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Review

A Comprehensive Review on the Integration of Renewable Energy Through Advanced Planning and Optimization Techniques

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Abstract: The expanding integration of wind and photovoltaic (PV) energy is disrupting the power system planning processes. Their incorporation poses limitations to forecasting due to their inherent variability. This review compiles a total of ninety studies conducted and published between 2019 and 2025, presenting for the first time an integrated approach that simultaneously optimizes the generation, transmission, storage, and flexibility of resources given high ratios of renewable generation. We present a systematic taxonomy of conflicting optimization approaches—deterministic, stochastic, robust, and AI-enhanced optimization—outlining meaningful mathematical formulations, real-world case studies, and the achieved trade balance between optimality, scale, and runtime. Emerging international cooperation clusters are identified through quantitative bibliometric analysis, and method selection in practice is illustrated using a table with concise snapshots of case study excerpts. Other issues analyzed include long-duration storage, centralized versus decentralized roadmap delineation, and regulatory and market drivers of grid expansion. Finally, we identified gaps in the literature—namely, resilience, sector coupling, and policy uncertainty—that warrant further investigation. This review provides critical insights for researchers and planners by systematically integrating methodological perspectives to tackle real-world, application-oriented problems related to generation and transmission expansion models amid significant uncertainty.

Keywords: energy storage systems; power system planning; renewable energy integration; stochastic optimization; transmission expansion planning

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1. Introduction

As wind and solar photovoltaic (PV) systems, among other renewable energy types, are increasingly adopted, there is a fundamental change occurring in long-term power-system planning. Even though these advancing technologies are crucial for meeting global decarbonization goals, they present problems for the stability and reliability of electricity supply due to their intermittency and uncertainty [1]. Weather-dependent fluctuations and the almost complete absence of controllability in real-time require planners to rethink the planning and scheduling of new asset additions.

Investment decisions as to generation, transmission, and storage expansion commit infrastructure for decades; sub-optimal choices can therefore lead to persistently higher costs or undermine the security of supply. Classical deterministic expansion models—built around a single trajectory for load and resource availability—struggle to capture the wide range of outcomes induced by weather, fuel-price swings, and policy uncertainty. This gap motivates planning tools that explicitly embrace uncertainty.

Against this backdrop, stochastic planning has emerged as a powerful approach to quantify and hedge risk. By modelling multiple scenarios of demand and renewable output, stochastic formulations provide a robust basis for deciding how much and where to expand electrical infrastructure while minimizing expected costs and avoiding grid overloads [2]. Moreover, accounting for statistical correlations between load patterns and renewable production improves siting decisions and boosts integration efficiency [3]. Far from being an abrupt methodological leap, stochastic optimization represents the logical evolution from deterministic methods once deep uncertainty is acknowledged.

A second pillar of planning for highly variable renewable energy (VRE) is the joint optimization of energy storage and transmission expansion. Battery energy-storage systems can absorb surplus generation when renewable output is high and release it during lulls, smoothing net-demand profiles, enhancing operational flexibility, and alleviating congestion [4,5]. Coordinating storage placement with transmission upgrades thus reduces curtailment, defers costly reinforcements, and accelerates renewable integration.

Extensive research—ranging from classic optimization techniques to hybrid schemes that fuse mathematical programming with artificial intelligence methods—has already enriched the planning toolkit [1]. Nonetheless, unlocking the full benefits of large-scale renewable deployment requires further methodological progress to co-optimize variable generation, storage, transmission, and emerging flexible resources under realistic uncertainty representations.

The notable increase in international cooperation that began in 2019 illustrates the increasing importance and prospects of research concerning power system expansions. Research centers in China, the United States, and some European countries have intensified collaboration with global partners, illustrating a collective concern towards addressing energy issues and creating sustainable, resilient energy grids. This growing collaboration network is illustrated in Figure 1.

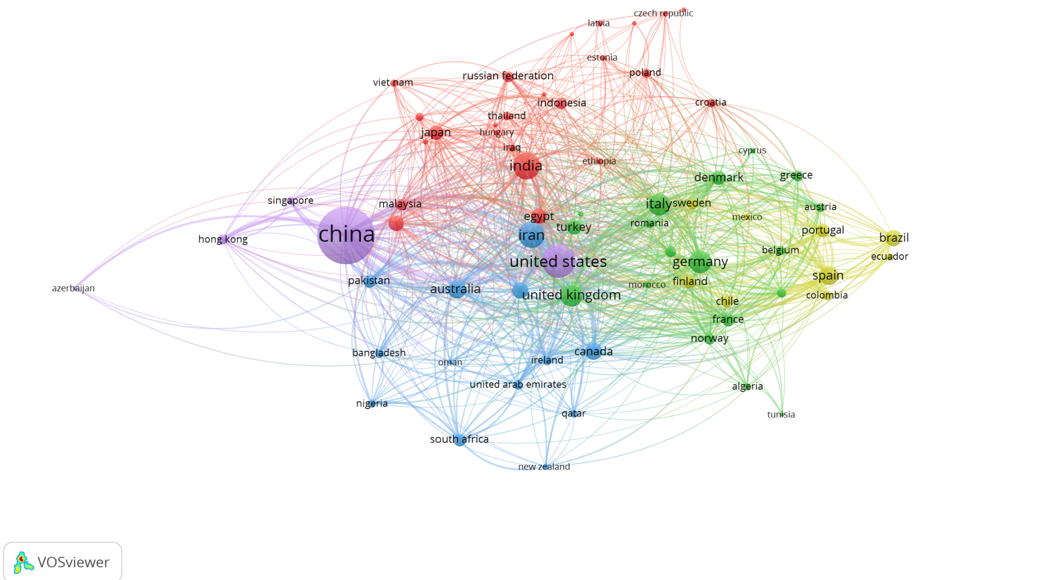

Figure 1. International collaboration map in research on power system expansion planning.

This paper surveys recent advances in power system planning for renewable integration. We trace the methodological evolution from deterministic formulations to scenario-based and stochastic approaches, review cutting-edge optimization tools for coordinating generation and transmission expansion, and assess the role of energy storage integration in mitigating variability. By synthesizing these strands of research, we clarify the state of the art and identify promising directions for future inquiry.

Earlier surveys have tended to examine either generation expansion, transmission reinforcement, or storage sizing in isolation, and most still rely on deterministic formulations. To the best of our knowledge, no prior review offers (i) a unified generation–transmission–storage–flexibility perspective under high shares of variable renewable energy; (ii) a systematic taxonomy that contrasts deterministic, stochastic, robust, and AI-enhanced optimization techniques; (iii) a quantitative bibliometric analysis of 90 peer-reviewed studies published between 2019–2025 that reveals emerging collaboration clusters; and (iv) a forward-looking research agenda that pinpoints unresolved issues such as co-optimizing resilience, market design, and policy uncertainty. By bridging methodological and application-oriented viewpoints, the present work fills this identifiable gap and provides a consolidated reference for researchers and practitioners developing next-generation planning models.

This document is divided into several parts including, first, a comprehensive review of classical power system planning methodologies, highlighting their shortcomings when it comes to coping with the issues introduced by the integration of renewables. Finally, we will discuss the intermittency and variability of these sources as well as emerging solutions, including stochastic planning and advanced optimization. In addition, the energy storage and emerging technologies that are changing the way the power system is planned will be discussed, along with the regulatory and market challenges related to them. Finally, future trends that will shape the evolution of power systems are described as well as research areas in need of further attention.

2. Traditional Power System Planning Methodologies

2.1. Description

Traditionally, power system planning involves deterministic approaches to generation expansion planning (GEP) and transmission expansion planning (TEP) with conventional energy sources: coal, natural gas, and nuclear power. Typically, these models use deterministic optimization methods, assuming a fixed demand and supply profile over time. However, this fails to account for significant variations or uncertainties [6].

Nevertheless, power systems are designed to provide for the projected peak demand, subject to a reserve capacity if a generation unit fails or in the event of an increase (or decrease) in the demand that was not accounted for when designing the system. In optimization efforts, investment and operational costs are minimized, and the expansion of the transmission is designed to maximize the capacity to transport energy between generation plants and consumption centers at the lowest cost [7].

As depicted in Figure 2, we illustrate a conceptual 20-year expansion horizon divided into three reference milestones:

- Year 1 (base year). Electricity demand corresponds to present-day levels, supplied mainly by the existing hydro and thermoelectric power plants.
- Year 10 (medium-term). Demand grows, prompting the first wave of utility-scale wind and solar additions that complement, rather than replace, legacy hydro and thermal units.
- Year 20 (long-term). The system reaches a fully diversified portfolio—wind, solar PV, hydro, and battery energy storage systems—while thermal generation is progressively retired; this mix provides the flexibility and zero-carbon supply needed to meet higher residential, commercial, and industrial loads.

The Figure 2 is therefore illustrative: It shows how sustained demand growth necessitates not only additional generation capacity but also commensurate transmission reinforcements and how the generation mix is expected to transition from fossil-dominated to predominantly renewable as policy and cost drivers evolve.

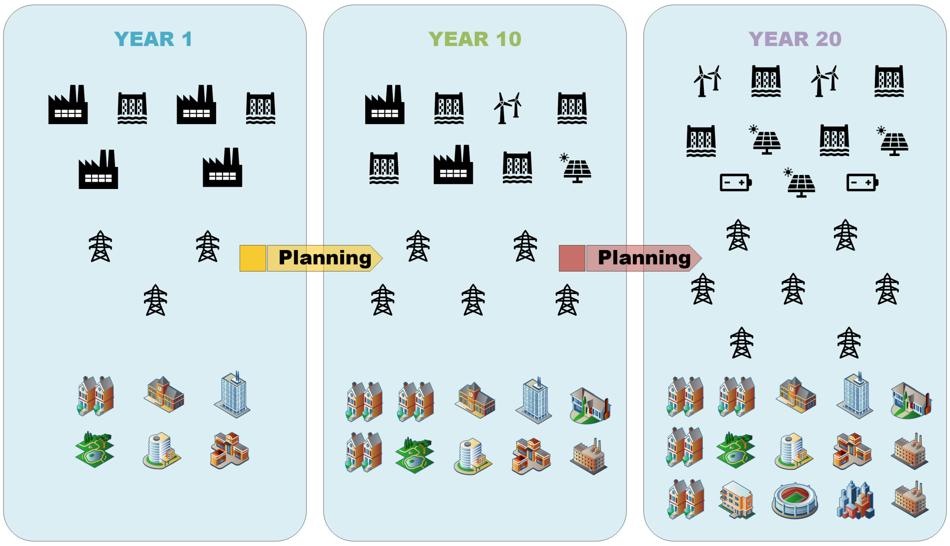

Figure 2. Illustration of the power system expansion process over time, from Year 1 to Year 20.

2.2. Limitations of Deterministic Planning Under High VRE

The integration of pre-defined planning methodologies has for years supported the development of a strong backbone power system; however, their application does not allow for the seamless incorporation of VRE due to a single-scenario approach [6]. The following outlined items justify the shift toward more complex methods:

- Intermittency: The fixed weather profile approach cannot model the fast-paced solar and wind weather-driven changes, thereby leading to sub-optimal investment and scheduling of assets [8,9].
- Rigid Structure: The fundamental need for rapid-response, flexible supply-side resources such as energy storage, demand response, as well as other resources, is neglected [10].
- Temporal mismatch: The poorly modeled discrepancies between VRE generation and load on an hourly or seasonal basis mask the investment needed for storage and transmission [11,12].
- Economic underestimation: The overall system cost is greatly understated due to driving variability costs, as well as cycling, curtailment, and backup costs being omitted [4,13].

These challenges from an operational as well as market perspective will be elaborated upon in detail in Section 3.

3. Challenges of Renewable Energy Integration

Section 2.2 has outlined, in modelling terms, why classical deterministic frameworks struggle with high shares of VRE. We now expand on those limitations from a technical and operational viewpoint, detailing the real-world phenomena—intermittency, flexibility requirements, stability constraints, and economic impacts—that planners must address when integrating VRE at scale.

3.1. Intermittency and Variability

Wind speed and solar irradiation can change rapidly and unpredictably, so the output of wind turbines and photovoltaic plants fluctuates on sub-hourly to seasonal time-scales. These fluctuations complicate generation scheduling and real-time balancing [14,15]. Forecast errors create a persistent gap between expected and actual production [16], often forcing system operators to commit more reserves or curtail VRE output. Deploying battery energy storage systems (BESS) to absorb surplus generation and discharge during lulls has been proven effective in cutting curtailment and mitigating net-load ramps [17,18].

3.2. System Flexibility Requirements

Flexibility is the ability of a power system to respond rapidly to changes in supply or demand. Traditional grids relied on dispatchable thermal and hydro units for this function; as their share declines, alternative flexibility providers—storage, demand response, multi-energy systems, and microgrids—become indispensable [10,14]. Recent studies propose quantitative flexibility indicators to guide investment in BESS, pumped-hydro storage, and demand-side resources [16,18].

3.3. Stability, Reliability, and Congestion

The displacement of synchronous machines reduces system inertia, creating frequency and voltage instability risks. Synthetic inertia from inverter-based resources and rigorous low-voltage ride through (LVRT) standards for PV plants help to maintain stability [15]. High VRE output can also trigger congestion on transmission corridors, leading to renewable curtailment [14]. Grid-enhancing technologies, dynamic line rating, and strategic transmission upgrades are therefore critical complements to storage and flexibility investments [16].

3.4. Economic and Market Implications

Ignoring variability-driven cycling, reserve costs, and curtailment can understate total system costs and misallocate capital. Meta-heuristic and AI-based optimization techniques are increasingly used to co-optimize VRE, storage, and backup capacity, capturing these hidden economic effects [4,13].

Table 1 summarizes the main challenges associated with the integration of renewable energy sources into power systems, along with representative strategies to mitigate each one.

Table 1. Key challenges of renewable energy integration and illustrative mitigation strategies.

Challenge	Description	Representative Solutions
Intermittency & Variability	Rapid, weather-driven output fluctuations.	Short-term storage, advanced forecasting, curtailment management.
Flexibility Needs	Demand for fast balancing resources grows with VRE share.	BESS, pumped hydro, demand response, multi-energy systems.
Stability & Reliability	Reduced inertia, voltage/frequency excursions, congestion.	Synthetic inertia, LVRT controls, dynamic line rating, targeted reinforcements.
Economic Impacts	Underestimated costs of reserves, cycling, curtailment.	Integrated optimization of VRE, storage, and backup; market mechanisms.

Collectively, these challenges underscore the need for planning frameworks that explicitly model uncertainty and co-optimize generation, storage, and transmission—topics addressed in the following sections.

4. Advances in Stochastic Planning and Optimization

Stochastic planning and advanced optimization techniques are the key contributors to the incorporation of renewable energy sources into power systems. These techniques enable the balance of variability and uncertainty inherent in renewable generation, thus improving the dependability of energy systems.

4.1. Stochastic Planning

Specifically, stochastic planning has come to the forefront due to its obvious applicability in helping to manage the inherent uncertainty in power systems with large amounts of RE penetration. Meteorological risks pose major challenges for renewable generation and transmission, as wind and solar output are extremely sensitive to weather variations. Therefore, stochastic models enable the examination of multiple scenarios, effectively capturing the variability in energy production and consumption [19,20].

For example, the Monte Carlo technique has gradually developed into one of the most often used stochastic approaches, with various possibilities for modelling a large number of scenarios related to fluctuations in wind intensity and solar radiation intensity over time. This method allows the simulation of probabilistic conditions and enables system operators to better analyze system efficiency and backup systems where needed [19,20]. Furthermore, stochastic models also complement the sophisticated probabilistic risk estimation approach that integrates the risk and economic aspects of the inherent randomness of the availability of renewable energy sources [21].

Therefore, stochastic planning acts as an advantage to the variability of renewable energy generation while also assisting with the long-term planning by helping system operators to envision different future possibilities. With the application of stochastic methods, operators can achieve more accurate and precise grid management and more cost-efficient investments in renewable equipment [21].

4.2. Overview of Optimization Methods and AI Support Tools

Optimization algorithms form the computational backbone of long-term generation–transmission planning. Exact methods such as mixed-integer linear programming (MILP) deliver provably optimal solutions for moderate-size instances. At the same time, meta-heuristic techniques—including genetic algorithms, particle swarm optimization, and ant colony optimization—can explore very large, highly non-convex search spaces to obtain near-optimal plans within practical runtimes. Machine learning and other AI techniques play a complementary rather than substitutive role: They supply high-fidelity forecasts of demand and renewable production and can act as fast surrogate models of complex network constraints, thereby feeding essential inputs into the optimization layers. This subsection, therefore, offers a concise qualitative survey of these three building blocks—exact solvers, meta-heuristics, and AI-assisted forecasting/surrogates—highlighting their key features and typical applications. Representative mathematical formulations for the exact and meta-heuristic approaches are presented in Section 4.3, where the integration points for ML outputs are also indicated.

(a) Mixed-Integer Linear Programming (MILP). MILP remains the dominant *exact* method because it can co-optimize binary siting decisions and continuous power-flow variables within a single framework. Applications range from voltage regulator siting and loss minimization [22] to joint placement of PV, wind, and battery energy storage systems [23,24] and long-term transmission expansion studies that weigh capital and operating costs [25,26]. Commercial and open-source solvers guarantee global optimality for moderate-sized instances, but computational burdens rise rapidly with network scale and scenario count.

(b) Meta-heuristic Algorithms. Bio-inspired techniques such as genetic algorithms (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) excel in large, non-linear, multi-objective search spaces where exact solvers struggle [27]. GA has improved PV maximum power point tracking under partial shading [28] and reduced operational costs in hybrid renewable systems [29]. PSO delivers fast convergence in power flow optimization for grids with high wind and solar penetration [30], and hybrid PSO variants help avoid local minima [31]. ACO has proven effective for routing new transmission lines and allocating generation in smart grid settings with growing renewable shares [32,33].

(c) Machine-Learning/AI-assisted Methods. Data-driven models complement optimization by improving forecasts of renewable generation and electricity demand [34]. Accurate predictions allow planners to better align variable supply with consumption patterns [35], thereby reducing reliance on costly backup resources. ML-enhanced load forecasting has already helped minimize curtailment and lower operational costs in systems with high PV and wind shares [36]. Beyond forecasting, AI surrogates can emulate complex network constraints, accelerating large-scale stochastic optimization.

In practice, planners often link these methods—e.g., MILP models driven by ML-based forecasts, or GA-initialized MILP runs—to exploit their complementary strengths. Representative mathematical formulations for each category follow in Section 4.3.

4.3. Mathematical Formulations

This section gives a representative formulation for each optimization family introduced qualitatively in Section 4.2. The aim is to highlight the modelling structure rather than provide an exhaustive derivation; additional constraints (e.g., security limits, emissions caps) can be readily appended for specific case studies.

Notation:

- Sets
  - $i \in N$—generation or storage sites
  - $t \in T$—time steps
  - $s \in S$—stochastic scenarios
- Parameters
  - $C_{gen,i}$—generation cost
  - $C_{batt,i}$—storage cost
  - C^{capex}—investment cost
  - D_t—demand at time t
  - π_s—probability of scenario s
  - $P_i^{\max}$—capacity limit of unit i
- Decision variables
  - $P_{i,t,s}$—power dispatch
  - $E_{i,t,s}$—stored energy
  - x_i—binary build decision

4.3.1. Deterministic MILP Model

The deterministic MILP seeks the lowest-cost hourly dispatch and capacity expansion over a single forecast of demand and VRE output:

$$\min_{x,P,E} \sum_{i \in N} C_i^{\text{capex}} x_i + \sum_{t \in T} \sum_{i \in N} \left(C_{gen,i} P_{i,t} + C_{batt,i} E_{i,t} \right) \tag{1}$$

$$\begin{aligned}
&\text{Power balance:} && \sum_i P_{i,t} = D_t, && \forall t && \text{(2a)}\\
&\text{Capacity limits:} && 0 \le P_{i,t} \le P_i^{\max} x_i, && \forall i,t && \text{(2b)}\\
&\text{Storage dynamics:} && E_{i,t} = E_{i,t-1} + \eta^{\text{ch}} P_{i,t}^{\text{ch}} - \eta^{\text{dis}} P_{i,t}^{\text{dis}}, && \forall i,t && \text{(2c)}
\end{aligned}$$

Equation (1) minimizes total investment and operating cost, while constraints (2a)–(2c) enforce energy balance, capacity limits, and storage dynamics. Huang et al. (2023) [2] applied a deterministic linear-programming GEP model with a 8760 h resolution to a three-area Chinese system, co-optimizing wind, PV, and two classes of storage (PHS/CAES and BESS). The model showed that adding both storage types enables the grid to satisfy China's 2030 carbon-peaking target and the 2060 carbon-neutrality goal while holding wind and PV curtailment below 5% and 3%, respectively—performance that a storage-free plan could not meet [37].

4.3.2. Two-Stage Stochastic MILP

To capture uncertainty in VRE output and load, a two-stage model selects first-stage investments x before realizations $s \in S$ unfold, then second-stage dispatch decisions (P_s, E_s)

$$\min_x \; C^{\text{capex}}(x) \; + \; \sum_{s \in S} \pi_s \min_{P_s, E_s} C_s^{\text{opex}}(P_s, E_s) \tag{3}$$

Subject to constraints analogous to (2a)–(2c) for every scenario s. This structure internalizes operational risk by weighting scenario-specific costs with probabilities π_s. Micheli et al. (2020) [38] developed a large-scale two-stage stochastic MILP for the Italian interconnected grid (663 buses) and solved it with a multi-cut Benders decomposition. The model considers six joint fuel- and CO_2-price scenarios across a 21-year horizon. With this stochastic treatment, the expansion plan converged to an expected total cost of EUR 404 billion, only 0.02% above the linear relaxation bound and noticeably lower than the deterministic benchmark reported by the authors, while meeting all reliability criteria. Operating costs—dominated by thermal generation fuel expenditures—account for about 85% of the objective, underscoring the value of explicitly modelling price uncertainty in long-term planning [38].

4.3.3. Meta-Heuristic Objective Function

When the search space becomes too large or highly non-convex, planners often retain the same cost objective but replace exact solvers with genetic algorithms, PSO, or ACO. A generic fitness function is

$$\text{Fitness}(x, P, E) = \text{NPV}\left(C^{\text{capex}}(x) + C^{\text{opex}}(P, E) \right), \tag{4}$$

While the technical constraints remain those of the MILP model. A meta-heuristic model iteratively updates (x, P, E) to minimize the fitness value, trading global exploration for computational speed. Keokhoungning et al. (2022) [39] tackled the IEEE 118 bus test system and Lao PDR's system with a PSO-driven transmission expansion model that simultaneously considers PV, wind, and battery resources. Running 10–20 particles over

≥140 generations, their algorithm produced expansion schedules in which PV siting and limited line reinforcements (USD 73 million on IEEE-118 and USD 378 million on the Lao grid) maintained N − 1 reliability while trimming system-wide losses and deferring several high-voltage corridors otherwise required under a deterministic MILP plan. The study demonstrates that a well-tuned PSO can yield near-optimal results for large, renewables-rich grids at a fraction of the computational burden of exact approaches [39].

4.3.4. ML-Based Forecasting Loss

Machine learning layers enhance planning models by reducing prediction error for load D_t and VRE generation P_t^{VRE}:

$$\mathcal{L}(\theta) = \sum_{t \in T} \left(\hat{D}_t(\theta) - D_t\right)^2 + \sum_{t \in T} \left(\hat{P}_t^{\mathrm{VRE}}(\theta) - P_t^{\mathrm{VRE}}\right)^2 \tag{5}$$

Here, θ denotes the ML model parameters, and the feature vector X_t includes meteorological forecasts, calendar effects, and socioeconomic indicators. The trained model feeds probabilistic scenarios or point forecasts into the optimization stages above.

The formulations presented above are not an end in themselves; they form a part that can be expanded as renewable penetration grows and new operating paradigms emerge. Deterministic and stochastic MILP models provide the structural backbone for capacity expansion, while meta-heuristics offer a computationally tractable route for very large, highly non-linear problems. AI-assisted forecasting, in turn, supplies the high-resolution scenarios that make these optimization layers truly actionable. Future research must continue to incorporate dynamic storage management, grid flexibility metrics, and sector coupling constraints so that planners can co-optimize reliability, efficiency, and sustainability in increasingly complex power systems. Thus, ongoing innovation in optimization remains indispensable for the next wave of renewable-driven grid expansion.

5. Energy Storage Integration

As indicated previously, integrating renewable energy sources such as solar PV and wind power into power systems presents great technical and operational challenges due to their intermittency and variable nature. These fluctuations introduce uncertainty into the real-time balancing of supply and demand and heighten the risk of system instability [40].

Energy storage systems integration is one of the most robust solutions to address this variability. Batteries, as well as technologies such as pumped hydro storage, may absorb energy when renewable output exceeds demand and release it when demand is higher than output. This, in turn, helps mitigate the intermittency of renewable energy sources and enhances the overall flexibility and reliability of the power system. Energy storage can help bridge the gap between supply and demand and make it possible to deliver more consistent power even when the power being generated from renewable sources varies. Additionally, storage systems can supply ancillary services such as frequency regulation and reserve capacity (one of the most important ancillary services) needed to keep the grid stable [41,42].

As the energy transition progresses, the role of storage in creating a more flexible and resilient grid becomes increasingly critical. Managing surplus generation during peak renewable output and dispatching it during high-demand periods is key to ensuring a stable and reliable power supply that allows a higher percentage of renewables on the grid without compromising system integrity. A key benefit of battery system implementation is that it supports frequency regulation and fast reserve that enhance system stability by responding immediately to sudden variations in renewable generation [43,44].

As most current grid deployments rely on short- to medium-duration storage, the following subsection reviews the technologies that are already commercially dominant or close to market maturity (e.g., lithium-ion batteries, pumped-hydro storage, and flow batteries). Beyond these options, however, high-VRE systems will also require long-duration seasonal storage capable of shifting energy across days, weeks, or even seasons. After discussing conventional solutions, a separate subsection is devoted to hydrogen, compressed-air, and thermal/CHP-based storage, which are increasingly recognized as essential complements to short-duration batteries.

5.1. Concepts for Storage Technologies

Energy storage technologies are widely used and researched in power system planning, with different special advantages suitable for different applications.

- Lithium-Ion Batteries: Among currently existing storage technologies, lithium-ion is the most common implementation, especially in grid-scale applications and in distributed energy systems. Due to their high energy density, fast response times, and decreasing cost, they remain the first choice for short-term energetic reserve, frequency regulation, and smoothing the variability of renewable generation. The utilization of lithium-ion batteries in residential and utility-scale applications make them integral for balancing supply and demand in renewable-heavy grids [45]. Despite this, they raise an issue of degradation over time and environmental issues due to the mining and disposal of lithium [46].
- Pumped Hydro Storage (PHS): Pumped hydro storage continues to be the most commonly deployed high-capacity energy storage technology globally and remains the most prevalent form of energy storage in the world. During periods of low demand, it uses gravitational energy to pump water to a higher elevation and then releases it to generate electricity during peak demand times. PHS offers particularly high reliability for backup power during high-demand periods and long-term storage capacity. Due to its high efficiency and reliability, PHS is well suited for enhancing grid stability and energy arbitrage; however, its applicability is restricted by geographic limits and high initial capital costs [47,48].
- Flow Batteries: These batteries, with separate electrolytes from reaction cells, offer a number of advantages over lithium-ion technology for medium- and long-term energy storage. They provide extended discharge durations, making them suitable for long-term constant energy supply applications. Flow batteries are very effective at integrating renewable energy because they have the ability to store energy for a long time while also delivering power over periods of several hours to several days. Moreover, they offer a long power cycle lifespan and are significantly more effective for frequent cycling at the cost of a low energy density when compared to lithium-ion batteries [49,50].

These technologies are part of the solution to increase power system stability and contribute to the grid's resilience to extreme events and demand peaks. Through the combination of various storage technologies, power systems are able to optimize energy supply and demand management, and ensure constant and reliable service even with a high penetration of renewable energy. Energy storage systems are applied not only to large interconnected power systems but also to isolated grid and microgrids to maintain grid stability and flexibility. For example, in microgrids, the mix of existing storage technologies such as lithium-ion batteries and flow batteries appears to enable a seamless integration of intermittent renewable sources while supporting both critical and non-critical loads during grid disruptions or outages [51].

5.2. Joint Planning Models for Generation, Transmission, and Storage

Since the effective way to improve the operational flexibility and efficiency of the system is related to controlling the integration of renewable generation and energy storage, the joint planning of renewable generation and energy storage turns out to be the most effective strategy to improve the system. This approach minimizes long-term operational and investment costs by using integrated optimization models that consider the placement of new renewable plants and storage capacity.

A typical optimization model for joint generation, transmission, and storage planning can be written as follows:

$$\text{Minimize } Z = \sum_{t=1}^{T}\left(\sum_{i=1}^{N} C_{gen,i}P_{gen,i,t} + C_{trans}P_{trans,t} + C_{inv,i}X_i + C_{stor}P_{stor,i,t}\right) \tag{6}$$

where:

- Z is the total system cost to minimize,
- $C_{gen,i}$ is the cost of generating power from unit i,
- $P_{gen,i,t}$ is the power generated by unit i at time t,
- C_{trans} is the cost of transmission expansion,
- $P_{trans,t}$ is the power transmitted at time t,
- $C_{inv,i}$ is the investment cost for expanding generation unit i,
- X_i is a binary variable representing whether new generation or transmission capacity is built at unit i,
- C_{stor} is the cost of energy storage,
- $P_{stor,i,t}$ is the energy stored or released by the storage system at time t.

The incorporation of storage models into power systems enhances flexibility and responsiveness to fluctuations in both demand and renewable electricity generation. These models can optimize the placement of both storage systems and renewable generation, maximizing efficient transmission and storage of energy across the network and enabling the decrease of operational costs while improving overall system reliability.

On the other hand, while the costs of storage batteries have been decreasing, the long-term affordability of storage solutions at a large scale is still uncertain. Furthermore, battery degradation over time involves associated costs due to maintenance, replacement, and lifecycle management that must be considered in the planning stage [45,46].

Thus, these future uncertainties demand robust optimization models capable of addressing both operational short-term challenges as well as long-term investment planning. For instance, optimization techniques for renewable energy systems should also consider the degradation of storage devices and the capacity expansion driven by the growing deployment of renewable energy. To develop a resilient power system, stochastic models are critical for quantifying uncertainty in renewable generation and storage cost [52]. A traditional objective function is related to the minimization of the investment and operation cost of the storage system as presented below:

$$\min\left(C_{\text{inv}} + C_{\text{npc}}\right) = \min\left(C_{\text{inv}} + C_{\text{grid}} + C_{\text{loss}} + C_{\text{maxDemand}}\right) \tag{7}$$

here,

- C_{inv} is the investment cost of BESS (battery energy storage systems),
- C_{npc} is the network operation cost,
- C_{grid} is the cost of power purchased from the grid,
- C_{loss} is the cost of network losses,
- $C_{\text{maxDemand}}$ is the cost of maximum demand or peak demand charge.

The challenges described previously are addressed using optimization. System planners may optimize the placement, sizing, and operation of energy storage systems along with renewable generation and transmission infrastructure by using advanced optimization models, including MILP and multi-objective evolutionary algorithms (MOEA) to determine optimal solutions. These models also account for economic and operational objectives, guaranteeing system reliability while achieving minimization of costs [45,46]. Optimization techniques offer power systems flexibility in coping with the dynamic conditions associated with fluctuating renewable generation and changing energy demands [53].

Moreover, the increasing use of AI methods, including ML, to optimize the integration of storage systems has been recognized. Accurate demand and renewable generation forecasts are critical in the optimization of storage system sizing and placement, and AI-based models can provide accurate demand and renewable energy generation forecasts. By aligning storage deployment during periods of high demand and low renewable output, these forecasts help with system planning [52,54].

5.3. Long-Duration and Seasonal Storage

Short-duration lithium-ion batteries dominate today's deployments, but several technologies can provide the multi-day to seasonal shifting that high-VRE systems ultimately require. A Central European market study shows that power-to-hydrogen with underground storage can supply up to 30% of annual hydrogen demand by 2040, delivering system-wide welfare gains of EUR 4–28 billion while acting as a seasonal buffer for surplus wind and solar [55]. For mechanical storage, dynamic simulations of an advanced adiabatic compressed-air energy storage (AA-CAES) plant indicate round-trip efficiencies near 70% and levelized storage costs below EUR 0.10/kWh when coupled with large wind portfolios [56,57]. At the thermal end, Denmark's district heating sector already couples wind and solar with large combined heat and power (CHP) units and seasonal hot water pits, demonstrating how CHP + thermal storage can shift renewable surpluses from summer to winter while providing low-carbon heat and ancillary services. Incorporating these long-duration options into expansion models can substantially cut curtailment and reduce reliance on short-duration batteries, but it raises new questions about siting constraints, round-trip efficiency, and gas-infrastructure repurposing that warrant further research [58].

6. Regulatory and Market Challenges

The successful integration of renewable energy sources into power systems is not just a technical challenge but also requires careful navigation of regulatory frameworks and market dynamics. Policies, incentives, and market structures must evolve to support a cleaner and more resilient grid.

6.1. Regulatory Framework

Solving the technical challenges of integrating renewable energy into power systems is only part of the equation; equally important is navigating the regulatory landscape and market dynamics. Achieving a cleaner and more resilient grid requires adapting policies, incentives, and market structures. Key areas for reform include the following concepts:

- Renewable Portfolio Standards (RPS): The utilities are mandated, under RPS, to source some percentage of electricity from renewable sources. This results in a direct market for renewable energy projects and always generates a long-term demand for renewables. Several regions have started implementing RPS policies, pushing utilities to gradually decrease their dependence on fossil fuels and replace them with renewable energy [59,60].

- Feed-In Tariffs (FiTs): FiTs guarantee long-term contracts with payment rates based on renewable energy production. They reduce market risks and give predictable returns to incentivize investment in renewable energy projects. FiTs have, however, proven to vary by region and have been subject to constant political and economic adjustments, affecting the long-term stability of the renewable energy market [60,61].
- Carbon Pricing Mechanisms: Policies such as carbon taxes and cap-and-trade systems require utilities and industries to price their carbon footprints. These mechanisms, by raising the cost of carbon-intensive energy sources, create a market-driven incentive for cleaner alternatives, indirectly giving renewables a competitive advantage and encouraging their integration into power systems [62].

Storage integration also raises regulatory challenges, with many markets still deciding what rules apply for storage technologies to take part in energy markets. However, the broader deployment of energy storage is hampered by a lack of regulatory clarity on whether energy storage counts as generation, transmission, or demand, and how it can be compensated for providing grid services [63].

6.2. Market Mechanisms

As the share of intermittent renewable energy sources continues to grow, electricity markets must evolve in parallel. Pricing structures and market mechanisms must become more dynamic and adaptive to effectively handle the variability in both demand and supply introduced by renewable generation. The following mechanisms are critical to enabling higher levels of renewable integration:

- Dynamic Pricing: Traditional electricity markets do not employ fixed pricing structures based on actual real-time supply and demand. Since solar and wind power vary over the course of a day, dynamic pricing approaches, such as time of use rates and real-time pricing (RTP), can offer consumers an incentive to shift their demand in the face of, or according to, levels of renewable generation. These models have been designed to promote consumption during periods of high renewable generation and reduce demands during periods of low renewable supply [60,64].
- Capacity Markets: These markets help to guarantee an adequate reserve generation capacity to meet peak demand even at times when renewable energy production is low. They pay generators to be available to supply when needed (grid reliability) and when they cannot supply (low renewable generation). Demand response and energy storage, which are proven to be crucial to deal with renewable energy variability, are also integrated into capacity markets [62,65,66].
- Ancillary Services Markets: Greater renewable energy penetration increases the need for ancillary services such as frequency regulation, voltage control, and spinning reserves to keep the system stable. Renewable generators and energy storage systems can be compensated for providing these critical services through markets for ancillary services, depending on the regulations of each country [67].

A challenge of integrating renewable energy sources into electricity markets is adapting electricity markets to be effective at managing the variability of renewable energy types in an efficient expansion of power systems while remaining economically sustainable and technically sound. It is shown that aligning regulatory policies toward more dynamic market mechanisms allows renewable energy to be integrated without compromising the useful grid stability in a power system expansion context. With this methodology, it becomes easier to build the infrastructure to support renewable generation and a resilient power grid that can handle more renewable energy.

7. Open Challenges and Future Directions

As can be deduced from the points discussed above, expanding power systems by incorporating renewable energy sources presents complex challenges that extend beyond technical considerations to include economic, regulatory, and operational complexities. Ongoing and additional research must focus on enhancing planning methodologies to include greater shares of renewable energy in a configuration that must be stable, resilient, and financially feasible. In this section, we identify some key research areas and some emerging trends that will play an important role in the future expansion of power systems.

7.1. Future Research Directions

As renewable energy penetration increases, several areas of power system planning require further exploration to ensure that systems can expand effectively:

- The growing complexity and uncertainty associated with renewable energy integration call for more sophisticated planning models. While mixed-integer linear programming (MILP) remains a widely used optimization method, it must be complemented by hybrid algorithms that incorporate meta-heuristics, machine learning, and artificial intelligence. These advanced approaches are well-suited for solving multi-objective optimization problems, balancing trade-offs between cost, grid reliability, and environmental impact. In particular, the development of algorithms that improve the accuracy of renewable generation forecasting and optimize network reinforcements while considering the variability of renewables is essential for effective power system expansion planning [68–70].
- Improving Long-Term Climate and Load Forecasting: Planning the expansion of power systems requires highly accurate forecasts. The lessons learned from these case studies will help enhance weather forecasting models for renewable energy production—especially wind and solar PV, and enable their integration into power system planning tools. This issue is approached from the perspective of long-term load forecasting, accounting for demand shifts driven by electrification trends (e.g., electric vehicles). With these improved forecasting capabilities, system planners will be better equipped to anticipate when and where capacity expansions are necessary [71,72].
- Incorporating Energy Storage in Expansion Models: To deal with the intermittency of renewable sources, research on the role of energy storage in expansion planning is of cardinal importance. More advanced models are needed to appropriately size and locate renewable generation in conjunction with storage systems. These models should include the entire lifecycle of storage technologies, including degradation, cost evolution, and operational constraints [73,74].
- Resilience in Planning for Extreme Events: As global warming becomes more apparent, power systems must be able to withstand the growing impacts of climate change, including hurricanes and wildfires. In future research, resilience metrics should be integrated into expansion planning models so that new infrastructure, including renewable generation and storage, can continue to serve its customers through these disruptive events [75,76].

7.2. Emerging Trends

Furthermore, multiple emerging trends will significantly change the expansion of power systems to incorporate renewable energy but also add to existing planning challenges. These trends will change power system planning on both the technological and operational sides.

- Blockchain for Energy System Transactions and Management: As a result, the articles [77,78] discuss the potential use of blockchain technology to decentralize energy markets and make the energy system more efficient. For expansion planning blockchain can enable peer-to-peer (P2P) energy trading whereby consumers can sell PV energy to others. Reduction in dependence on centralized generation and transmission assets could change traditional grid planning.

- AI and Digitalization in Expansion Planning: In this way, grid expansion decisions are being revolutionized based on their use of AI and digital twins. Digital twins, virtual replicas of physical power systems, allow planners to simulate how the integration of new renewable assets, storage systems, or transmission lines affects a power system by making costly investments. In addition, AI-driven models can optimize expansion through supervised learning from historical data and unsupervised learning to predict future grid behaviors under different scenarios. Creating more flexible and adaptive power grids that can further adapt to dynamic conditions introduced by renewables is essential with this technology [79,80].
- Sector Coupling and Integrated Energy Systems: Expansion planning now also focuses on the concept of sector coupling, connecting the electricity sector with the other energy sectors, such as heating and transport. Planners can design more integrated and flexible energy systems by using renewable electricity to serve other sectors, for example, by using surplus solar power for heating or hydrogen production. In order to continue along this track, the grid will need to expand its infrastructure to support electrification in different sectors, thereby raising yet another need for careful and concerted expansion planning [81–83].
- Future Market Reforms and Flexible Pricing Mechanisms: To anticipate this, electricity markets must develop to accommodate more flexible and dynamic operations as variable renewable penetration increases. New market structures such as capacity markets, demand response programs, and time-of-use rates will have to be accounted for in future grid expansion planning. By institutionalizing these reforms, incentives will be provided for distributed generation and storage, which will reduce the need to expand the underlying large-scale grids at a tremendous cost [60,84].

8. Discussion

The large-scale integration of wind and solar PV introduces both valuable opportunities and significant technical challenges for power system expansion. In this discussion, we revisit the main planning methodologies reviewed, ranging from deterministic formulations to AI-enhanced models, and critically evaluate their ability to handle uncertainty, computational scalability, and real-world deployment constraints. Special attention is given to the trade-offs identified between modelling precision and tractability, as well as between centralized and decentralized architectures. Additionally, the role of long-duration storage and emerging flexibility solutions is considered essential to ensure reliability and economic efficiency under high renewable penetration. This integrative perspective helps contextualize the strengths and limitations of each method in guiding future grid expansion under uncertain conditions.

8.1. Mathematical Formulations in Renewable-Energy Planning

Integrating high shares of renewables calls for mathematical models that balance cost, reliability, and computational tractability. Table 2 contrasts the main optimization families concerning optimality guarantee, scalability, and runtime—metrics that strongly influence a planner's choice of tool.

MILP offers reproducible, globally optimal plans, but becomes intractable when binary siting variables or stochastic scenarios proliferate. Meta-heuristics (GA, PSO, and ACO) sacrifice guarantees of optimality for the ability to handle much larger or highly non-convex search spaces; PSO is fastest but most prone to local minima, whereas ACO excels for discrete routing at the cost of longer runs. GA provides a robust all-rounder for multi-objective studies.

Table 2. Qualitative comparison of optimization families for generation–transmission planning.

Method	Opt. Guarantee	Scalability *	Runtime	Key Strengths/Limitations	Key Refs.
MILP	Global (gap $\leq$0.1%)	$\lesssim 10^5$ vars	min–h	+ Exact, rich modelling; mature solvers − Exponential growth with binaries/scenarios; licence cost	[22,25]
GA (heuristic)	1–5% gap	10^6 vars	min–h	+ Robust global search; multi-objective ready − Parameter tuning; premature convergence risk	[27,29]
PSO (heuristic)	1–3% gap	10^6 vars	s–min	+ Very fast; simple implementation − Local-optima susceptibility; inertia sensitivity	[30,31]
ACO (heuristic)	1–4% gap	10^6 vars	min–h	+ Good for routing / discrete siting − Slower than PSO; many control parameters	[32,33]
ML/AI support	—	$\geq 10^7$ samples	ms–s (inf.)	+ High-fidelity forecasts; surrogate constraints speed optimization − Requires large datasets; no optimality guarantee itself	[34,35]

* Order-of-magnitude variables/scenarios solvable on a workstation.

Machine-learning layers do not optimize the plan directly; instead, they supply accurate demand/VRE forecasts or act as surrogate constraints, which can shrink scenario sets and cut MILP runtimes by an order of magnitude. Hybrid workflows—e.g., GA-initialized MILP fed by ML forecasts—combine the strengths of each family, achieving near-optimal cost with acceptable computational effort.

Hybrid workflows—e.g., GA-initialized MILP fed by ML forecasts—combine the strengths of each family, achieving near-optimal cost with acceptable computational effort. To illustrate these methods in action, Table 3 provides a snapshot of published case studies that employ each technique.

Table 3. Snapshot of published case studies that employ the reviewed methods.

Method	Study/System	Decision Problem	Key Outcome
Deterministic MILP	Huang et al. (2023) [2] —Three-area Chinese grid	Co-optimization of wind, PV, and dual storage (PHS/CAES & BES)	Met 2030 and 2060 targets with wind/PV curtailment below 5%/3%
Two-stage stochastic MILP	Micheli et al. (2020) [38] —Italian grid (663 buses)	Gen + TX expansion under fuel/CO_2 price uncertainty	Expected cost €404, 0.02 optimality gap; all reliability criteria met
Heuristics	Keokhoungning et al. (2022) [39] —IEEE-118 & Lao PDR	Transmission expansion with PV, wind, and battery siting	Maintained N-1 reliability, reduced losses,s and deferred corridors in ≈90 s

Thus, method selection depends on the problem's size, desired solution quality, available data, and runtime constraints. Planners increasingly deploy hybrids to balance these competing objectives.

Increasing system flexibility—through battery energy-storage systems (BESS), demand response, or sector coupling—raises capital expenditure but can markedly reduce curtailment and operating costs at high renewable penetration. For the Iberian (Spain–Portugal)

2030 roadmap, boosting useful BESS capacity from 31 GWh to 223 GWh raises annual storage-related capital charges from EUR 0.97 billion to EUR 1.62 billion (≈+67%), yet drives wind-plus-PV spillage down from 14.7% to 4.1% (−72 %) and cuts the average cost of supplied energy from EUR 74.9 to EUR 70.2/MWh (≈−6%) [85]. A complementary bulk-system study shows that pairing 100 GW of PV with a 200 GWh BESS on the IEEE-118 benchmark reduces PV curtailment by 69.5% during a high-irradiance month and by 95.2% during a low-irradiance month compared with the zero-storage case [86]. These results illustrate the balance planners must strike between upfront cost and long-term operational flexibility.

Another topic that increasingly shapes expansion studies is the trade-off between centralized and decentralized planning. Centralized roadmaps exploit economies of scale in bulk transmission and storage, yet the entire system can suffer sizeable disruption when a single asset fails. By contrast, community micro-grids and peer-to-peer trading strengthen local resilience and may defer long-distance line reinforcements. A resilience analysis based on the IEEE-14 benchmark shows that the worst-case bus inoperability after identical fault scenarios drops from 11.4% in a fully centralized layout to below 0.45% when distributed resources are connected at every node—an improvement close to 95% [87]. At the distribution level, day-ahead optimization of three interconnected micro-grids raises total operating costs by only 2.47% while still complying with a net-zero energy-exchange target and explicit greenhouse gas caps [88]. Complementing these results, a multi-agent reinforcement-learning dispatcher for networks with multiple micro-grids achieves a further 3.4% reduction in operating costs and a 5.2% cut in carbon emissions relative to a centralized model-based benchmark [89]. These findings suggest that modest increases in capital or coordination effort can purchase substantial gains in resilience, flexibility, and sustainability—factors regulators will need to weigh when deciding how far future expansion plans should push towards decentralized architectures.

8.2. Challenges in Expanding Renewable Energy Systems

The expansion of power systems with a high penetration of renewable energy faces several critical challenges. Table 4 summarizes these challenges and potential solutions.

Table 4. Challenges and solutions in renewable energy system expansion.

Challenge	Description	Proposed Solutions
Variability and Intermittency	Unpredictable output from solar and wind	Energy storage and demand-side management
Grid Stability	Lack of inertia in renewables	Synthetic inertia and enhanced grid flexibility
Economic Optimization	High costs of storage and renewables integration	Advanced optimization techniques and cost reduction

Challenges include managing variability, enhancing grid stability, and optimizing economic outcomes for renewable systems.

Wind and solar PV generation are inherently variable and intermittent, making it challenging to balance power between supply and demand in real time. Mitigation of these issues requires storage technologies such as batteries and demand-response strategies. It is additionally interesting that as renewable penetration increases, the lack of rotational inertia becomes a concern in terms of maintaining grid stability. To address these stability issues, Ref. [90] proposes synthetic inertia and grid flexibility solutions. Also, economic optimization is challenging, as the renewable integration and the related storage are expensive.

8.3. Future Research Directions

Looking forward, research must continue to address the challenges identified. Table 5 highlights key areas for future investigation.

Table 5. Future research directions in renewable energy planning.

Research Area	Description	Expected Impact
Advanced Optimization Algorithms	Development of more robust algorithms for planning	Increased efficiency in system planning
Climate Modeling Improvements	Integration of more accurate climate models in planning	Enhanced accuracy in renewable forecasting
Energy Storage Innovations	Development of cost-effective storage technologies	Greater reliability and grid resilience

Future research should focus on improving optimization algorithms, climate modelling, and energy storage technologies.

The successful expansion of power systems with high renewable energy penetration depends critically upon further development of advanced optimization techniques, integration of energy storage systems, and improved forecasting models. Overcoming the technical and operational challenges that wind and solar integration present will require addressing these areas to have power systems ready to meet future demands with the stability and efficiency needed. Research in these fields beyond the results demonstrated here is critical to enabling the large-scale adoption of renewables and increasing grid reliability.

9. Conclusions

The successful integration of renewable energy sources into power systems is crucial to transitioning to sustainable and resilient energy systems. This review has pointed out major challenges associated with renewable energy integration, such as intermittency and variability in wind and solar energy, the need for flexibility, and grid stability assurance. In order to overcome these challenges, stochastic planning and advanced optimization methods are developing into key tools for efficiently managing generation, transmission, and storage assets. Moreover, machine learning as an artificial intelligence method is suggested as a powerful technique to enhance forecast accuracy and optimize power system operations with renewables.

Battery technologies, part of energy storage systems, are playing an increasingly crucial role in reducing variability in renewable generation and increasing flexibility and reliability in modern power systems. Complete integration of these technologies into power system planning models is essential for improving system performance and lowering operational costs.

Renewable integration faces huge regulatory and market challenges. To promote distributed generation, market mechanisms need to be adapted to incentivize flexibility and dynamic pricing structures. More advanced optimization algorithms and more accurate climate models need to be developed, and more sophisticated utilization of emerging technologies such as blockchain and digitalization to deal with the increasing complexity of power system planning should be explored in future research.

Finally, power system planning methodologies evolve with the growing demand for renewable energy for stable, efficient, and resilient long-term operation of the electrical grid. The key to successful integration of diverse energy sources and the challenges of modern power systems will depend upon the progress in these areas.

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Abbreviations

The following abbreviations are used in this manuscript:

ACO	Ant colony optimization
AI	Artificial intelligence
BESS	Battery energy storage system
CAES	Compressed air energy storage
DG	Distributed generation
GEP	Generation expansion planning
FiT	Feed-in tariffs
LVRT	Low-voltage ride through
MILP	Mixed-integer linear programming
ML	Machine learning
MOEA	Multi-objective evolutionary algorithms
P2P	Peer-to-peer
PHS	Pumped hydro storage
PSO	Particle swarm optimization
PV	Photovoltaic
RPS	Renewable portfolio standards
RTP	Real-time pricing
TEP	Transmission expansion planning
VRE	Variable renewable energy

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