy system transformation pathways, such as the pace of renewable penetration, fossil fuel phase-outs, and the role of negative emission technologies.

Despite these advantages, and having undergone tremendous advances, energy models are not free of limitations. The limitations span oversimplified assumptions, exclusion of critical social and environmental dimensions, inadequate representation of institutional and behavioral dynamics, and constrained policy relevance. Energy transition pathways are accompanied by a host of nontechnical implications like asset stranding, job loss, community displacement, and livelihood disruption. It includes not only technological upgrades but also structural changes in infrastructure, consumption behavior, institutional frameworks, and economic relationships. Poorly designed transitions risk job loss, fiscal instability, and resistance from affected communities. A deeper examination reveals that energy transition models have tended to focus primarily on techno-economic optimization, with limited incorporation of broader social and economic dimensions, which are neither adequately assessed and quantified nor routinely modeled, nor are they included in optimization objectives or system constraints.

In conclusion, the landscape of energy system modeling is at a crossroads. Despite advancements in model sophistication, the fundamental shortcomings in addressing societal, institutional, and environmental realities persist. If energy models are to serve as meaningful guides for the transition, they must evolve beyond their optimization-centric, techno-economic paradigms. Future model development must embed social complexity, policy diversity, and resource constraints into its core architecture.

5. CONCLUSION

The transition to low-carbon electricity systems is critical for achieving global climate goals, as highlighted by the Paris Agreement and subsequent international commitments. Electricity planning models have evolved over decades to address increasingly complex challenges, from optimizing a conventional electricity generation mix to integrating variable RE sources, storage, and DR. Future efforts must focus on hybrid and open-source models, enhancing the usability and transparency of these tools while fostering collaboration among policy makers, researchers, and industry stakeholders along the value chain and including both the development and the application phases. This approach will ensure that energy planning models remain relevant and effective in guiding the global transition to sustainable and resilient electricity systems.

SUMMARY POINTS

1. Demand for energy is growing, and that for electricity is significantly faster.
2. Fossil fuel energy supply chains emit greenhouse gases and other pollutants, and renewable energy (RE) integration in electricity systems is a promising solution for their mitigation.
3. Electricity systems are capital-intensive, long-lived assets, and their viability is strongly influenced by the technology, policy, regulatory, and market conditions. Accordingly, planning and operation of these systems utilize modeling approaches.
4. RE is variable and uncertain. Its increasing share in the system calls for a paradigm shift in how the electricity sector is organized and operated.
5. Electricity systems with significant share of RE necessitates provisioning of flexibility to ensure reliability. This entails accounting of RE variability in the planning and

operations processes, which are increasingly underpinned by modeling. These electricity systems are increasingly linked with climate and water systems as well as across economic sectors including mobility and industry.

6. The increasing electrification of mobility and industrial sectors has led to exposure to bottlenecks in international supply chains of critical minerals, which are scarce and for which production is geographically concentrated.
7. A range of actors is needed to make decisions related to the electricity system integration of RE; these actors include national and regional governments, planners, utilities, system operators, and large industrial consumers of electricity.
8. The electricity system modeling landscape is constituted by a complex interplay of economic, academic, and government agents with open-source and proprietary models.
9. The attributes of the modeling analysis, including stakeholder engagement, data, and source code, have a bearing on impact and buy-in, especially for public policy-making.
10. The energy transition is not merely a technological shift but a deep structural transformation with socioeconomic implications.

FUTURE ISSUES

1. Future efforts must focus on hybrid and open-source models, enhancing the usability and transparency of these tools while fostering collaboration among policy makers, researchers, and industry stakeholders along the value chain, including both the model development as well as its application.
2. Modeling needs to integrate data from climate and water systems to better assess the resilience of RE-dominated electricity systems.
3. Supply chain bottlenecks and diversification strategies need to be explicitly modeled to understand their impact on the energy transition.
4. Generation of solar photovoltaic and other RE-related waste and its management should receive greater attention, as the scale of waste stream will be as high as the scale of RE integration.
5. Electricity system models need to expand to include other energy carriers and sectors to more accurately represent the electrification of mobility and industrial sectors.
6. Lack of integrative modeling of equity and climate justice are emerging as major criticisms; thus, inclusion of these areas in future research will be useful.
7. Future model development must embed social complexity, policy diversity, and resource constraints into its core architecture.
8. Review of model types and their applications across geographies can bring out the extent of their underrepresentation across select regions.
9. Interventions to streamline and better organize the modeling landscape can improve the insight, resulting in processes that yield improved decision intelligence.

DISCLOSURE STATEMENT

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

AUTHOR CONTRIBUTIONS

B.P. provided conception, supervision, coordination, review, and revision, while A.D., P.P., and T.S. wrote the original draft and reviewed the final version. A.D. worked on the figures, P.P. and A.D. formatted the citations, and T.S. structured the outline.

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