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TOPICAL REVIEW

A Review of Evolving Challenges in Transmission Expansion Planning Problems

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ABSTRACT Transmission Expansion Planning (TEP) is a well-established field in power systems, focused on identifying the best timing and location for new transmission lines and related infrastructure. Its main goals are to meet growing electricity demand, ensure system reliability, and maintain economic efficiency. However, recent changes in the energy sector–such as the rapid growth of renewable energy, the push for decarbonisation, and the rise of electric vehicles–have introduced new challenges and uncertainties for TEP. This paper reviews more than 150 research articles to explore how these trends are reshaping TEP. We identify key insights, emerging challenges, and research gaps, emphasizing the need for improved tools and approaches to address the complexities of modern power systems. Finally, we discuss the need for research in TEP to incorporate uncertainties like energy storage systems (ESS), electric vehicle adoption, and high renewable energy integration, using advanced algorithms and real-world data to enhance accuracy and relevance.

INDEX TERMS Electricity markets, transmission expansion planning, renewable energy sources, energy storage, optimal power flow, mathematical programming, optimization.

I. INTRODUCTION

As nations around the globe commit to the 2050 net-zero carbon emissions target, the reduction of carbon emissions in the energy sector has become a top priority. Electricity systems are at the forefront of this transition and are playing a key role in decarbonisation of the energy system. This global shift is accelerating a transition from traditional fossil fuel-based power plants to cleaner renewable energy sources (RES). With the ongoing advancements in renewable energy technologies and the associated decline in power generation costs, the global power generation landscape is undergoing a significant transformation. Projections indicate that by 2050, the share of RES in global power generation could rise to 85%, a stark contrast to the 25% recorded in 2017 [1].

While large-scale development of RES is a critical step towards reducing carbon emissions, it also introduces a range of challenges. RES generation is inherently variable, influenced by time, geography, and weather conditions. This variability can lead to extreme scenarios, such as sudden shifts or even complete shut-downs in power generation [2]. The renewable resources are often located in remote areas, far from demand centres. This necessitates the construction of new transmission infrastructure to connect these resources to the existing grid.

In this context, efficient planning of transmission assets becomes crucial to balance the benefits of RES with the costs associated with integrating them into the electricity infrastructure. Transmission Expansion Planning (TEP) has emerged as a vital area of research, focusing on key questions such as how much, where, and when to invest in transmission infrastructure. The objective of TEP is to maintain the future sustainability of the transmission network, ensuring a balance between supply and demand with minimal investment and operating costs [3], [4], [5], [6], [7].

TEP is a complex problem due to the large scale of electricity networks and the inherent uncertainties in various input variables. These uncertainties include demand projections, expected locations and capacities of electricity generation, and future weather patterns [8]. The planning

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horizon for TEP can span years to decades [9], adding to the complexity. To address these computational challenges, much of the academic literature on TEP has relied on deterministic models that assume perfect foresight over the planning horizon [10]. However, such simplifying assumptions have significant limitations, particularly as uncertainties in multiple dimensions continue to grow. This highlights the need for more sophisticated approaches beyond simple what-if analyses using deterministic models [11].

For example, robust optimisation techniques require minimal information about the probability distribution of random variables but tend to be overly conservative, potentially leading to suboptimal performance in certain scenarios [12], [13]. On the other hand, stochastic optimisation models require complete information on probability distributions and aim to minimize the expected cost of achieving feasibility across all scenarios. However, these models often require a large number of scenarios to accurately capture uncertainty, which can pose computational challenges. Chance-constrained optimisation offers a trade-off between stochastic and robust optimisation models [14].

This paper provides a comprehensive review of cutting-edge research on uncertainty modelling in transmission expansion planning (TEP). We analysed over 150 of the most innovative studies published in the past decade. The review covers key research trends, findings, and persistent challenges in the field. We also identify critical research gaps and highlight areas requiring further exploration to address emerging challenges, such as the increasing integration of renewable energy sources (RES) and the widespread deployment of energy storage. Our analysis offers actionable insights, emphasizing use cases, limitations, and potential directions for advancing this essential area of research. The key contributions of this paper are summarised as follows:

- *Comprehensive Review*. An in-depth analysis of uncertainty modelling in TEP over the past decade.
- *Current Methods and Challenges*. Evaluation of existing approaches and their limitations.
- *Research Gaps*. Identification of open problems and future research opportunities.
- *Actionable Insights*. Recommendations for advancing TEP research to address emerging industry challenges.

The remainder of this paper is structured as follows. Section III provides a review of the state-of-the-art literature on solving TEP problems using stochastic and robust programming. Section IV discusses the current challenges on methods of TEP and evolving requirements. Section V presents opportunities for methodological developments. Section VI concludes the paper by suggesting potential directions for future research.

II. CHALLENGES FOR ELECTRICITY TRANSMISSION PLANNING

The transition towards a more sustainable and resilient energy system presents a multitude of challenges for electricity transmission planning. As the energy landscape evolves, driven by the increasing adoption of renewable energy sources, advancements in energy storage technologies, and shifts in electricity demand, transmission networks must adapt to maintain reliability, efficiency, and cost-effectiveness. This section explores the key challenges facing Transmission Expansion Planning (TEP) in this dynamic environment, focusing on the integration of renewable energy, the emergence of new energy storage technologies, and other critical factors that shape the future of electricity transmission.

A. INCREASING RENEWABLE ENERGY SOURCES

The penetration of renewable energy sources (RES) in electricity systems has increased significantly in recent years. Figure 1 illustrates the evolution of renewable generation to date and projects its expected growth by 2030. The figure highlights a substantial increase, primarily driven by wind and solar capacity, supported by the declining costs of installation [15]. This upward trend is expected to continue.

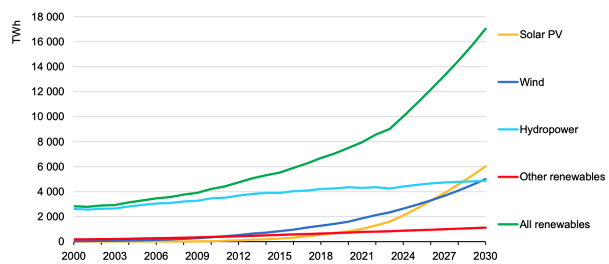

FIGURE 1. Increasing penetration of renewable generation in electricity systems. Source: [16].

To fully utilise the potential of wind and solar energy, RES power plants are often built in remote locations, far from high-demand urban centres. This requires strengthening existing transmission systems or establishing entirely new connections between these regions. Furthermore, the rapid expansion of offshore wind power necessitates the development of additional transmission infrastructure to link offshore generation to the onshore grid. Figure 2 presents expected investments in the Great Britain (GB) transmission network to support the upcoming renewable generation connections in the north sea and the north of the country.

The integration of RES also requires enhancing the capacity of transmission lines between different regions to balance local load and generation discrepancies. This broadens the scope of Transmission Expansion Planning (TEP) research. For instance, China's West-East Power Transmission Project, initiated nearly two decades ago, aims to transmit abundant hydroelectric power from the resource-rich western regions to the more energy-demanding eastern areas by constructing new transmission lines [18]. Similarly, the North Sea Wind Power Hub has proposed an ambitious plan to build an artificial island in the North Sea, centralizing offshore wind resources and transmitting the power via high-voltage direct current (HVDC) lines to countries like the UK, Germany, and Denmark [19].

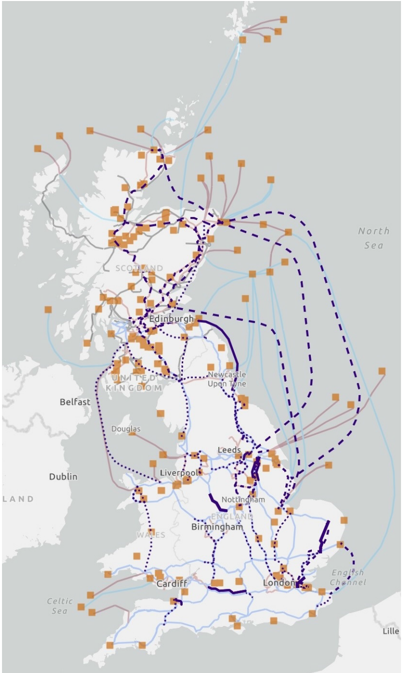

FIGURE 2. A map showing under construction and expected transmission investments in Great Britain electricity system. Solid lines show projects that are under construction and dashed lines are project are at planning stage. Source: [17].

Furthermore, the increasing penetration of RES introduces significant uncertainties in power generation. These uncertainties manifest as both stochastic (e.g., fluctuations in wind and solar output) and non-stochastic (e.g., generation investments, costs, and policies) variations [20]. Consequently, traditional deterministic planning approaches are no longer suitable for future TEP problems. Research has demonstrated that transmission investment decisions made under conditions of uncertainty are more robust than those based on deterministic models [21]. Techniques such as Monte Carlo Simulation (MCS) and Probability Distribution Function (PDF) estimation, based on historical data, are increasingly applied to TEP to address these uncertainties [22]. As a result, more advanced optimisation methods, incorporating probabilistic TEP models, are necessary to handle the variability of RES output [9].

B. SYNERGIES BETWEEN GENERATION EXPANSION PLANNING AND TRANSMISSION EXPANSION PLANNING

The goal of Generation Expansion Planning (GEP) is to ensure that the electric system is able to meet future electricity demand by building new generation facilities to increase the system's generating capacity [23], [24]. In contrast, the goal of transmission line expansion planning (TEP) is to ensure that power can be efficiently and reliably transmitted from generation sources to load centres [25], i.e., to ensure that the grid's transmission capacity is sufficient to cope with the addition of new generating capacity and growing load demand.

Starting with the objective function, we find that there is a high degree of similarity between GEP and TEP in terms of planning models, and both objective functions can be written in the form of Formulation 1 and 2. That is, both have two types of cost considerations at the operational level and at the investment (decision) level. Moreover, the operating costs in the TEP problem are closely related to parameters such as generation expansion/generation costs. This suggests that there is some research overlap between TEP and GEP, which has the significance of synergistic planning.

$$\min \sum_{t\in T}\left[\sum_{l\in L} C_l^{\mathrm{cap}} x_l + C_l^{\mathrm{op}}(t)\right] \tag{1}$$

$$\min \sum_{t\in T}\left[\sum_{g\in G} C_g^{\mathrm{cap}} x_g + C_g^{\mathrm{op}}(t)\right] \tag{2}$$

where:

- C_g^{cap} - Capital cost of building generation unit g.
- C_l^{cap} - Capital cost of building new transmission line l.
- x_g - Binary decision variable (1 if unit g is built, 0 otherwise).
- x_l - Binary decision variable (1 if unit l is built, 0 otherwise).
- $C_l^{\mathrm{op}}(t)$ - Operational cost of unit g in time period t, including generation, maintenance, and O&M costs.
- $C_g^{\mathrm{op}}(t)$ - Operational cost of unit g in time period t, including fuel, maintenance, and variable O&M costs.
- G - Set of candidate generation units.
- T - Planning horizon (years or periods).
- $P_g(t)$: Power output of generation unit g at time t.
- $D(t)$: Total demand at time t.

However, the most significant difference between GEP and TEP is the study of power flow. The issue of transmission network capacity is often ignored in GEP problems, focusing more on generation cost/siting considerations. The TEP problem, on the other hand, focuses on transmission capacity expansion. This is reflected in the power balance constraints as shown in Equation 3 4 and. It is easy to see that the core of the TEP problem and the biggest difference with the GEP problem is whether the power flow on the transmission line is used as part of the modeling.

$$\sum_{g\in G} P_g(t) = D(t), \quad \forall t \in T \tag{3}$$

$$\sum_{g\in G_b} P_G(g) - \sum_{d\in D_b} P_D(d) - \sum_{l\in L_b} P_L(l) = 0 \tag{4}$$

where:

- G: The set of all generators.
- $P_g(t)$: The power output of generator g at time t.
- $D(t)$: The total demand at time t.
- T: The set of time periods considered.
- G_b: The set of all generation units connected to bus b.
- D_b: The set of all loads (demand) connected to bus b.
- L_b: The set of all transmission lines connected to bus b.
- $P_G(g)$: Power output of generation unit g at bus b.
- $P_D(d)$: Power demand of load d at bus b.

- $P_L(l)$: Power flow on transmission line l connected to bus b.

Even within the TEP problem, the modeling of power flow can be decisive for the study. For example, Equation 5 gives the power flow model of ACOPF. And Equation 6 gives the power flow model of DCOPF. It is obvious that the TEP problem also needs to consider voltage stability and the power flow model of ACOPF is more complex, often nonlinear and computationally intensive, compared to DCOPF which requires a linearized processing means for its solution. In other words, the power flow model directly affects the complexity and speed of solving the TEP model modeling.

$$P_L(l) = V_i V_j \big(G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}\big) \tag{5}$$

$$P_L(l) = B_l \Delta\theta_l \tag{6}$$

where:

- V_i, V_j: bus voltages.
- G_{ij}, B_{ij}: the conductance and susceptance
- B_l: the susceptance.
- $\Delta\theta_l$:the phase angle difference between the connected buses.

In summary, GEP mainly optimises generation capacity, and power flow is only for verifying load satisfaction; TEP mainly optimises transmission network, and power flow is the core part for analyzing line power distribution and bottlenecks [26]. If GEP ignores transmission constraints, it may lead to transmission bottlenecks in some areas, which may affect power supply. Therefore, the introduction of Integrated Generation and TEP can optimise both generation and transmission to obtain a more reasonable power system expansion plan [27].

C. EMERGING ENERGY STORAGE TECHNOLOGIES

The rapid advancement of energy storage technologies in recent years has had a profound impact on TEP. The development of distributed power generation, smart grids, energy storage systems, electric vehicles, and micro-grids has not only transformed distribution networks but also indirectly influenced load, consumer behaviour, and the overall power system. The widespread adoption of energy storage devices enables bi-directional power flow, challenging the traditional unidirectional generation-transmission-distribution-load model [28].

At the operational level, this bi-directional flow of power requires greater flexibility and intelligent management of the grid to be able to regulate current flow in a timely manner [29] and ensure system stability, especially in high penetration distributed generation and energy storage systems [30]. At the planning level, the grid needs to have a more flexible infrastructure to cope with bidirectional power flows. For example, the construction of higher-capacity transmission/distribution lines and substations will result in the need for large-scale grid modifications to support the access of distributed generation and storage [31], and to effectively manage and coordinate bidirectional power flows between different power sources and loads [32]. Reflected in the model, which makes the TEP problem require hierarchical and synergistic planning with the distribution network [33].

Energy storage plays a crucial role in modern power systems by addressing several key challenges. First, in congestion management, storage helps alleviate congestion by charging when transmission lines are constrained or when there is an excess of generation or discharge, thereby reducing the immediate need for transmission expansion and offering a cost-effective alternative [34]. Second, in peak shaving and valley filling, energy storage mitigates peak power flows by storing energy during off-peak periods and supplying it during peak demand, thus delaying or reducing the necessity for new transmission lines [35]. Third, energy storage enhances reliability and resilience by providing backup power, ensuring system stability during failures or extreme weather events [36]. Finally, strategically placed storage can defer transmission investments by managing power flows and enhancing grid capacity, providing a flexible solution compared to capital-intensive and time-consuming traditional transmission line construction [37].

The inclusion of energy storage adds complexity to TEP. First, it introduces new decision-making problems at the upper planning levels, as the collaboration between generation expansion planning and TEP must now account for the role of energy storage [38]. Additionally, the power balance equation in the power system becomes more complicated with the inclusion of energy storage, particularly in alternating current (AC) modelling [39]. While energy storage increases model complexity, it also affects load distribution across transmission lines at different times of the day, thereby influencing TEP decision-making [40].

The increasing prevalence of electric vehicles, coupled with advancements in energy storage and distributed generation, is expected to further complicate the mathematical models used in TEP [41]. Some studies suggest that energy storage can reduce line losses and mitigate the need for TEP upgrades, making it a critical component in future planning [42]. Collaborative planning models, which consider trade-offs between power supply, demand, and storage investments, are emerging as effective strategies to reduce unnecessary TEP expansion [43]. Consequently, the future of TEP will likely involve close integration with energy storage devices, leading to increasingly complex planning models.

Common types of energy storage are pumped storage, compressed air energy storage (CAES), lead-acid batteries, and hydrogen storage. There are also emerging technologies such as lithium-ion battery storage, flywheel storage, Vanadium redox flow batteries(VRB), and superconducting magnetic energy storage(SMES). The research in [44], [45], [46], and [47] analyze the characteristics of the above energy storage are summarized in Table 1. Where ms stands for milliseconds, s for seconds and min for minutes.

According to Table 1, it can be found that with the development of energy storage technology, the application of

TABLE 1. Types of energy storage devices and their characteristics.

Types	Storage Efficiency	Total capital cost($/kWh)	Response time	Power rating(MW)	Lifetime(Years)
Pumped Storage	75%-80%	106-200	min	10–5000	40-100
CAES	70%-75%	94-229	s-min	5–400	30-40
Hydrogen	40%-60%	450-960	s	0.3–50	20
Lead-acid Batteries	87%-92%	319-540	ms-min	20	20-25
Lithium-ion Battery	90%-98%	308-419	ms-min	0.01	>30
Flywheel	80%-95%	4,320-11,520	ms-s	0.25	>15
VRB	70%-80%	555-951	s-min	0.03-3	20-25
SMES	95%-98%	5,800-6,700	ms-s	0.1–10	15–20

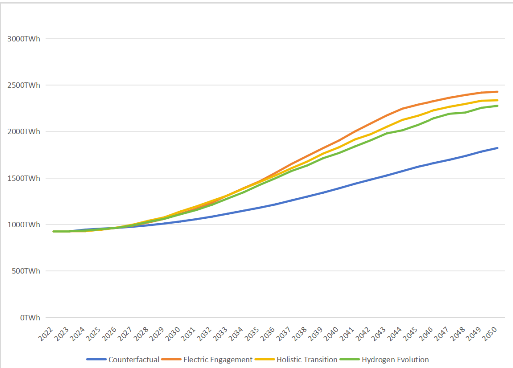

FIGURE 3. Four electricity demand pathways in great britain.

energy storage equipment will be more extensive. However, different types of energy storage devices differ greatly in terms of lifetime, efficiency, capacity, and cost. Therefore, when combining energy storage devices and transmission lines for cooperative planning, the above characteristics will become important variables affecting the decision of TEP.

D. ADAPTING TO EVOLVING ELECTRICITY DEMAND

As electricity demand evolves, driven by factors such as population growth, technological advancements, and energy policy shifts, TEP faces new challenges. For example, energy research institutes in the UK have proposed seven distinct decarbonisation pathways, each predicting different levels of electricity demand growth by 2050 [48]. The most conservative pathway projects a 51% increase, while the most aggressive predicts a 150% rise in demand.

Figure 3 presents the expected growth in electricity demand in the UK based on the four scenarios outlined in the National Energy System Operator's (NESO) Future Energy Scenarios (FES) report [49]. This growth is mainly driven by the electrification of heat, transport, and industry. A similar trend is observed worldwide, where ambitious plans to decarbonise energy systems rely heavily on decarbonising electricity systems [50].

These scenarios highlight the importance of incorporating decision-making techniques under uncertainty into Transmission Expansion Planning (TEP). Long-term planning must account for possible increases in demand over the medium to long term, often requiring the analysis of multiple scenarios. This increases the complexity of both the modelling and computation involved in TEP [51].

In addition, the move towards renewable energy as part of decarbonisation efforts involves phasing out conventional energy sources. This creates potential power supply gaps in areas with limited renewable resources [25]. To address these challenges, large-scale power networks must enhance interconnection capacity between regions. This will help ensure a reliable electricity supply, even in areas where resources like wind and solar are scarce or unavailable [22].

E. THE IMPACT OF LIBERALIZED ELECTRICITY MARKETS

The transition from vertically integrated electricity systems to liberalized markets over the past three decades has introduced both opportunities and challenges for TEP. In the past, electricity companies controlled generation, distribution, transmission, and retailing, allowing for comprehensive and efficient investment in transmission infrastructure [52]. However, concerns about monopolistic practices led to the adoption of competitive market models, where different companies handle various aspects of the electricity supply chain under regulated guidelines.

While market liberalisation has enhanced cost efficiency and reduced electricity prices, it has also introduced new uncertainties. These include regulatory changes, price fluctuations, and unpredictable electricity demand, all of which complicate the TEP problem [53]. The competitive landscape, particularly in the generation sector, has led to uncertainties in the citing of power plants, installed capacity, and construction time periods, further increasing the complexity of TEP [54].

Despite the challenges, the presence of a single monopoly transmission company in a region can ensure economical operation by avoiding over-engineering. However, as inter-regional energy transmission demand grows, TEP must increasingly consider the interoperability of different transmission and generation companies to maintain system reliability and boundary power transfer capabilities [55], [56]. For example, Scottish Power's planned £5.4 billion investment in a 10-year transmission upgrade program aims to connect more renewable energy sources to the UK transmission system, contributing to the country's decarbonisation goals while also reducing energy costs [57].

F. ADDRESSING BROADER UNCERTAINTIES IN TEP

The evolving nature of electricity systems introduces additional uncertainties beyond those associated with RES and demand fluctuations. Factors such as load variations, extreme weather events, and the geographic distribution of RES can significantly impact TEP planning. Co-planning of TEP+GEP by using stochastic optimisation. It can be used to deal with uncertainty due to weather changes, load fluctuations, generation fluctuations [58], [59]. By considering different failure scenarios of the system and combining them with probabilistic predictions, based on principles such as N-1 can enable the TEP model to find an expansion plan that effectively handles uncertain events [60].

Existing research suggests that scenario uncertainty in load and RES outputs can be addressed through stochastic planning, which considers different assumptions:

- *Independence of Load and Generation*: Assumes that load and generation are independent, allowing for stochastic scenarios that treat them separately [61].
- *Correlation between Load and Generation*: Assumes a direct correlation, where factors like cold and windy weather increase both electricity demand and generation capacity [62].
- *Multivariate Correlation*: Considers spatial correlations between demand and generation at different locations [63].

Additionally, TEP must account for potential RES shutdowns or decommissioning due to extreme weather or system failures. This is often addressed using the N-1 criterion, which considers the failure of a single component in the system [64]. Factors such as geographic location, weather patterns, system faults, and load variations all contribute to the increasing complexity of TEP, offering new research directions for addressing these challenges.

The key to dealing with the aforementioned influences is how to handle the added uncertainty in the model. In the TEP problem, uncertainty leads to changes at the decision level (whether or not to extend a particular transmission line) mainly by affecting variables at the operational level [65]. For example, renewable energy generation is affected by natural conditions such as weather and seasons, which causes the model to show more and more drastic changes in generation at the operational level, which in turn drives the decision to expand/newly build a transmission line [66]. The stability and operation of the transmission system, on the other hand, is affected by uncertainties such as equipment failures and line damages. Faults may cause some transmission lines to fail, resulting in operational interruptions or load increases in the power system, which in turn affects the reliability of the grid [67]. Therefore after accounting for these operational problems in the TEP model, the decision level for transmission line expansion is bound to change in order to better maintain the stability of transmission lines.

III. UNCERTAINTY AWARE TRANSMISSION EXPANSION PLANNING

To effectively manage the inherent uncertainties in Transmission Expansion Planning (TEP), the academic literature generally adopt two main approaches: scenario-based stochastic planning, often referred to as Stochastic TEP (STEP) [68], and robust optimisation grounded in uncertainty sets, known as Robust TEP (RTEP) [69]. A third hybrid approach combines robust optimisation with stochastic planning to address uncertainty in a more comprehensive manner [70].

In the context of stochastic TEP, the uncertainties involved are particularly complex. Figure 4 highlights several key variables that commonly influence TEP problems. It is important to note that the inputs, outputs and methods presented are not exhaustive, but are meant to capture the key aspects. Figure 5 presents the main drivers behind investments in transmission expansion problems. These are divided into four categories of policy, electrification, risks and flexibility.

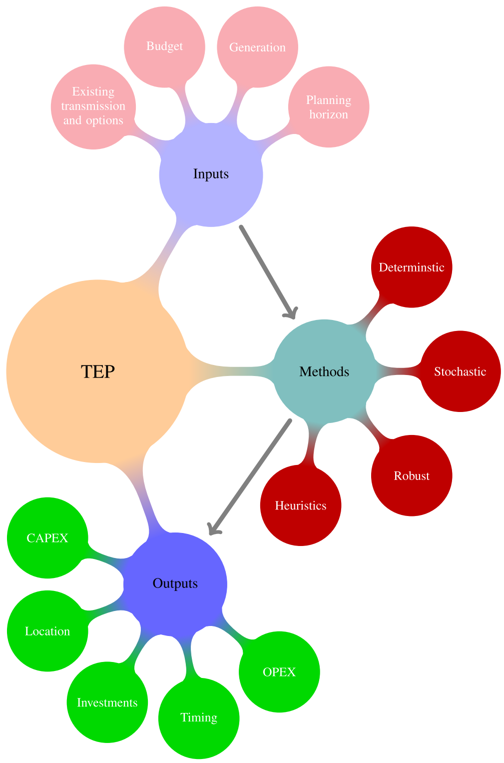

FIGURE 4. Inputs, outputs and solution approaches used to solve transmission expansion planning (TEP) problems.

A. ROBUST OPTIMISATION

Robust optimisation is a powerful tool for TEP, ensuring that the transmission expansion plan remains effective under a range of possible changes in power demand and renewable energy generation. Even in worst-case scenarios, robust optimisation can deliver solutions that guarantee stable system operation. This method is widely used in TEP security analyses, as evidenced by studies [71], [72], [73] which employ robust optimisation to guide investment decisions aimed at minimizing operational costs while effectively responding to worst-case scenario outcomes. Consequently, robust optimisation plays a critical role in the reliability and risk management of TEP.

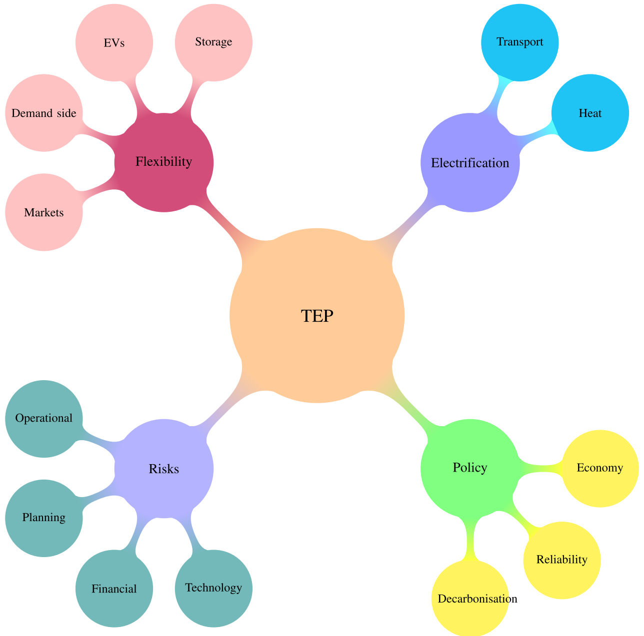

FIGURE 5. Key drivers of transmission expansion planning problems.

However, robust optimisation has notable limitations. Firstly, it tends to be overly conservative by focusing primarily on worst-case scenarios, which may lead to suboptimal results in more typical situations [74]. Secondly, the method demands significant computational resources, often making it inefficient when dealing with numerous scenarios or complex power systems [75]. Finally, the robustness of the optimisation outcomes is highly dependent on the choice of uncertainty sets, which introduces another layer of complexity [76].

B. STOCHASTIC OPTIMISATION

In contrast to robust optimisation, stochastic optimisation is better suited for dealing with parameter uncertainties, which are central to the TEP problem [77]. This approach seeks to find an optimal solution across a range of potential scenarios, resulting in more adaptable and comprehensive outcomes [78]. Furthermore, stochastic optimisation supports a more flexible decision-making process, allowing planners to evaluate trade-offs between different outcomes based on a range of possible scenarios and their associated probabilities [79].

Stochastic optimisation is particularly advantageous when uncertainties can be quantified or modelled probabilistically. Conversely, robust optimisation may be preferred in situations where uncertainty is difficult to quantify. Recognizing the strengths of both methods, hybrid approaches that integrate stochastic and robust optimisation are increasingly employed to leverage the benefits of each [80].

C. DETERMINISTIC OPTIMISATION

Deterministic optimisation means that all the inputs are assumed with perfect foresight of future [81]. Because of the determination of the parameters, it results in the absence of randomness in deterministic optimisation and the optimal solution is easily obtained, computationally efficient and accurate [82].

However, this optimisation method also has shortcomings, because the lack of randomness leads to the inability to deal with problems containing uncertainty, and the ability to deal with complex, uncertain or dynamic problems is weak [83]. The traditional deterministic optimisation method may encounter difficulties when facing complex problems such as high-dimensional and non-convex problems.

However, deterministic and stochastic optimisation are closely related, and both [84] and [85] suggest that deterministic and stochastic optimisation are nearly identical before the limitations of non-anticipativity in the choice of control strategy. In other words, stochastic optimisation can be viewed as a two-stage (multi-stage) dimensional complexified deterministic optimisation problem with the introduction of a probability distribution.

D. HEURISTICS

The most important feature of the heuristic algorithm compared to the previous three optimisation methods is that it is an algorithm based on an intuitive or empirical construction that gives a feasible solution for each instance of the combinatorial optimisation problem to be solved at an acceptable cost (meaning computational time and space) [86], rather than finding an optimal solution or an incalculable gap between the optimal and feasible solutions [87].

Therefore, heuristic algorithms tend to have the advantages of algorithmic simplicity, computational efficiency, ability to handle complex large-scale computational problems [88], and the ability to deal with uncertainty and dynamic changes [89]. However, because they focus on finding feasible solutions, they can sometimes only find local optimal or approximate solutions [90], and the quality and stability of the solutions are sometimes unpredictable [91].

IV. FORMULATIONS AND SOLUTION APPROACHES

A. THE FORMULATION OF TEP

In Transmission Expansion Planning (TEP), the objective function (OF) typically includes investment costs (CapEx), operational costs (OpEx), and/or unreliability costs. These costs are balanced against forecasted demand and, if necessary, the need to maintain system stability.

When TEP is approached as a multi-objective problem, it can be broken down into four key components, as suggested by [92]

- Decision Variables: These usually involve choices related to additional equipment such as transmission lines, transformers, and other infrastructure.
- Criteria: In the context of TEP, criteria generally involve minimizing costs or maximizing the efficiency of transmission.

- Objectives: The primary objectives are to either minimize or maximize the objective function, depending on the planning goals.
- Goals: These are the specific targets to be achieved, such as reducing carbon emissions by a certain percentage or enhancing system stability by a defined margin.

In summary, the TEP problem revolves around the optimisation of the objective function, which must be done within the constraints imposed by physical factors (like equipment limits), cost considerations, and system stability requirements.

Many TEP studies use cost as the primary objective function. Costs are generally categorized into two main types:

- CapEx (Capital Expenditure): This represents the upfront investment needed for the project. CapEx is usually calculated by multiplying the unit cost by the volume of work, as well as summing the costs of equipment based on published reports [93], [94].
- OpEx (Operational Expenditure): This involves the ongoing costs of operating the system. OpEx is more complex to calculate, as it includes maintenance costs [95], the cost of energy losses [96], and other operational factors.

It's important to note that CapEx and OpEx are not entirely independent. For example, a higher initial investment (CapEx) might lead to increased operational costs (OpEx). Additionally, unexpected events, such as equipment failures, can cause fluctuations in OpEx, which may, in turn, affect the overall investment costs (CapEx) [97].

Given the complexity of modelling costs as an objective function in TEP, with various influencing factors and uncertainties, the following section will categorize and discuss the different methods for formulating TEP found in the existing literature.

B. EXISTING LITERATURE ON TEP

This research paper thoroughly analyzes 53 references, each categorized based on multiple criteria related to the optimisation of Transmission Expansion Planning (TEP). The analysis focuses on the programming method, optimisation method, model type, planning horizon, temporal resolution, and whether the study combines TEP with other systems. Additionally, key aspects like the objective function, the stage of the model, whether the study is jointly conducted with TEP, the involvement of stochastic optimisation scenarios, and the use of real data are all meticulously examined. A total of 12 characteristics are analysed across these references to provide a comprehensive understanding of the state-of-the-art in this field.

In this analysis, various acronyms are used to describe complex methodologies and objectives. For instance:

- Programming Methods:
  - **MILP**: Mixed-Integer Linear Programming
  - **MNILP**: Mixed Integer Nonlinear Programming
  - **NLP**: Nonlinear Programming
- Optimisation Methods:
  - **S**: Stochastic Optimisation
  - **R**: Robust Optimisation
- Algorithms:
  - **SA**: Simheuristic Algorithm
  - **PSO**: Particle Swarm Optimisation
  - **HEA**: Heuristic Algorithms
  - **MHA**: Meta-heuristic Algorithms
  - **GA**: Genetic Algorithms
- TEP Combined With:
  - **RES**: Renewable Energy Resources
  - **ESS**: Energy Storage Systems
  - **TN**: Thermal Network
  - **GHG**: Greenhouse Gas
  - **CCS**: Carbon Capture and Storage
  - **EV**: Electric Vehicles
  - **RCE**: Reactive Compensation Equipment

  Moreover, the objectives of the studies are classified as follows:
- Objectives:
  - **MOC**: Minimize Operation Cost
  - **MIC**: Minimize Investment Costs
  - **MRC**: Minimize Reliability Cost
  - **MGE**: Minimize GHG Emissions
  - **PL**: Power Losses
  - **SC**: Storage Capacity
  - **PC**: Price Competitiveness

  The Scenario Types explored include:
- Scenario Type:
  - **Ge**: Generation
  - **De**: Demand
  - **TS**: Transmission Switching
  - **CD**: Contingency-Dependent
  - **(N-1)**: (N-1) Criterion
  - **M&R**: Market and Regulatory
  - **GHG**: Greenhouse Gas
  - **TC**: Transmission Congestion
  - **DTR**: Dynamic Thermal Rating

  Finally, the cost categories are classified as:
- Cost:
  - **Ca**: Capital Expenditure (CapEx)
  - **Op**: Operating Expenditure (OpEx)

This comprehensive categorisation provides a detailed overview of the various approaches and considerations in the literature, offering valuable insights into the current trends and methodologies used in Transmission Expansion Planning.

C. CLASSICAL METHODS OF PROGRAMMING

1) LINEAR AND MIXED-INTEGER LINEAR PROGRAMMING

Linear Programming (LP) was one of the earliest methods applied to Transmission Expansion Planning (TEP). Its primary advantage lies in its computational efficiency and speed. However, LP has significant limitations as it treats

TABLE 2. Modelling approaches, key assumptions and use of real-world data in existing literature.

Citation	Programming	Optimisation methods	Model	Planning Horizon	Temporal resolution	TEP combined with	Objectives	Model stages	GEP+TEP	Scenario(uncertainty) types	Cost	Real Data
[64]	MILP	S(MHA)	DCOPF	15-30 years	Yearly	RES	MIC+MOC	Two		Ge+De	Ca+Op	✓
[98]	NLP	S(PSO)	ACOPF	A Year	Yearly	ESS+RES	TC+MIC+MOC	Two		Ge	Ca+Op	
[99]	MILP	S	DCOPF	4Year	Yearly	N-1	MRC	Two	✓	CD-TS	Ca+Op	✓
[100]	MILP	S	DCOPF	30Year	Yearly	ESS+RES+DG	MIC+MOC	Two	✓	Ge	Ca+Op	✓
[101]	MINLP	S+R	DCOPF	Yearly	Hourly	RES	MIC+MOC	Two	✓	De+Ge	Ca+Op	
[102]	MILP	S	DC+AC OPF	5 Years	Yearly	RES+ESS	MIC+MOC	Two	✓	De+Ge	Ca+Op	
[103]	MILP	S+R	DCOPF	30 Years	Yearly	RES	MIC+MOC	Two	✓	De+Ge+N-1	Ca+Op	
[104]	MILP	S	DC+AC OPF	15 Years	Yearly	ESS+RES	MIC+MOC	Two	✓	GE+De+N-1	Ca+Op	
[105]	MILP	S(MHA)	PLF	20 Years	Yearly	TN	PL+MIC+MOC	Two		De	Ca+Op	
[106]	MINLP	S(MHA)	ACOPF	5 Years	Yearly		MIC+MRC	Two		De	Ca+Op	
[107]	MILP	S	DCOPF	25 Years	Yearly	ESS+RES	MIC+SC	Multi		De+Ge	Ca+Op	
[108]	MINLP	S	DLPF	3 Years	0.5 year	ESS+RES	MIC+MRC	Two		De+Ge+DTR	Ca+Op	✓
[109]	MILP	S	DCOPF	Year		RES	MIC+PC	Two		De+Ge	Ca+Op	
[110]	MILP	S	DCOPF			RES	MIC+MOC	Two		De+Ge+Invest	Ca+Op	✓
[111]	MILP	S	DCOPF	30 Years	Yearly	RES	MIC+MOC	Two		De+Ge+N-1	Ca+Op	✓
[112]	MILP	S	DCOPF	15 Years	Yearly	TN	MIC+MOC	Two		De+Ge+Interest	Ca+Op	✓
[113]	MILP	S	DCOPF	10 Years	Yearly	Hydro	MIC+MOC+MGE	Two	✓	De+Ge+GHG+N-1	Ca+Op	✓
[59]	MILP	S(HEA)	DCOPF	15 Years	Yearly	RES+GHG+CCS	MIC+MOC+MGE	Two	✓	De+Ge+GHG	Ca+Op	✓
[114]	MILP	S	DCOPF			RES	MIC+MOC	Two		De+N-1	Ca+Op	
[115]	MILP	S(HEA)	DCOPF	20 years	Yearly	RES	MIC+MOC	Two		M&R	Ca+Op	✓
[116]	MILP	S	DCOPF	15 years	5 Years	ESS+Transformer	MIC+MOC	Two		Ge+N-1	Ca+Op	✓
[117]	MILP	S(MHA)	DCOPF	5 years	Yearly	RES	MIC+MOC+MRC	Two		Ge+De+N-1	Ca+Op	
[118]	MILP	S(MHA)	DCOPF	15 years	5 years	RES	MIC+MRC	Two		Ge+De	Ca+Op	
[119]	MINLP	S(MHA)	DCOPF	10 years	Yearly	RES	MIC	Two		Ge+De	Ca+Op	
[120]	NLP	S(MHA)	DCOPF			RES+EV	MIC+MOC	Two		Ge+De	Ca+Op	
[121]	MINLP	S(MHA)	ACOPF	5 Years	Yearly	RES	MIC+MOC	Two	✓	Ge+De	Ca+Op	

TABLE 3. Cont. Modelling approaches, key assumptions and use of real-world data in existing literature.

Citation	Programming	Optimisation methods	Model	Planning Horizon	Temporal resolution	TEP combined with	Objectives	Model stages	GEP+TEP	Scenario(uncertainty) types	Cost	Real Data
[122]	MILP	S	DCOPF			RES	MIC+MOC	Two		Ge+De	Ca+Op	
[123]	MNILP	S(MHA)	ACOPF			RES	MIC+MOC	Two		Ge+De	Ca+Op	
[124]	MILP	S(MHA)	DCOPF			RES	MIC+MOC	Two		Ge+De	Ca+Op	
[125]	MILP	S(HEA)	DCOPF			RES	MIC	Multi		Ge+De	Ca+Op	
[126]	MILP	S(HEA)	DCOPF	15 Years	Yearly	RES+CCS	MIC	Two	✓	Ge+De+M&R	Ca+Op	✓
[127]	MILP	S(HEA)	DCOPF			RES	MIC	Two		Ge+De	Ca+Op	
[128]	MILP	S(HEA)	DCOPF	20 Years	5 Years	RES	MIC	Two	✓	Ge+De	Ca+Op	
[129]	MILP	S	DCOPF			RES	MIC+MOC	Two	✓	Ge+De	Ca+Op	
[130]	MILP	S(HEA)	DCOPF	A Year	Hourly	RES+ESS	MIC+MOC	Two		Ge+De+SC	Ca+Op	
[131]	MILP	S	DCOPF			RES	MIC+MGE	Two	✓	Ge+De	Ca+Op	✓
[132]	MILP	S(HEA)	DCOPF		Yearly	RES+TN	MIC+MOC	Two	✓	Ge+De	Ca+Op	✓
[133]	MILP	S	DCOPF	A Year	Daily	RES	MIC+MOC	Two		Ge+De	Ca+Op	✓
[134]	MILP	S(HEA)	DCOPF	A Year	Monthly	RES	MIC+MOC	Two	✓	Ge	Ca+Op	
[135]	MILP	S	DCOPF			RES	MIC+MOC	Two		Ge+TC	Ca+Op	
[136]	MILP	S	DCOPF	6 Years	Yearly	RES	MIC+MOC	Two		Ge+De+N-1	Ca+Op	
[137]	MILP	S	DCOPF	8 Years	Yearly	RES	MIC+MOC	Two		Ge+De	Ca+Op	✓
[138]	MNILP	S	DC+AC OPF	10 Years	Yearly	RES+HVDC+HVAC	MIC+MOC	Two		Ge+De	Ca+Op	
[139]	MILP	S	ACOPF	10 Years	Yearly	RES	MIC+MOC+MPL	Two		Ge+De+N-1	Ca+Op	
[140]	MILP	S	ACOPF	A year		RES+RCE	MIC+MOC	Multi		Ge+De+N-1	Ca+Op	
[141]	MINLP	S(MHA)	ACOPF		Hourly	RES	MIC+MOC+TC	Two		Ge+De+N-1	Ca+Op	
[142]	MNILP	S(SA)	ACOPF			RES	MIC+MOC	Two		Ge+De	Ca+Op	
[143]	MILP	S	ACOPF	5 Years	Yearly	RES+RCE	MIC+MOC+MRC	Two		Ge+De	Ca+Op	
[101]	MILP	S+R	DCOPF		Yearly	RES	MIC+MOC	Two	✓	Ge+De+Gc	Ca+Op	
[144]	MILP	S+R	ACOPF		Yearly	RES	MIC+MOC	Two		Ge+De	Ca+Op	
[145]	MILP	S(PSO)	DCOPF		Yearly	RES	MIC+MOC+MRC	Multi		Ge+De+N-1	Ca+Op	
[146]	MILP	S(GA)	DCOPF	10 Years	Yearly	RES+TN	MIC+MOC	Two	✓	Ge+De	Ca+Op	
[147]	MILP	S+R	DCOPF			RES	MIC+MOC	Two		Ge+De	Ca+Op	

uncertain variables as deterministic, leading to potential biases and inaccuracies, especially in complex, real-world TEP scenarios [148].

Mixed-Integer Programming (MIP) offers an improvement over LP by better accommodating uncertainties across different scenarios. A typical example is using binary variables to determine whether transmission lines should be installed or not [149]. This approach ensures the model accurately reflects the discrete nature of investment decisions, thereby enhancing both the practicality and accuracy of TEP models. Furthermore, Mixed-Integer Nonlinear Programming (MINLP) can handle nonlinear calculations, which are crucial for smaller systems that require AC power flow modelling.

Despite these advantages, the complexity and computational demands of MIP often necessitate the use of Benders' decomposition. This technique is particularly effective when a large problem can be broken down into smaller, more manageable subproblems [150]. Among the references analyzed, 42 studies employed MILP or converted MINLP problems into MILP by linearizing nonlinear equations. For example, some studies used Karush–Kuhn–Tucker (KKT) conditions to transform a stochastic bi-level problem into a more manageable bilinear single-level problem, reducing computational complexity and speeding up solution time [151].

2) NONLINEAR PROGRAMMING

Nonlinear Programming (NLP) is less commonly used in TEP, with only 11 articles identified. This is largely due to the tendency of many studies to approximate AC networks as DC networks, thereby eliminating the need for nonlinear parameters. However, when accurate modelling of AC networks is necessary, NLP is indispensable despite its drawbacks, for example, slower solution speeds and greater computational effort. This trade-off between accuracy and computational efficiency often restricts the use of NLP to smaller models. For instance, some studies use the IEEE 24-bus model or limit scenarios to a shorter period (e.g., 24 hours) to balance accuracy and computational demands [98], [101].

D. OPTIMISATION METHODS

Stochastic optimisation methods are essential for managing the uncertainties inherent in TEP. These methods can be broadly categorized into classical and non-classical approaches.

1) CHALLENGES OF SOLVING TEP WITH CLASSICAL OPTIMISATION METHODS

Stochastic optimisation in TEP is challenging, especially for long-term planning that involves complex investment scenarios. These complexities increase the computational burden and can introduce biases if low-probability scenarios unduly influence investment decisions. One solution is to selectively remove certain investment scenarios to streamline the optimisation process.

Benders' decomposition is an effective technique for managing the large number of scenarios typically involved in stochastic TEP. Several studies have demonstrated that this approach enhances model convergence speed, reduces computational time and iterations, and improves the scalability of the solution method [152], [153], [154], [155]. These benefits make Bender's decomposition a valuable tool for addressing the difficulties posed by stochastic optimisation in complex TEP systems.

2) NON-CLASSICAL METHODS

Non-classical methods, such as heuristic and meta-heuristic algorithms, are also frequently employed to address the challenges of TEP under uncertainty [59], [115], [125], [128], [130], [132], [134]. Heuristic algorithms can quickly generate relatively accurate feasible solutions within simplified models, making them efficient in dealing with complex problems. However, these solutions may not be globally optimal and might struggle with the complexities of real-world power systems.

Meta-heuristic algorithms build upon heuristics by incorporating advanced search processes, making them better suited for complex situations where investment decisions are difficult. These algorithms can handle large, complex systems and real power networks, often achieving optimal or near-optimal solutions. However, their computational efficiency can suffer due to the extensive calculations required.

For example, Particle Swarm Optimisation (PSO) is often used as a complement to meta-heuristic and heuristic methods [98], [145]. PSO rapidly searches for the most suitable solution among initial investment decisions, ensuring efficiency while aiming for global optimality. It can be seen as a tool for accelerating the process of finding a feasible global solution.

Similarly, Genetic Algorithms (GA) treat investment programs as a series of chromosomes. By continuously comparing and cross-evaluating these programs, GA identifies the best solution according to the principles of natural selection. While GA can yield superior results, it comes at the cost of significant computational resources [146].

Lastly, Simheuristic Algorithms combine simulation with meta-heuristic approaches to solve stochastic combinatorial optimisation problems. Simheuristic refers to a hybrid of simulation and metaheuristic algorithms [156], which are "white-box" methods specifically designed for solving large-scale NP-hard combinatorial optimisation problems with stochastic elements, which can be in the form of stochastic objective functions or probabilistic constraints [157]. Monte Carlo simulations process stochastic data, which are then optimised using a meta-heuristic algorithm to find the best solution [142].

E. MODEL

During our review of the state-of-the-art transmission expansion planning models, we found that most studies use a linear approximation of the nonlinear power flow. The most commonly linearisation used is the DC power flow model. Out of 53 references considered, 40 employed DCOPF to model power flows, while the rest used either a more detailed linear approximation or a nonlinear formulation (ACOPF), as summarised in Tables 2 and 3.

Although fewer studies employ ACOPF, those that do tend to yield more accurate results, as ACOPF better reflects real-world conditions compared to DCOPF. However, the trade-off is that ACOPF's computational demands often necessitate smaller model sizes, leading to slower solutions. Among the 53 papers reviewed, those using ACOPF exclusively relied on real-world data. This reliance is due to the complexity of real power system networks and the non-linear nature of ACOPF, which can result in significant computational challenges.

In addition, some studies have explored hybrid models combining DCOPF and ACOPF. For instance, [102], [104], [138] investigate the feasibility of inter-converting AC and DC networks in Transmission Expansion Planning (TEP) problems. They also discuss the potential impact of this approach on TEP investment decisions, particularly in smaller test models where a balance between computational speed and accuracy is crucial.

Another unique model is the Direct Linear Power Flow (DLPF) model proposed in [108]. This model is specifically designed for electric-thermal hybrid networks, where standard DCOPF analysis would be insufficient for addressing the planning challenges in natural gas networks. The DLPF model effectively handles power flow modelling in such hybrid networks.

F. PLANNING HORIZON

TEP is generally considered a long-term planning issue for the grid, typically spanning a period of 10 years or more. Among the 53 references reviewed, 13 studies considered a planning horizon of more than 15 years, while 12 studies focused on periods between 5 and 10 years. This indicates that nearly half of the scholars prefer to examine TEP stochastic optimisation problems over a period exceeding five years.

However, it is important to note that a planning horizon is not always a necessary component of TEP studies. For example, [122] and [125] focus on improving the speed of solving TEP problems. In these cases, the planning cycle is treated as a scalar quantity without spatio-temporal continuity, making the planning horizon irrelevant to this type of research.

G. TEMPORAL RESOLUTION

Of the 53 papers reviewed, 29 used a yearly temporal resolution, making it the most common practice in TEP studies. Other temporal resolutions included hourly (3 papers), daily (1 paper), monthly (1 paper), 0.5-year (1 paper), and 5-year intervals (3 papers). The majority of studies combining yearly temporal resolution with a planning horizon of more than five years suggest that this approach is prevalent in long-term planning.

Non-yearly temporal resolutions, on the other hand, are typically associated with shorter planning horizons (less than five years) or focused on algorithmic improvements. Some studies even limit their temporal resolution to a 24-hour period, concentrating on the speed of stochastic optimisation algorithms in handling uncertainties and calculating single investment outcomes.

H. TEP COMBINED WITH OTHER EQUIPEMT

With the increasing flexibility of power systems and the development of collaborative planning strategies, TEP is no longer limited to the siting and construction of transmission lines. Modern TEP studies increasingly consider the impact of other equipment on the power system.

Renewable Energy Sources (RES) are the most commonly addressed factor in TEP studies. Out of the 53 papers reviewed, only four did not involve RES, highlighting the significance of RES-related uncertainties in TEP. Energy Storage Systems (ESS) are another critical element frequently co-planned with TEP, often appearing alongside RES. Studies such as [98], [100], [104], [107], [108], and [130] investigate parameters like installed capacity, operating costs, and the impact of ESS on system stability within TEP.

Hybrid energy networks also feature prominently in TEP planning. These networks often involve synergistic planning of hybrid thermal-electric systems, as seen in studies [105], [112], [132], [145]. These studies explore the economics and system stability of planning issues related to combined heat and power (CHP) plants, gas-fired power generation, and power and heat storage facilities.

Additionally, references [140] and [143] examine joint planning schemes involving Reactive Compensation Equipment (RCE) in TEP problems. The presence of such devices significantly influences system stability and operating costs, particularly in AC networks using ACOPF for TEP studies.

Some studies, such as references [59] and [126], address TEP problems related to Carbon Capture and Storage (CCS) from a policy perspective. These studies incorporate policies on carbon capture technologies and CO2 emission limits as constraints within TEP planning.

Other examples of equipment co-planned with TEP include:

- Rainfall and hydropower siting [113]
- Transformer siting and installed capacity planning [116]
- The effect of the N-1 criterion on TEP [99]
- HVAC and HVDC collaborative planning using DCOPF and ACOPF models [138]
- Co-planning of Electric Vehicles (EVs) and distributed grids with TEP [100], [120]

I. OBJECTIVE FUNCTIONS

The objective function of a deterministic transmission expansion planning problem can be expressed as follows:

$$\min_{x} f(x) \tag{7}$$

where we seek an optimal value of decision variables x that minimises the objective function $f(x)$. The objective function is typically composes of more than one components and includes investment costs and operational costs. mathematically we can express this as: $f(x) = I(x) + O(x)$, where I models the investment costs and O models the operational costs. In stochastic optimisation, the objective function in extended as follows:

$$\min_{x} \left(I(x) + \mathbb{E}_s(O(x))\right) \tag{8}$$

where the expected cost is over a set of scenarios. There is an entire area of research how to model scenarios for renewable generation sources and how best standard probability distributions may be able to capture these. For transmission expansion planning problems, scenarios are considered as an input.

Investment costs represent the one-time expenses incurred during the decision-making stage, such as the cost of building new transmission lines and associated loan interest. Operating costs include line losses, routine operation, maintenance expenses, and other related costs. Stabilisation operating costs encompass penalties for line congestion, failures, or compensation for load shedding due to power shortages.

Most of the 53 papers reviewed use a combination of MIC and MOC, the most common pairing for two-stage optimisation. Studies addressing stabilisation costs often introduce the N-1 criterion in their scenarios, indicating that MIC/MOC remains the primary objective function in practical stochastic optimisation TEP studies.

J. MODEL STAGES

The majority of stochastic optimisation TEP problems use a two-stage model. The first stage involves decision-making, while the second stage evaluates the operating results based on the investment decisions made in the first stage. The results from the second stage are fed back into the first stage to assess the potential investment and operating costs under different scenarios.

Some studies employ multi-stage modelling, essentially building upon the decision-operation model by increasing the number of decision points throughout the planning cycle. This approach allows for more detailed and accurate modelling over longer planning horizons, particularly when dealing with equipment with shorter life cycles than the overall planning period. An example of this is the use of battery storage in [107].

K. GEP+TEP

TEP problems often intersect with Generation Expansion Planning (GEP), but addressing both simultaneously increases computational complexity. In such cases, Karush-Kuhn-Tucker (KKT) conditions are employed. Most current GEP-TEP problems assume that new power plants will be renewable energy plants, making GEP a scenario variation of the uncertainty in power generation within TEP.

A few GEP-TEP studies still consider conventional power plants, incorporating fuel price fluctuations and carbon dioxide emissions as penalty parameters. These uncertainties are used as scenarios in stochastic optimisation, reflecting the influence of government policies.

L. SCENARIO(UNCERTAINTY) TYPES

Generation and demand uncertainties are the most frequently addressed in stochastic optimisation TEP studies. Both are often employed simultaneously as a set of uncertainty parameters, though occasionally, they are used individually to reduce scenario complexity.

The N-1 criterion is another common uncertainty parameter, as some studies consider potential equipment failure scenarios to enhance model stability or to determine the costs associated with maintaining system stability. These scenarios influence model decisions and final optimisation results.

Price and interest rate fluctuations are also sources of uncertainty in stochastic optimisation, as explored in references [99], [105], [101], and [115]. These studies suggest that changes in energy policy can affect energy prices, decarbonisation progress, and even energy trading prices and fuel costs for electricity generation. These are potential uncertainties that may impact the stochastic optimisation of TEP.

Additional examples of uncertainty in TEP include:

- Stochastic planning based on contingency-dependent transmission switching (CD-TS) (reference [77])
- Stochastic optimisation considering Dynamic Thermal Rating (DTR) uncertainty in hybrid networks (reference [97])
- Different scenarios of GHG emissions as uncertainty parameters (references [102] and [103])
- Uncertainty in the storage capacity of ESS over its service life (reference [119]).

M. COST

All 53 papers reviewed used a combination of Capital Expenditure (CapEx) and Operating Expenditure (OpEx) in their cost analyses. Even when dealing with parameters like CO2 emissions, which are not directly quantified monetarily, scholars incorporate taxes and penalties into the model. These penalties guide the model's optimisation decisions.

N. REAL DATA

Model testing using real data is crucial for the practical application of TEP. However, among the 53 papers reviewed, only 13 used real data for testing, and all were based on DCOPF models. This finding suggests that real data testing in TEP is not widespread in current research. Moreover, most studies related to TEP involving algorithmic improvements remain focused on theoretical advancements and testing with IEEE models rather than applying real-world data.

V. CHALLENGES, OPPORTUNITIES AND RESEARCH GAPS

This paper delves into the application of stochastic programming in Transmission Expansion Planning (TEP), addressing current TEP challenges, emerging opportunities, and the key research findings from recent modelling efforts. Through an extensive literature review, the following critical insights were uncovered:

A. CHALLENGES AND OPPORTUNITIES

1) IMPORTANCE AND COMPLEXITY OF TEP

TEP plays a crucial role in ensuring the reliable and efficient operation of power systems. Its complexity necessitates detailed modelling and robust study. This paper highlights the importance of understanding TEP's intricacies and provides a thorough description of the modelling techniques employed.

2) EMERGING UNCERTAINTIES IN TEP

In recent years, uncertainties in load and generation have become increasingly significant, requiring TEP to focus more on medium- to long-term planning. Ensuring the stability of the power system in the face of these uncertainties is paramount.

3) INTEGRATED PLANNING

TEP issues cannot be addressed in isolation. Effective planning must involve coordination with various power system components and stakeholders, reflecting the interconnected nature of modern power systems.

4) STOCHASTIC OPTIMISATION AS A TOOL

Stochastic optimisation is a powerful tool for addressing the persistent uncertainties in power systems. It can help in optimising TEP under complex, uncertain scenarios, making it a valuable approach for future planning.

5) ADVANCES IN STOCHASTIC PLANNING ALGORITHMS

Improved stochastic planning algorithms have the potential to accelerate the solution process for TEP models and reduce the number of potential options, leading to more optimal solutions. This is crucial as the complexity of scenarios increases.

B. RESEARCH GAPS

Despite these advancements, the literature review also reveals several research gaps that need to be addressed:

1) DOMINANCE OF DCOPF MODELS

Although DC Optimal Power Flow (DCOPF) models dominate TEP research, AC Optimal Power Flow (ACOPF) models offer a more comprehensive analysis by considering reactive power and other factors. However, the computational intensity of ACOPF makes it challenging to apply in large-scale modelling or real grid planning, despite its potential for more accurate results. There remains a significant gap in the practical application of ACOPF in TEP.

2) UNDERUTILISATION OF ENERGY STORAGE SYSTEMS (ESS)

While many studies explore the synergy between renewable energy sources (RES) and ESS in TEP planning, they often limit ESS's role to balancing supply and demand across various scenarios. There is insufficient exploration of ESS's potential to replace or defer the need for new transmission lines or upgrades, despite suggestions from scholars that this is a feasible approach.

3) NEGLECTED FACTORS IN SCENARIO PLANNING

Most studies focus on generation, demand, and the N-1 criterion as key scenarios, overlooking other critical factors such as the lifecycle, capacity changes (decay or expansion), and cost reductions of storage equipment. These factors could significantly influence TEP planning, especially as ESS deployment increases. Furthermore, existing research has not adequately addressed the impact of evolving policies, decarbonisation targets, and other factors that could reshape the power system in the future.

4) LIMITED USE OF REAL DATA

Despite the importance of real data in validating TEP models, only a small fraction of studies employ real-world data for testing. Moreover, these studies often focus on short-term scenarios, which do not align well with the medium- and long-term planning objectives, such as achieving carbon neutrality by 2050.

VI. CONCLUSION

This paper provides a literature review of Transmission Expansion Planning problem and highlights the need for more research and innovation in this area. The review provides a summary of the state-of-the-art, identifies emerging trends, and highlights gaps in the area.

Our findings suggest that with the increasing penetration of renewable energy, uncertainty in TEP planning is unavoidable. As such, TEP models must be inherently designed to accommodate this uncertainty. Current research is increasingly focused on improving algorithms to enhance computational speed and integrating TEP with various power system components, such as RES, ESS, and microgrids.

Looking forward, we propose that future TEP research should prioritize stochastic planning based on the uncertainties introduced by RES, ESS, electric vehicles (EVs), and microgrids. The adoption of these new technologies will undoubtedly alter the landscape of TEP, making it essential for models to be more grounded in reality and validated with real data. Additionally, advancements in TEP-related algorithms are critical to managing the growing complexity of scenarios and uncertainty parameters, ultimately improving the accuracy and applicability of TEP models for planners and decision-makers.

REFERENCES

[1] M. Karatayev, G. Movkebayeva, and Z. Bimagambetova, "Increasing utilisation of renewable energy sources: Comparative analysis of scenarios until 2050," in *Proc. Energy Secur., Policy Challenges Solutions Resource Efficiency*, 2019, pp. 37–68.

[2] M. Jahangiri, R. Ghaderi, A. Haghani, and O. Nematollahi, "Finding the best locations for establishment of solar-wind power stations in middle-east using GIS: A review," *Renew. Sustain. Energy Rev.*, vol. 66, pp. 38–52, Dec. 2016.

[3] J. Choi, T. Tran, A. A. El-Keib, R. Thomas, H. Oh, and R. Billinton, "A method for transmission system expansion planning considering probabilistic reliability criteria," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1606–1615, Aug. 2005.

[4] A. Henao, E. Sauma, and A. Gonzalez, "Impact of introducing flexibility in the Colombian transmission expansion planning," *Energy*, vol. 157, pp. 131–140, Aug. 2018.

[5] J. Choi, T. D. Mount, and R. J. Thomas, "Transmission expansion planning using contingency criteria," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 2249–2261, Nov. 2007.

[6] R. L. Sullivan, *Power System Planning*. New York, NY, USA: McGraw-Hill Book, 1977.

[7] N. González-Cabrera, J. Ortiz-Bejar, A. Zamora-Mendez, and M. R. A. Paternina, "On the improvement of representative demand curves via a hierarchical agglomerative clustering for power transmission network investment," *Energy*, vol. 222, May 2021, Art. no. 119989.

[8] T. Akbari and M. Tavakoli Bina, "Approximated MILP model for AC transmission expansion planning: Global solutions versus local solutions," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 7, pp. 1563–1569, May 2016.

[9] S. Lumbreras and A. Ramos, "The new challenges to transmission expansion planning. Survey of recent practice and literature review," *Electric Power Syst. Res.*, vol. 134, pp. 19–29, May 2016.

[10] G. Latorre, R. D. Cruz, J. M. Areiza, and A. Villegas, "Classification of publications and models on transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 938–946, May 2003.

[11] S. Dehghan, A. Kazemi, and N. Amjady, "Multi-objective robust transmission expansion planning using information-gap decision theory and augmented ϵ-constraint method," *IET Gener., Transmiss. Distrib.*, vol. 8, no. 5, pp. 828–840, May 2014.

[12] T. De la Torre, J. W. Feltes, T. G. S. Roman, and H. M. Merrill, "Deregulation, privatization, and competition: Transmission planning under uncertainty," *IEEE Trans. Power Syst.*, vol. 14, no. 2, pp. 460–465, May 1999.

[13] M. Aldeghi, F. Häse, R. J. Hickman, I. Tamblyn, and A. Aspuru-Guzik, "Golem: An algorithm for robust experiment and process optimization," *Chem. Sci.*, vol. 12, no. 44, pp. 14792–14807, 2021.

[14] T. Homem-De-Mello and G. Bayraksan, "Monte Carlo sampling-based methods for stochastic optimization," *Surveys Operations Res. Manage. Sci.*, vol. 19, no. 1, pp. 56–85, Jan. 2014.

[15] *Renewable Power Generation Costs 2023*, Int. Renew. Energy Agency, Masdar City, United Arab Emirates, 2023.

[16] IEA. (2023). *Renewables 2023*. [Online]. Available: https://www.iea.org/reports/renewables-2023

[17] N. E. S. Operator. (2023). *Beyond 2030 Report*. [Online]. Available: https://www.neso.energy/publications/beyond-2030/web-map

[18] Z. Ming, L. Honglin, M. Mingjuan, L. Na, X. Song, W. Liang, and P. Lilin, "Review on transaction status and relevant policies of southern route in China's West–East power transmission," *Renew. Energy*, vol. 60, pp. 454–461, Dec. 2013.

[19] N. S. W. P. Hub. (2020). *Vision| North Sea Wind Power Hub*. [Online]. Available: https://northseawindpowerhub

[20] P. S. Drachev and V. V. Trufanov, "Market-based transmission expansion planning," *Energy Power Eng.*, vol. 4, no. 6, pp. 387–391, 2012.

[21] E. B. Cedeño and S. Arora, "Performance comparison of transmission network expansion planning under deterministic and uncertain conditions," *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 7, pp. 1288–1295, Sep. 2011.

[22] D. Z. Fitiwi, F. de Cuadra, L. Olmos, and M. Rivier, "A new approach of clustering operational states for power network expansion planning problems dealing with RES (renewable energy source) generation operational variability and uncertainty," *Energy*, vol. 90, pp. 1360–1376, Oct. 2015.

[23] O. M. Babatunde, J. L. Munda, and Y. Hamam, "A comprehensive state-of-the-art survey on power generation expansion planning with intermittent renewable energy source and energy storage," *Int. J. Energy Res.*, vol. 43, no. 12, pp. 6078–6107, Oct. 2019.

[24] N. E. Koltsaklis and A. Dagoumas, "State-of-the-art generation expansion planning: A review," *Appl. Energy*, vol. 230, pp. 563–589, Sep. 2018.

[25] D. Z. Fitiwi, "Strategies, methods and tools for solving long-term transmission expansion planning in large-scale power systems," M.S. thesis, TU Delft, 2016, doi: 10.4233/uuid:e8dbb294-dd57-4c10-b733-b4aded62607c.

[26] S. L. Gbadamosi and N. I. Nwulu, "Reliability assessment of composite generation and transmission expansion planning incorporating renewable energy sources," *J. Renew. Sustain. Energy*, vol. 12, no. 2, Mar. 2020, Art. no. 026301.

[27] S. L. Gbadamosi and N. I. Nwulu, "A comparative analysis of generation and transmission expansion planning models for power loss minimization," *Sustain. Energy, Grids Netw.*, vol. 26, Jun. 2021, Art. no. 100456.

[28] M. Valocchi, J. Juliano, and A. Schurr, "Switching perspectives: Creating new business models for a changing world of energy," in *Smart Grid Applications and Developments*. Cham, Switzerland: Springer, 2014, pp. 165–182.

[29] N. Mahmud and A. Zahedi, "Review of control strategies for voltage regulation of the smart distribution network with high penetration of renewable distributed generation," *Renew. Sustain. Energy Rev.*, vol. 64, pp. 582–595, Oct. 2016.

[30] X. Li and S. Wang, "Energy management and operational control methods for grid battery energy storage systems," *CSEE J. Power Energy Syst.*, vol. 7, no. 5, pp. 1026–1040, Sep. 2021.

[31] U. P. Müller, "Combined optimization of grid and storage expansion in the German power system," Ph.D. dissertation, Europa-Universität Flensburg, Zentrale Hochschulbibliothek, Flensburg, Germany, 2021.

[32] S. Rui, C. Zhong, C. Yanxia, and L. Zhou, "Bidirectional power transfer control based on V2G concept," in *Proc. IEEE PES Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Dec. 2014, pp. 1–5.

[33] J. Liu, P. P. Zeng, H. Xing, Y. Li, and Q. Wu, "Hierarchical duality-based planning of transmission networks coordinating active distribution network operation," *Energy*, vol. 213, Dec. 2020, Art. no. 118488.

[34] A. Arteconi, N. J. Hewitt, and F. Polonara, "State of the art of thermal storage for demand-side management," *Appl. Energy*, vol. 93, pp. 371–389, May 2012.

[35] M. M. Almenta, J. Morrow, R. Best, B. Fox, and A. Foley, "An aggregated fridge-freezer peak shaving and valley filling control strategy for enhanced grid operations," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Oct. 2015, pp. 1–5.

[36] M. I. Khan, F. Asfand, and S. G. Al-Ghamdi, "Progress in research and technological advancements of thermal energy storage systems for concentrated solar power," *J. Energy Storage*, vol. 55, Nov. 2022, Art. no. 105860.

[37] N. Jayasekara, M. A. S. Masoum, and P. J. Wolfs, "Optimal operation of distributed energy storage systems to improve distribution network load and generation hosting capability," *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 250–261, Jan. 2016.

[38] I.-C. Gonzalez-Romero, S. Wogrin, and T. Gomez, "Proactive transmission expansion planning with storage considerations," *Energy Strategy Rev.*, vol. 24, pp. 154–165, Apr. 2019.

[39] S. Goodarzi, M. Gitizadeh, A. R. Abbasi, and M. Lehtonen, "Tight convex relaxation for TEP problem: A multiparametric disaggregation approach," *IET Gener., Transmiss. Distrib.*, vol. 14, no. 14, pp. 2810–2817, Jul. 2020.

[40] Q. Xu and B. F. Hobbs, "Transmission planning and co-optimization with market-based generation and storage investment," in *Transmission Network Investment in Liberalized Power Markets* (Lecture Notes in Energy), vol. 79, M. R. Hesamzadeh, J. Rosellón, and I. Vogelsang, Eds. Cham, Switzerland: Springer, 2020, doi: 10.1007/978-3-030-47929-9_7.

[41] M. F. Akorede, H. Hizam, and E. Pouresmaeil, "Distributed energy resources and benefits to the environment," *Renew. Sustain. Energy Rev.*, vol. 14, no. 2, pp. 724–734, Feb. 2010.

[42] M. Abbott and B. Cohen, "Issues associated with the possible contribution of battery energy storage in ensuring a stable electricity system," *Electr. J.*, vol. 33, no. 6, Jul. 2020, Art. no. 106771.

[43] V. Krishnan, J. Ho, B. F. Hobbs, A. L. Liu, J. D. McCalley, M. Shahidehpour, and Q. P. Zheng, "Co-optimization of electricity transmission and generation resources for planning and policy analysis: Review of concepts and modeling approaches," *Energy Syst.*, vol. 7, no. 2, pp. 297–332, May 2016.

[44] B. Zakeri and S. Syri, "Electrical energy storage systems: A comparative life cycle cost analysis," *Renew. Sustain. Energy Rev.*, vol. 42, pp. 569–596, Feb. 2015.

[45] J. Intrator, "Strategic analysis of energy storage in california: Final project report," Univ. California, Berkeley School Law, California Energy Commission, Sacramento, CA, USA, Project CEC-500-2011-047 2011. [Online]. Available: https://www.ourenergypolicy.org/wp-content/uploads/2013/08/2020.pdf

[46] A. Abele et al., "Electricity energy storage technology options: A white paper primer on applications, costs and benefits," Electric Power Res. Inst., EPRI, Palo Alto, CA, USA, Tech. Rep. 1020676, 2010. [Online]. Available: http://large.stanford.edu/courses/2012/ph240/doshay1/docs/EPRI.pdf

[47] K. Mongird, V. V. Viswanathan, P. J. Balducci, M. J. E. Alam, V. Fotedar, V. Koritarov, and B. Hadjerioua, "Energy storage technology and cost characterization report," Pacific Northwest Nat. Lab. (PNNL), Richland, WA, USA, Tech. Rep. PNNL-28866, 2019. [Online]. Available: https://energystorage.pnnl.gov/pdf/pnnl-28866.pdf

[48] J. Dixon, K. Bell, and S. Brush, "Which way to net zero? A comparative analysis of seven U.K. 2050 decarbonisation pathways," *Renew. Sustain. Energy Transition*, vol. 2, Aug. 2022, Art. no. 100016.

[49] E. National Grid, "Future energy scenarios," 2024. [Online]. Available: https://www.neso.energy/publications/future-energy-scenarios-fes

[50] *European Commission: Directorate-General for Climate Action, Directorate-General for Energy, Directorate-General for Mobility and Transport, De Vita, A., Capros, P. et al., EU reference scenario 2020*, Energy, Transport GHG Emissions, Trends, Publications Office, 2021. [Online]. Available: https://data.europa.eu/doi/10.2833/35750

[51] B. Pickering and R. Choudhary, "District energy system optimisation under uncertain demand: Handling data-driven stochastic profiles," *Appl. Energy*, vol. 236, pp. 1138–1157, Feb. 2019.

[52] J.-M. Glachant, P. L. Joskow, and M. G. Pollitt, "Introduction to the handbook on electricity markets," in *Handbook on Electricity Markets*. Ann Arbor, MI, USA: Edwards, 2021, pp. 1–11.

[53] P. V. Gomes and J. T. Saraiva, "State-of-the-art of transmission expansion planning: A survey from restructuring to renewable and distributed electricity markets," *Int. J. Electr. Power Energy Syst.*, vol. 111, pp. 411–424, Oct. 2019.

[54] M. Shivaie and M. T. Ameli, "Risk-constrained multi-level framework for coordination of generation and transmission expansion planning in liberalised environments—Part I: Theory and formulation," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 13, pp. 3183–3190, Oct. 2016.

[55] L. A. Barroso, F. Porrua, L. M. Thome, and M. Pereira, "Planning for big things in Brazil," *IEEE Power Energy Mag.*, vol. 5, no. 5, pp. 54–63, Jan. 2007.

[56] K. van de Biezenbos, "The case against regional transmission monopolies," *101 Wash. U. L. Rev.*, vol. 69, Feb. 2023. [Online]. Available: http://dx.doi.org/10.2139/ssrn.4348932

[57] G. Heynes. (2024). *Scottishpower Unveils 'biggest Issued Contract Opportunity Ever' for Its Electricity Network*. [Online]. Available: https://www.current-news.co.uk/scottishpower-unveils-biggest-issued-contract-opportunity-ever-for-its-electricity-network/

[58] A. Moreira, D. Pozo, A. Street, E. Sauma, and G. Strbac, "Climate-aware generation and transmission expansion planning: A three-stage robust optimization approach," *Eur. J. Oper. Res.*, vol. 295, no. 3, pp. 1099–1118, Dec. 2021.

[59] O. J. Guerra, D. A. Tejada, and G. V. Reklaitis, "An optimization framework for the integrated planning of generation and transmission expansion in interconnected power systems," *Appl. Energy*, vol. 170, pp. 1–21, May 2016.

[60] T. Akbari, A. Rahimikian, and A. Kazemi, "A multi-stage stochastic transmission expansion planning method," *Energy Convers. Manage.*, vol. 52, nos. 8–9, pp. 2844–2853, Aug. 2011.

[61] Y. Han, C. Y. Chung, K. P. Wong, and J. Zhang, "A chance constrained transmission network expansion planning method with consideration of load and wind farm uncertainties," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1568–1576, Jul. 2009.

[62] S. Dehghan and N. Amjady, "Robust transmission and energy storage expansion planning in wind farm-integrated power systems considering transmission switching," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 765–774, Apr. 2016.

[63] M. Sun, I. Konstantelos, and G. Strbac, "Transmission network expansion planning with stochastic multivariate load and wind modeling," in *Proc. Int. Conf. Probabilistic Methods Appl. Power Syst. (PMAPS)*, Oct. 2016, pp. 1–7.

[64] S. Lumbreras, A. Ramos, and F. Banez-Chicharro, "Optimal transmission network expansion planning in real-sized power systems with high renewable penetration," *Electr. Power Syst. Res.*, vol. 149, pp. 76–88, Aug. 2017.

[65] P. V. Gomes, J. T. Saraiva, L. Carvalho, B. Dias, and L. W. Oliveira, "Impact of decision-making models in transmission expansion planning considering large shares of renewable energy sources," *Electric Power Syst. Res.*, vol. 174, Sep. 2019, Art. no. 105852.

[66] K. Forssén, K. Mäki, M. Räikkönen, and R. Molarius, "Resilience of electricity distribution networks against extreme weather conditions," *ASCE-ASME J. Risk Uncertainty Eng. Syst., B, Mech. Eng.*, vol. 3, no. 2, Jun. 2017, Art. no. 021005.

[67] M. Abdi-Khorsand, M. Sahraei-Ardakani, and Y. M. Al-Abdullah, "Corrective transmission switching for N-1-1 contingency analysis," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1606–1615, Mar. 2017.

[68] N. E. Koltsaklis and K. Nazos, "A stochastic MILP energy planning model incorporating power market dynamics," *Appl. Energy*, vol. 205, pp. 1364–1383, Nov. 2017.

[69] R. A. Jabr, "Robust transmission network expansion planning with uncertain renewable generation and loads," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4558–4567, Nov. 2013.

[70] A. Baharvandi, J. Aghaei, T. Niknam, M. Shafie-Khah, R. Godina, and J. P. S. Catalão, "Bundled generation and transmission planning under demand and wind generation uncertainty based on a combination of robust and stochastic optimization," *IEEE Trans. Sustain. Energy*, vol. 9, no. 3, pp. 1477–1486, Jul. 2018.

[71] C. Ruiz and A. J. Conejo, "Robust transmission expansion planning," *Eur. J. Oper. Res.*, vol. 242, no. 2, pp. 390–401, Apr. 2015.

[72] R. Mínguez and R. García-Bertrand, "Robust transmission network expansion planning in energy systems: Improving computational performance," *Eur. J. Oper. Res.*, vol. 248, no. 1, pp. 21–32, Jan. 2016.

[73] R. García-Bertrand and R. Mínguez, "Dynamic robust transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 32, no. 4, pp. 2618–2628, Jul. 2017.

[74] B. Alizadeh, S. Dehghan, N. Amjady, S. Jadid, and A. Kazemi, "Robust transmission system expansion considering planning uncertainties," *IET Gener., Transmiss. Distrib.*, vol. 7, no. 11, pp. 1318–1331, Nov. 2013.

[75] R. Mahroo, A. Kargarian, M. Mehrtash, and A. J. Conejo, "Robust dynamic TEP with an security criterion: A computationally efficient model," *IEEE Trans. Power Syst.*, vol. 38, no. 1, pp. 912–920, Jan. 2023.

[76] Z. Liang, H. Chen, S. Chen, Y. Wang, C. Zhang, and C. Kang, "Robust transmission expansion planning based on adaptive uncertainty set optimization under high-penetration wind power generation," *IEEE Trans. Power Syst.*, vol. 36, no. 4, pp. 2798–2814, Jul. 2021.

[77] K. Marti, *Stochastic Optimization Methods*, vol. 2. Cham, Switzerland: Springer, 2008.

[78] T. Niknam, R. Azizipanah-Abarghooee, and M. R. Narimani, "An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation," *Appl. Energy*, vol. 99, pp. 455–470, Nov. 2012.

[79] G. Mavromatidis, K. Orehounig, and J. Carmeliet, "Comparison of alternative decision-making criteria in a two-stage stochastic program for the design of distributed energy systems under uncertainty," *Energy*, vol. 156, pp. 709–724, Aug. 2018.

[80] A. Nikoobakht and J. Aghaei, "Integrated transmission and storage systems investment planning hosting wind power generation: Continuous-time hybrid stochastic/robust optimisation," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 21, pp. 4870–4879, Nov. 2019.

[81] B. Grillone, S. Danov, A. Sumper, J. Cipriano, and G. Mor, "A review of deterministic and data-driven methods to quantify energy efficiency savings and to predict retrofitting scenarios in buildings," *Renew. Sustain. Energy Rev.*, vol. 131, Oct. 2020, Art. no. 110027.

[82] M.-H. Lin, J.-F. Tsai, and C.-S. Yu, "A review of deterministic optimization methods in engineering and management," *Math. Problems Eng.*, vol. 2012, no. 1, Jan. 2012, Art. no. 756023.

[83] A. Maheri, "A critical evaluation of deterministic methods in size optimisation of reliable and cost effective standalone hybrid renewable energy systems," *Rel. Eng. Syst. Saf.*, vol. 130, pp. 159–174, Oct. 2014.

[84] R. J.-B. Wets, "On the relation between stochastic and deterministic optimization," in *Proc. Control Theory, Numer. Methods Comput. Syst. Modelling, Int. Symp., Rocquencourt*, Cham, Switzerland: Springer, 1974, pp. 350–361.

[85] M. Cavazzuti, "Deterministic optimization," in *Optimization Methods: From Theory To Design Scientific and Technological Aspects in Mechanics*. Berlin, Germany: Springer, 2013, pp. 77–102. [Online]. Available: https://doi.org/10.1007/978-3-642-31187-1

[86] J. Pearl, *Heuristics: Intelligent Search Strategies for Computer Problem Solving*. Reading, MA, USA: Addison-Wesley, 1984.
[87] E. A. Silver, "An overview of heuristic solution methods," *J. Oper. Res. Soc.*, vol. 55, no. 9, pp. 936–956, Sep. 2004.
[88] V. C. S. S. and A. H. S., "Nature inspired meta heuristic algorithms for optimization problems," *Computing*, vol. 104, no. 2, pp. 251–269, Feb. 2022.
[89] M. Alqahtani and M. Hu, "Dynamic energy scheduling and routing of multiple electric vehicles using deep reinforcement learning," *Energy*, vol. 244, Apr. 2022, Art. no. 122626.
[90] N. Van Thieu and S. Mirjalili, "MEALPY: An open-source library for latest meta-heuristic algorithms in Python," *J. Syst. Archit.*, vol. 139, Jun. 2023, Art. no. 102871.
[91] Y. Huang, X.-N. Shen, and X. You, "A discrete shuffled frog-leaping algorithm based on heuristic information for traveling salesman problem," *Appl. Soft Comput.*, vol. 102, Apr. 2021, Art. no. 107085.
[92] C. A. C. Coello, *Evolutionary Algorithms for Solving Multi-objective Problems*. Cham, Switzerland: Springer, 2007.
[93] Z. M. Al-Hamouz and A. S. Al-Faraj, "Transmission expansion planning using nonlinear programming," in *Proc. IEEE/PES Transmiss. Distrib. Conf. Exhib.*, vol. 1, Oct. 2002, pp. 50–55.
[94] M. Shafiee, F. Brennan, and I. A. Espinosa, "A parametric whole life cost model for offshore wind farms," *Int. J. Life Cycle Assessment*, vol. 21, no. 7, pp. 961–975, Jul. 2016.
[95] J. Serrano González, M. Burgos Payán, and J. Riquelme Santos, "Optimum design of transmissions systems for offshore wind farms including decision making under risk," *Renew. Energy*, vol. 59, pp. 115–127, Nov. 2013.
[96] B. Van Eeckhout, D. Van Hertem, M. Reza, K. Srivastava, and R. Belmans, "Economic comparison of VSC HVDC and HVAC as transmission system for a 300 MW offshore wind farm," *Eur. Trans. Electr. Power*, vol. 20, no. 5, pp. 661–671, Jul. 2010.
[97] H. Bains, A. Madariaga, M. C. M. Troffaes, and B. Kazemtabrizi, "An economic model for offshore transmission asset planning under severe uncertainty," *Renew. Energy*, vol. 160, pp. 1174–1184, Nov. 2020.
[98] R. Hemmati, H. Saboori, and M. A. Jirdehi, "Stochastic planning and scheduling of energy storage systems for congestion management in electric power systems including renewable energy resources," *Energy*, vol. 133, pp. 380–387, Aug. 2017.
[99] M. Peker, A. S. Kocaman, and B. Y. Kara, "A two-stage stochastic programming approach for reliability constrained power system expansion planning," *Int. J. Electr. Power Energy Syst.*, vol. 103, pp. 458–469, Dec. 2018.
[100] B. Canizes, J. Soares, F. Lezama, C. Silva, Z. Vale, and J. M. Corchado, "Optimal expansion planning considering storage investment and seasonal effect of demand and renewable generation," *Renew. Energy*, vol. 138, pp. 937–954, Aug. 2019.
[101] L. Baringo and A. Baringo, "A stochastic adaptive robust optimization approach for the generation and transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 792–802, Jan. 2018.
[102] M. R. Ansari, S. Pirouzi, M. Kazemi, A. Naderipour, and M. Benbouzid, "Renewable generation and transmission expansion planning coordination with energy storage system: A flexibility point of view," *Appl. Sci.*, vol. 11, no. 8, p. 3303, Apr. 2021.
[103] S. Yin and J. Wang, "Generation and transmission expansion planning towards a 100% renewable future," *IEEE Trans. Power Syst.*, vol. 37, no. 4, pp. 3274–3285, Jul. 2022.
[104] A. Lotfjou, Y. Fu, and M. Shahidehpour, "Hybrid AC/DC transmission expansion planning," *IEEE Trans. Power Del.*, vol. 27, no. 3, pp. 1620–1628, Jul. 2012.
[105] A. R. Abbasi and A. R. Seifi, "Simultaneous integrated stochastic electrical and thermal energy expansion planning," *IET Gener., Transmiss. Distrib.*, vol. 8, no. 6, pp. 1017–1027, Jun. 2014.
[106] S. Alaee, R.-A. Hooshmand, and R. Hemmati, "Stochastic transmission expansion planning incorporating reliability solved using SFLA meta-heuristic optimization technique," *CSEE J. Power Energy Syst.*, vol. 2, no. 2, pp. 79–86, Jun. 2016.
[107] T. Qiu, B. Xu, Y. Wang, Y. Dvorkin, and D. S. Kirschen, "Stochastic multistage coplanning of transmission expansion and energy storage," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 643–651, Jan. 2017.
[108] J. Zhan, W. Liu, and C. Y. Chung, "Stochastic transmission expansion planning considering uncertain dynamic thermal rating of overhead lines," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 432–443, Jan. 2019.
[109] K. A. Alnowibet, A. M. Alshamrani, and A. F. Alrasheedi, "A bilevel stochastic optimization framework for market-oriented transmission expansion planning considering market power," *Energies*, vol. 16, no. 7, p. 3256, Apr. 2023.
[110] M. Sun, F. Teng, I. Konstantelos, and G. Strbac, "An objective-based scenario selection method for transmission network expansion planning with multivariate stochasticity in load and renewable energy sources," *Energy*, vol. 145, pp. 871–885, Feb. 2018.
[111] M. Majidi-Qadikolai and R. Baldick, "Stochastic transmission capacity expansion planning with special scenario selection for integrating $N-1$ contingency analysis," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4901–4912, Nov. 2016.
[112] V. Khaligh and A. Anvari-Moghaddam, "Stochastic expansion planning of gas and electricity networks: A decentralized-based approach," *Energy*, vol. 186, Nov. 2019, Art. no. 115889.
[113] A. H. Seddighi and A. Ahmadi-Javid, "Integrated multiperiod power generation and transmission expansion planning with sustainability aspects in a stochastic environment," *Energy*, vol. 86, pp. 9–18, Jun. 2015.
[114] M. Majidi-Qadikolai and R. Baldick, "A generalized decomposition framework for large-scale transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 1635–1649, Mar. 2018.
[115] F. D. Munoz, B. F. Hobbs, J. L. Ho, and S. Kasina, "An engineering-economic approach to transmission planning under market and regulatory uncertainties: WECC case study," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 307–317, Jan. 2014.
[116] I. Konstantelos and G. Strbac, "Valuation of flexible transmission investment options under uncertainty," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 1047–1055, Mar. 2015.
[117] J. Qiu, K. Meng, J. Zhao, and Y. Zheng, "Power network planning considering trade-off between cost, risk, and reliability," *Int. Trans. Electr. Energy Syst.*, vol. 27, no. 12, p. 2462, Dec. 2017.
[118] A. Moradi, Y. Alinejad-Beromi, and K. Kiani, "Multi-objective transmission expansion planning with allocation of fixed series compensation under uncertainties," *Int. Trans. Electr. Energy Syst.*, vol. 27, no. 11, p. e2417, Nov. 2017.
[119] M. Jadidoleslam, A. Ebrahimi, and M. A. Latify, "Probabilistic transmission expansion planning to maximize the integration of wind power," *Renew. Energy*, vol. 114, pp. 866–878, Dec. 2017.
[120] C. Rathore and R. Roy, "Impact of wind uncertainty, plug-in-electric vehicles and demand response program on transmission network expansion planning," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 59–73, Feb. 2016.
[121] R. Hemmati, R.-A. Hooshmand, and A. Khodabakhshian, "Coordinated generation and transmission expansion planning in deregulated electricity market considering wind farms," *Renew. Energy*, vol. 85, pp. 620–630, Jan. 2016.
[122] J. Zhan, C. Y. Chung, and A. Zare, "A fast solution method for stochastic transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4684–4695, Nov. 2017.
[123] J. Qiu, Z. Y. Dong, J. Zhao, Y. Xu, F. Luo, and J. Yang, "A risk-based approach to multi-stage probabilistic transmission network planning," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4867–4876, Nov. 2016.
[124] A. S. Sousa and E. N. Asada, "Long-term transmission system expansion planning with multi-objective evolutionary algorithm," *Electric Power Syst. Res.*, vol. 119, pp. 149–156, Feb. 2015.
[125] P. V. Gomes and J. T. Saraiva, "Static transmission expansion planning using heuristic and Metaheuristic techniques," in *Proc. IEEE Eindhoven PowerTech*, Jun. 2015, pp. 1–6.
[126] O. J. Guerra, D. A. Tejada, and G. V. Reklaitis, "Climate change impacts and adaptation strategies for a hydro-dominated power system via stochastic optimization," *Appl. Energy*, vols. 233–234, pp. 584–598, Jan. 2019.
[127] Z. Zhuo, E. Du, N. Zhang, C. Kang, Q. Xia, and Z. Wang, "Incorporating massive scenarios in transmission expansion planning with high renewable energy penetration," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 1061–1074, Mar. 2020.
[128] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and M. Moeini-Aghtaie, "A multi-objective transmission expansion planning framework in deregulated power systems with wind generation," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 3003–3011, Nov. 2014.
[129] K. A. Alnowibet, A. F. Alrasheedi, and A. M. Alshamrani, "Integrated stochastic transmission network and wind farm investment considering maximum allowable capacity," *Electric Power Syst. Res.*, vol. 215, Feb. 2023, Art. no. 108961.
[130] M. BiazarGhadikolaei, M. Shahabi, and T. Barforoushi, "Expansion planning of energy storages in microgrid under uncertainties and demand response," *Int. Trans. Electr. Energy Syst.*, vol. 29, no. 11, p. 12110, Nov. 2019.

[131] A. Papakonstantinou, C. Bergaentzlé, and L.-L. Pade, "Regional coordination in grid expansion with offshore wind: The case of the Baltic sea region," in *Proc. 16th Int. Conf. Eur. Energy Market (EEM)*, Sep. 2019, pp. 1–6.
[132] M. Ihlemann, I. Kouveliotis-Lysikatos, J. Huang, J. Dillon, C. O'Dwyer, T. Rasku, M. Marin, K. Poncelet, and J. Kiviluoma, "SpineOpt: A flexible open-source energy system modelling framework," *Energy Strategy Rev.*, vol. 43, Sep. 2022, Art. no. 100902.
[133] C. A. Sima, G. C. Lazaroiu, V. Dumbrava, M. Roscia, D. Zaninelli, and P. Duquenne, "Stochastic programming approach for TEP optimization considering RES integration in electricity market," in *Proc. Int. Conf. Energy Environ. (CIEM)*, Oct. 2017, pp. 485–489.
[134] Z. Zhuo, N. Zhang, J. Yang, C. Kang, C. Smith, M. J. O'Malley, and B. Kroposki, "Transmission expansion planning test system for AC/DC hybrid grid with high variable renewable energy penetration," *IEEE Trans. Power Syst.*, vol. 35, no. 4, pp. 2597–2608, Jul. 2020.
[135] Z. Wu, P. Zeng, X.-P. Zhang, and Q. Zhou, "A solution to the chance-constrained two-stage stochastic program for unit commitment with wind energy integration," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4185–4196, Nov. 2016.
[136] Z. Wu, P. Zeng, and X.-P. Zhang, "Two-stage stochastic dual dynamic programming for transmission expansion planning with significant renewable generation and N-k criterion," *CSEE J. Power Energy Syst.*, vol. 2, no. 1, pp. 3–10, Mar. 2016.
[137] H. Park, R. Baldick, and D. P. Morton, "A stochastic transmission planning model with dependent load and wind forecasts," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3003–3011, Nov. 2015.
[138] H. Doagou-Mojarrad, H. Rastegar, and G. B. Gharehpetian, "Probabilistic multi-objective HVDC/AC transmission expansion planning considering distant wind/solar farms," *IET Sci., Meas. Technol.*, vol. 10, no. 2, pp. 140–149, Mar. 2016.
[139] H. Zhang, G. T. Heydt, V. Vittal, and J. Quintero, "An improved network model for transmission expansion planning considering reactive power and network losses," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3471–3479, Aug. 2013.
[140] M. F. Cankurtaran and E. Karatepe, "Flexible transmission expansion and reactive power planning with wind energy considering N-1 security," in *Proc. 5th Int. Istanbul Smart Grid Cities Congr. Fair (ICSG)*, Apr. 2017, pp. 22–26.
[141] G. B. Mir and E. Karatepe, "Stochastic AC transmission expansion planning: A chance constrained distributed slack bus approach with wind uncertainty," *IEEE Access*, vol. 10, pp. 56796–56812, 2022.
[142] R. M. Sanchez, L. R. Villacres, S. P. Torres, and C. A. Castro, "AC transmission expansion planning considering uncertainty," in *Proc. IEEE PES Innov. Smart Grid Technol. Eur. (ISGT-Europe)*, vol. 21, Sep. 2019, pp. 1–5.
[143] Z. Zhou, C. He, T. Liu, X. Dong, K. Zhang, D. Dang, and B. Chen, "Reliability-constrained AC power flow-based co-optimization planning of generation and transmission systems with uncertainties," *IEEE Access*, vol. 8, pp. 194218–194227, 2020.
[144] K. A. Alnowibet and M. A. El-Meligy, "A stochastic programming approach using multiple uncertainty sets for AC robust transmission expansion planning," *Sustain. Energy, Grids Netw.*, vol. 30, Jun. 2022, Art. no. 100648.
[145] G.-R. Kamyab, M. Fotuhi-Firuzabad, and M. Rashidinejad, "A PSO based approach for multi-stage transmission expansion planning in electricity markets," *Int. J. Electr. Power Energy Syst.*, vol. 54, pp. 91–100, Jan. 2014.
[146] M. Malakoti-Moghadam, A. Askarzadeh, and M. Rashidinejad, "Transmission and generation expansion planning of energy hub by an improved genetic algorithm," *Energy Sour., A, Recovery, Utilization, Environ. Effects*, vol. 41, no. 24, pp. 3112–3126, Dec. 2019.
[147] D. Liu, H. Cheng, and S. Fang, "Coupled stochastic and robust transmission expansion planning," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2017, pp. 1–5.
[148] A. Marin and J. Salmeron, "Electric capacity expansion under uncertain demand: Decomposition approaches," *IEEE Trans. Power Syst.*, vol. 13, no. 2, pp. 333–339, May 1998.
[149] S. Y. Lee, K. Hicks, and E. Hnyilicza, "Transmission expansion by branch-and-bound integer programming with optimal cost-capacity curves," *IEEE Trans. Power App. Syst.*, vols. PAS–93, no. 5, pp. 1390–1400, Sep. 1974.
[150] R. Rahmaniani, T. G. Crainic, M. Gendreau, and W. Rei, "The benders decomposition algorithm: A literature review," *Eur. J. Oper. Res.*, vol. 259, no. 3, pp. 801–817, Jun. 2017.
[151] K. A. Alnowibet, "A strategic bi-level framework for wind power investment considering grid strength index: A stochastic programming approach," *Sustain. Energy, Grids Netw.*, vol. 31, Sep. 2022, Art. no. 100718.
[152] S. Lumbreras and A. Ramos, "How to solve the transmission expansion planning problem faster: Acceleration techniques applied to Benders' decomposition," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 10, pp. 2351–2359, Jul. 2016.
[153] Y. Li, J. Wang, and T. Ding, "Clustering-based chance-constrained transmission expansion planning using an improved benders decomposition algorithm," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 4, pp. 935–946, Feb. 2018.
[154] S. Lumbreras and A. Ramos, "Transmission expansion planning using an efficient version of Benders' decomposition. A case study," in *Proc. IEEE Grenoble Conf.*, Jun. 2013, pp. 1–7.
[155] O. Alizadeh-Mousavi and M. Zima-Bočkarjova, "Efficient benders cuts for transmission expansion planning," *Electric Power Syst. Res.*, vol. 131, pp. 275–284, Feb. 2016.
[156] A. A. Juan, Y. Li, M. Ammouriova, J. Panadero, and J. Faulin, "Simheuristics: An introductory tutorial," in *Proc. Winter Simul. Conf. (WSC)*, Dec. 2022, pp. 1325–1339.
[157] M. Chica, A. A. Juan, C. Bayliss, O. Cordón, and W. D. Kelton, "Why simheuristics? Benefits, limitations, and best practices when combining Metaheuristics with simulation," *SORT, Statist. Oper. Res. Trans.*, vol. 44, no. 2, pp. 311–334, Feb. 2020.

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