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Generation expansion planning optimisation with renewable energy integration: a review

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Abstract

Generation expansion planning consists of finding the optimal long-term plan for the construction of new generation capacity subject to various economic and technical constraints. It usually involves solving a large-scale, non-linear discrete and dynamic optimisation problem in a highly constrained and uncertain environment. Traditional approaches to capacity planning have focused on achieving a least-cost plan. During the last two decades however, new paradigms for expansion planning have emerged that are driven by environmental and political factors. This has resulted in the formulation of multi-criteria approaches that enable power system planners to simultaneously consider multiple and conflicting objectives in the decision-making process. More recently, the increasing integration of intermittent renewable energy sources in the grid to sustain power system decarbonisation and energy security has introduced new challenges. Such a transition spawns new dynamics pertaining to the variability and uncertainty of these generation resources in determining the best mix. In addition to ensuring adequacy of generation capacity, it is essential to consider the operational characteristics of the generation sources in the planning process. In this paper, we first review the evolution of generation expansion planning techniques in the face of more stringent environmental policies and growing uncertainty. More importantly, we highlight the emerging challenges presented by the intermittent nature of some renewable energy sources. In particular, we discuss the power supply adequacy and operational flexibility issues introduced by variable renewable sources as well as the attempts made to address them. Finally, we identify important future research directions.

Keywords: Multi-criteria decision making; multi-objective optimisation; generation expansion planning; intermittent renewable energy resources; operational flexibility.

1. Introduction

Relentless increase in electricity demand calls for new investments in generation capacity on a regular basis. Efficient planning of new generation units is an optimisation problem that entails answering the following four basic questions so as to ensure that the installed generation capacity adequately meets the forecasted demand growth over a medium to long-term planning horizon:

i. WHAT - the types of generation technologies that will be added to the grid

ii. HOW MUCH - the size of each new generation plant

iii. WHERE - the location of these plants

iv. WHEN - the stage of the planning horizon when the new units must be implemented.

Generation Expansion Planning (GEP) has been the focus of active research since the 1950s when linear programming (LP) models were successfully used to approximate the objective function and the constraints to linear functions, starting with the work of Masse and Gibrat [1]. However, the complexity associated with GEP has risen dramatically due to the variety of generation technology options available to the planners, the numerous stakeholders involved and the diversity of constraints derived from limitations imposed by physical processes, generation capacity, reliability of electrical supply, resource availability and economic considerations, among others. Initially, the aim of GEP was to search for the most economical scheme that could provide an adequate supply of electricity to meet the projected demand growth subject to a set of constraints over a planned period of time. The cost function typically included investment, fuel, and generation costs over the entire planning period. LP models cannot deal satisfactorily with the large number of constraints inherent to a realistic GEP problem. Furthermore, the need for greater accuracy in the modelling uncovered non-linear relationships among the decision variables and the objective function. To overcome this problem, a variety of mathematical optimisation methods was developed and applied to the GEP problem including non-linear programming (NLP) [2], mixed integer programming [3], dynamic programming [4] and decomposition techniques [5–7]. Moreover various approximations and assumptions were made on the model to keep the optimisation problem computationally tractable. For example, aspects of the real-time operations of the power system were often neglected and parameters like spinning reserves and variable heat rates were rarely considered.

As the portfolio of available generation technologies grew and reliability concerns became more stringent for power system planners, the issue of generation capacity addition developed into a highly constrained, non-linear discrete dynamic optimisation problem. Finding satisfactory solutions to such problems requires complete enumeration of combinations of candidate generation expansion options [8]. Since the number of potential solutions grows explosively with the problem size, an exhaustive search is infeasible. Moreover, planning over the long term inevitably gives rise to uncertainties in each step of the modelling process and in the model parameters. In light of these new dimensions, the traditional least-cost objective function alone could no longer drive the generation expansion decision-making process. Additional objectives were taken into consideration to guide decisions beyond the economic perspective. The GEP literature has been thoroughly surveyed in the past. The reviews have mostly focused on the methodological aspect by analysing the models developed to integrate the latest changes in GEP formulation. For example, heuristic and metaheuristic algorithms are known to provide reasonably good solutions within realistic time to problems that are intractable to conventional optimisation methods. Thus, Zhu and Chow [15] thoroughly reviewed heuristic techniques that could potentially be used to solve single-objective GEP problems. Since these methods were emerging at that time, the authors focused on the various heuristic algorithms as well as their merits and drawbacks. Subsequently, Nara [16] reviewed the actual application of the heuristic methods to power system planning. On the other hand, Hobbs [9] performed a literature survey of optimisation models that incorporated new concepts in GEP: demand side management (DSM) programmes as an alternative to additional generation capacity, the presence of uncertainties in several parameters, inclusion of objectives other than the least-cost and the transformation of the electricity production industry from a centralised monopoly to a more competitive market. The latter was further addressed in a review by Kagiannas et al. [17] where the reformulation of GEP optimisation models to accommodate the changes brought by the evolution from a monopolistic electricity market to a deregulated and competitive one were highlighted. Besides, works related to energy planning models with multiple conflicting objectives were reviewed by Voropai et al. [18], Pohekar and Ramachandran [21], Løken [19] and Wang et al. [20].

Over the last two decades, concerns about the likelihood of fossil fuel prices soaring in the long-term, geopolitical changes, energy security and the environmental impact of the fossil fuels have resulted in concerted efforts to reduce greenhouse gas (GHG) emissions worldwide. Consequently, interest in harnessing renewable energy (RE) resources has intensified. In particular, the consistent growth of intermittent RE resources, mainly sun and wind, has been key to the energy transition. In addition to mitigation of pollutant emissions, the integration of variable renewables in the electricity grid caused the emergence of other crucial aspects in the energy planning scenario such as the reliability, flexibility and efficiency of the power system. This paper evaluates different models that have been applied to account for the push towards a carbon-constrained power system. It reports a wide range of research papers relevant to this topic chronologically, starting from the early minor improvements made to existing models, to state-of-the-art models that deal with contemporary challenges. This review also attempts to propose a classification of approaches adopted in this field. In this context, the paper has been divided into four distinct sections to demarcate different approaches that have been employed to address the needs of decision-makers in response to additional requirements of GEP following the integration of RE in the electricity grid. They are as follows:

- traditional methods of integrating environmental considerations as constraints or external costs in GEP
- formulation of GEP as a multiple-objective optimisation problem whereby the ecological footprint is considered as one of the objectives
- techniques used for the inclusion of additional uncertainties in the planning process brought by variable RE sources
- new dynamics introduced by increased integration of intermittent RE resources in the power system and associated challenges experienced by power system planners

The intricacies of the models as well as their strengths and limitations are highlighted. In addition to methodological contributions, we elaborate on future research with new questions that are being asked by planners working in GEP and the corresponding paradigms that must be captured within the planning models to answer these questions.

2. Early environmental considerations

Initially, environmental impacts were handled as constraints imposed on the operation of the power grid by setting tolerance thresholds for the maximum acceptable emission rates. Another common approach integrated the external costs associated to environmental impacts of energy production by the various power plants in the system.

2.1 Environmental constraints

Sirikum and Techanitisawad [8] added air pollutant emission and concentration limits to the usual capacity, power balance, reliability, location and resource availability constraints of their mixed integer non-linear programming (MINLP) model. The authors appended environmental and investment costs in demand side management (DSM) programmes and outage costs into the objective function. The complex MINLP task was decomposed into two parts. Firstly, a combinatorial problem is solved by GA search to determine a feasible generation mix considering only reserve margin, reliability and location constraints. Then, an optimum level of power generation is found by a continuous LP method under demand, capacity and emission constraints. The proposed technique was validated on seven different case studies of a scaled-down model of the Thailand power system with different planning periods and problem sizes. Chen et al. [9] reported a GEP model that integrates a series of low-carbon factors in the objective function, decision variables and constraints. Additional decision variables are used to indicate the level of retrofit of conventional coal plants with carbon capture and storage (CCS) technologies, the implementation of new low-carbon technology plants and the overall CO_2 traded allowance. In addition to the usual cost components, the economic objective function consisted of income from CO_2 trading mechanisms, CO_2 emission penalty and CCS retrofit expenses. Limits are imposed on the total CO_2 emission levels and on the overall tradable CO_2 allowance. The model was tested on the power system of China to reveal the prospects of CO_2 mitigation measures until 2030. Both [8] and [9] considered only thermal power plants and limited scenarios in their analysis.

Cormio et al. [10] applied a linear programming optimisation procedure based on the energy flow optimisation model (EFOM) to support regional energy planning in Apulia located in southern Italy. The total cost of the entire energy system was minimised by a LP procedure over a time horizon of some decades. A financial estimation of the burdens incurred to the environment as a result of the setting up and operation of the electrical power plants was included in the cost objective. Two scenarios that consider different regional economic and environmental policies were simulated. The results showed that the regional policy, aimed at meeting heat and energy loads by various end-use sectors through cleaner technologies, can rely heavily on combined cycle power plants with less contribution from wind power, waste-to-energy, biomass and industrial cogeneration systems. Mejia-Giraldo et al. [11] formulated a linear optimisation model for the GEP where CO_2 emission tax formed part of the cost function to be minimised and annual CO_2 emission reductions were enforced as one of the constraints. When the model was applied to a simplified 11-region representation of the US power system, considering ten candidate generation technologies over a planning period of twenty years, it was found that polluting technologies were largely rejected by the optimisation process. Karaki et al. [12] used tunnel DP to minimise either the cost or the environmental impact or some weighted function of these two functions in the GEP problem. The environmental impact is integrated in the objective function by appending the cost of cleaning the pollutants emitted by the additional generation units. The algorithm divides the problem into stages, where each sub-period of the planning horizon represents a stage having several expansion options. At each stage, the algorithm determines the feasible expansion options of the next stage by adding generation units to the options of the present stage. The number of options is kept within manageable limits by applying tunnel-heuristic rules. A probabilistic production costing simulation is run to determine the expected energy not served (EENS) and the total cost incurred up to that stage for each remaining option. Generation units were added to the power system only if the EENS exceeded a pre-determined threshold.

2.2 Internalisation of External Costs

While models considering environmental impacts as constraints in the form of emission taxes and penalties have the advantage of simplicity as they use existing deterministic models, their main limitation is that they assume a constant average emission level for each generation technology. In doing so, they preclude the impact that operating conditions of thermal power plants have on pollutant emission levels [13]. Another alternative is to consider environmental and health impacts of energy generation, whose costs are generally not directly borne by consumers. For example, every stage in the generation of electricity from coal-fired power plants releases harmful emissions that contribute to environmental and health degradation in the long term as illustrated in Figure 1. However, the low price of coal-generated electricity does not account for the real cost that society ultimately pays. Internalisation of external costs refers to the integration of the environmental and health adverse effects into the decision-making process. Several authors have applied existing energy models to study the internalisation of external costs of power production in GEP. A robust and exhaustive quantification of external costs is required to evaluate, in monetary terms, the impact of emissions from power plants on the environment and the human health [14]. Energy models are ideal tools for such analysis as they are based on strong economic foundations that use rigorous mathematical formulations to process quantitative data and provide numerical solutions related to economics and the environment [15].

Nguyen [16] used MARKAL, a dynamic and multi-period LP model that adopts a bottom-up approach to a generalised energy system, to devise a capacity expansion plan for Vietnam over a 20-year period. The damage costs of CO_2, NO_x, SO_2 and particulate matter (PM) emissions for every generation technology were estimated on the basis of the outcomes of the European Commission ExternE Project [14]. This project tracked the ecological and social footprints of pollution produced during the whole lifecycle of each generation technology. The external costs were then incorporated in the model as an externality tax for conventional fuels and as part of the variable costs for RE technologies. When minimising the overall cost of the expansion plan, it was found that inclusion of external costs caused an increase in the share of RE, natural gas combined cycle and advanced coal-based technologies in the generation mix. The results further indicated that the drop in external costs resulting from the reduction in emissions would be higher than the rise in the generation cost of electricity induced by the adoption of cleaner generation technologies. Rafaj and Kypreos [17] considered the cost of environmental and health damages in GEP for five regions of the world with the Global Multiregional MARKAL model over successive ten-year periods starting in 1990. External costs were derived from the ExternE project and scaled by factors needed by the model, such as regional population density, fuel quality, conversion efficiency and compliance of the technologies with emission control schemes. Modelling results indicated that internalising the external costs of SO_2 and NO_x favoured low-emission technologies and emission control systems in the generation mix. When external costs of CO_2 were introduced in the model, fossil fuel-based generation plants were clearly restrained and RE along with fuel cells were more competitive. Klaasen and Riahi [18] analysed the impacts of internalising the external costs of electricity generation using a combination of three models: MESSAGE, a bottom-up LP model to find the best expansion plan by tracking energy flows through the system; MACRO, a top-down macroeconomic model that evaluates a series of economic parameters required to assess the impact of the external costs on the gross domestic product of the regions under consideration; and SG, a scenario generation model consisting of extensive economic and energy historical datasets for various regions that help in the formulation of different potential scenarios. Like in the previous two studies, it is noted that internalising the external costs of energy production fostered the use of technologies such as clean coal, natural gas combined cycles, fuel cells, wind and biomass in the generation mix instead of conventional fuels. Yet another energy model, WASP-IV, was employed by

Becker and al. [19] to assess the impact of environmental externalities on capacity expansion planning in Israel over the period 2011-2025. Although the objective was to minimise the overall costs subject to several technological and demand constraints, each of the pollutants considered in the study was treated as a separate objective because their valuations could not be integrated into a single function. A wide range of scenarios was simulated by varying the weights assigned to the tax rate for each pollutant. Seven scenarios were shortlisted as potentially providing the best results in terms of pollution reduction-cost ratio for consideration by policy-makers.

3. Managing Conflicting Objectives

Although accounting for the environmental impact of power plants from a financial perspective enabled a more holistic approach to GEP by capturing the indirect costs borne by society on power system expansion, these models had several drawbacks. The methods and the scientific data commonly used to elicit the monetary valuation of the impact are devised on the basis of a wide range of assumptions. It is obvious that uncertainties abound when estimating the costs associated to externalities in the long term. Evaluating the extent of the uncertainties is complex and requires changes to the traditional planning models. Moreover, these models still employ much simplified operating constraints to depict the operational characteristics of the power system. More importantly, as the environmental impacts of power generation became increasingly critical, it was essential to expand GEP beyond an absolute economic analysis exercise. Consequently, the classical formulation of the least-cost GEP was no longer suitable as realistic generation expansion models had to incorporate distinct evaluation attributes as incommensurable objective functions rather than aggregating them in a single economic objective function [20]. Multi-Criteria Decision Making (MCDM) methods enable power system planners to make decisions in the presence of multiple and conflicting objectives that have to be considered simultaneously. These methods help the decision-maker (DM) in identifying the most satisfactory alternative from a set of feasible solutions.

3.1 Multi-attribute decision making

One popular approach used to solve MCDM problems is multi-attribute decision making (MADM), in which a discrete, predefined set of alternatives is compared and evaluated against a set of decision attributes or criteria. The output will usually consist of ranking the alternatives in terms of their total preferences when all the decision criteria are considered simultaneously. Diakoulaki et al. [21] stated that the main strength of MADM models is their ability to structure problems that are not clearly defined and to provide a good understanding of their components. Their popularity also stems from their simplicity. They further make the task of the DM more comfortable by presenting a set of detailed alternatives with an order of precedence as opposed to models where complex mathematical functions are involved. In addition, these methods have the ability to consider both quantitative and qualitative criteria simultaneously. In his literature review of MADM methods applied to energy planning, Løken [22] distinguished between three types of MADM models. The classification is summarised in Figure 2.

Value measurement methods assign a numerical score to the alternatives so as to arrange them in an order of merit. The two most common value measurement models are Multi-Attribute Utility Theory (MAUT) and Analytical Hierarchy Process (AHP). MAUT aggregates the criteria into a utility function that scales the importance of each criterion from 0 to 1 based on the preferences of the DM. It then evaluates the alternatives and assigns weights with the purpose of trade-off between attributes [23]. The alternative with the best value of the aggregated function is considered as the optimal one. MAUT has not been extensively applied to the energy planning field mainly due to the requirement of the DM to interact dynamically with the model as well as the complexity of computing some parameters involved in the algorithm [24,25]. AHP has been widely applied to decompose the GEP problem into a hierarchy with objectives occupying the top position, criterions and sub-criterions at levels and sub-levels, and decision alternatives at the bottom of the hierarchy [25–28]. The hierarchical tree is used to weigh the relative importance of the criteria using an assessment scale. The alternatives are then scored and ranked based on the subjective criteria.

Goal programming (GP) uses mathematical algorithms to find alternatives that are closest to achieving predefined goals for each objective function. In many cases, GP is applied as the first step in a multi-criteria process involving numerous alternatives to eliminate the most unsuitable ones in an efficient way [22]. Two GP techniques have been commonly applied to solve energy planning problems: Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) and step method. TOPSIS compares alternative solutions with two artificial ideal and worst solutions. It then selects the alternative that is closest to the ideal solution and furthest to the worst solution in terms of Euclidean distances [25]. Kaya and Kahraman [29] proposed a modified fuzzy TOPSIS approach to find the most appropriate energy technology based on various technical, economic, environmental and social criteria. The weights of the selection criteria were determined using a fuzzy AHP. The stem method uses an ideal point as a goal and then applies the Tchebycheff norm as a distance metric to minimise the maximum distance from the goal [30]. Once the best alternatives for the objective functions are obtained, the DM can formulate preferences. According to Pokharel and Chandrashekar [31], the step method allows direct comparison among alternate solutions, thereby helping DMs to experience the impact of their preference for an objective function on the solution. Nevertheless, they should be able to articulate their goals precisely at each iteration.

The final type of MADM model, known as outranking models, compare the alternatives among each other with respect to each attribute in order to determine the best alternative for each pair [25]. They do not output a single best alternative but the degree of dominance of one alternative over another. Two outranking approaches, Preference Ranking Organisation METHod for Enrichment Evaluation (PROMETHEE) and Elimination Et Choix Traduisant la Realité (ELECTRE), have been successfully applied to many GEP studies. In both methods, a pairwise comparison between the alternatives is performed to identify and retain the non-dominated alternatives on the basis of the selected criteria. PROMETHEE additionally considers the degree to which the non-dominated alternative is better and uses this piece of information to rank alternatives. Newer versions of PROMETHEE and ELECTRE with improved features were subsequently developed. Pohekar and Ramachandran [25] reviewed more than 90 published papers that dealt with the application of MADM techniques to sustainable energy planning. The authors observed that AHP is the most popular method followed by outranking techniques, PROMETHEE and ELECTRE. Wang et al. [32] performed a thorough review of the published literature on MADM applications in sustainable energy systems focusing on the different criteria considered in the formulation of the problem. Løken [22] illustrated that a multitude of MADM techniques have been used to solve energy planning problems. Each method has its own advantages and drawbacks and the choice of the methodology used depends on the DM. The author asserted that 'black-box' models should be avoided as they are poorly understood by DMs. Several studies have also combined two or more methods to exploit the strengths of each algorithm.

3.2 Multi-Objective Decision Making (MODM)

One of the key assumptions of MADM techniques is that the DM is aware of the alternatives *a priori* and can rank them using an explicit model of his preferences. Moreover, MADM methods focus on problems with discrete decision spaces, characterised by a limited number of predetermined alternatives. The task of the DM is therefore eased as compared to models involving complex mathematical functions. Unfortunately, due to the complexity of GEP, most decisions must be made in an environment where the available alternatives are not known precisely beforehand and the number of potential decision alternatives is large. In these circumstances, it becomes difficult for the DM to elicit preferences. MODM is the other basic approach of MCDM, where the alternatives are not predetermined but instead a set of objectives functions are optimised subject to a set of constraints [25]. One characteristic of models used to solve MODM problems is that they output a set of alternatives with different trade-offs which are equally good mathematically [33]. In other words, these Pareto optimal or non-dominated solutions, cannot be improved in any objective function without deteriorating their performance in at least one of the other objective functions [34]. Figure 3 illustrates the concept of Pareto optimality in a problem with two objective functions. MODM models provide decision support to DMs by rationalising the comparison among different alternatives in order to allow the DM to grasp the inherent correlations among the distinct objectives for selecting a satisfactory compromise solution [20].

One of the earliest efforts to consider multiple objectives simultaneously in GEP was performed by Climaco et al. [35]. The model optimised three objective functions in the form of total expansion costs, reliability and environmental impacts subject to load requirements, operational capacity and fund availability constraints. The authors used an interactive tri-criteria LP tool, TRIMAP, to help the DM in progressively learning the set of non-dominated solutions. TRIMAP allows the DM to grasp in an interactive way, the boundaries of the non-dominated surface so that he can guide the model to focus on the regions where the solutions better relate to his preferences. The results demonstrated that among the three generation technologies investigated, minimum cost was achieved with a mix of nuclear and coal units, whereas the minimum environmental impact occurred when additional units were oil-based. Martins et al. [36] extended the interactive multi-objective LP model based on TRIMAP by integrating DSM as a separate power generation group defined by the same type of parameters as the other generation alternatives. Three objective functions were considered: the total expansion cost, the environmental impact associated with the additional installed capacity during the planning period and the environmental externalities associated with the energy output. Five sets of constraints dealing with the reliability of the supply system, the generating capacity of power plants and the DSM unit, the total new generation capacity, and pollutant emissions were imposed on the system. When the model was simulated with realistic data, the resulting expansion plans exhibited a high diversity of generation technologies.

Chattopadhyay et al. [37] evaluated the benefits of integrating DSM options in capacity expansion planning considering the annual system cost, the CO_2 emissions and the reliability of the system in terms of loss-of-load expectation (LOLE), as its three objective functions. The model adopted a compromise programming approach deriving optimal solutions in which the distance of each objective from its ideal value was minimised. Depending on the type of savings achieved, each DSM option was categorised as one of four possible supply-side resources. The methodology was validated on an Indian utility over the 1990-2000 planning horizon. Linares and Romero [38] integrated decision-makers' preferences into a GEP problem featuring an overarching cost objective along with several environmental objectives subject to various power flow, generation capacity and resource availability constraints. The economic objective comprised of investment, decommissioning, operation and maintenance costs while the environmental objectives aimed at minimising the emissions of CO_2, SO_2, NO_X and radioactive wastes. The authors formulated a compromise programming model based on preferential weight elicitation by the decision-makers using AHP. When tested on the Spanish electrical power network with a planning horizon extending until 2030, the best compromise solutions involved a higher share of renewable and gas-based technologies with coal and nuclear technologies accounting for less than 10% of the generating mix.

Unlike the previous attempts to solve the GEP problem that were LP-based and used continuous variables, Antunes et al. [20] adopted a multi-objective mixed integer linear programming (MOMILP) model which integrates the discrete nature of the additional generation capacity required for each technology during the planning horizon. An interactive approach, whereby the DM intervenes to direct the computation phase towards his preferences, is applied to cater for the increased computational complexity resulting from considering the modular capacities of generation units. The same three objectives used by Martins et al. [36] were considered. DSM programmes implementing peak demand shaving were modelled as an equivalent DSM generating unit. As such, investment and operating costs as well as loss of revenues due to decrease in sales of electricity resulting from DSM programmes are included in the cost objective function. Mavrotas et al. [39] claimed that applying an interactive procedure as a strategy to solve MOMILP problems does not generate the entire set of efficient solutions, even for small-scale problems. To curb this shortcoming, the authors suggested a mixed 0-1 multi-objective LP model based on modified version of the branch and bound algorithm. It has the ability to generate the whole set of efficient solutions by implicitly enumerating all potentially efficient solutions and then eliminating the non-efficient ones through pairwise comparison. Annual electricity production cost and yearly SO_2 emissions were minimised by the model subject to capacity, minimum load requirements, demand satisfaction, natural gas supply and reserve margin constraints.

Aghaei et al. [34] formulated a MOMILP model to simultaneously optimise five objectives: total costs, CO_2 emissions, fuel consumption, fuel price risk and system reliability. Total costs is an all-encompassing objective function that involves cost of DSM programmes, benefits of RE generation and cost of wind intermittency in addition to the usual investment, operation and maintenance costs. Outage cost is used as a metric to represent the reliability of the system and is evaluated using the EENS index. Simulations carried out on three cases with different sets of weights for objective functions showed better results as compared to conventional and augmented ε-constraints methods. The authors proposed another multi-objective model for multi-period GEP problems based on a Corrected Normal Boundary Intersection (CNBI) method to minimise the total cost and the amount of CO_2 emissions and maximise the reliability of the system [40]. The latter objective function is evaluated using an analytical probabilistic method that computes Z values which are associated to the expected surplus of available generation. The CNBI method outputs efficient solutions that are evenly spread on the Pareto front while ensuring that dominated solutions are not produced. The efficiency of the model was demonstrated on three test cases with seven types of generating technologies in a 6-year planning horizon consisting of three 2-year stages and produced reliable portfolios of resources.

3.3 Heuristic algorithms

For most real optimisation problems, the search space is so huge that an exhaustive search to come up with an optimum solution is not envisaged. The complexity of multi-objective GEP problems has caused an upsurge in the development of heuristic algorithms due mainly to their inherent ability to find many alternative solutions under different boundary conditions within an acceptable time. While their principal weakness is that they cannot guarantee optimality of their solutions as opposed to exact methods, heuristic methods are normally used as part of a global procedure to ensure that optimum solutions are found. The multi-objective optimisation models for GEP that have been reviewed so far in this paper involved unique formulations involving single objective optimisation. They determine one Pareto solution at a time, and each solution is obtained through single-objective optimisation. Evolutionary optimisation algorithms have been recognised to be well-suited for multi-objective optimisation as they work with a population of solutions in each iteration [41]. Therefore, they can search for several Pareto optimal solutions simultaneously in a single run to provide the DM with an insight into the different trade-offs among objectives.

Kannan et al. [42] analysed two different formulations for the GEP problem using the elitist Non-dominated Sorting Genetic Algorithm Version II (NSGA-II). Each formulation contained two objective functions. The first one aimed at minimising both the total cost and the sum of normalised constraint violations while the second one was designed to minimise investment costs and maximise the system reliability. NSGA-II implements elitism so as to retain all non-dominated solutions and preserves diversity among the solutions through an explicit mechanism based on the crowding distance [43]. The authors encountered convergence problems when implementing the standard NSGA-II algorithm on the GEP problem. The overall additional generation capacity required by an expansion plan was found to be excessively sensitive to small changes in the decision vector. A Virtual Mapping Procedure (VMP) was introduced to modify the solution representation into dummy decision variable which ranks the candidate solutions according to their additional generation capacity in ascending order. In doing so, the number of decision variables was significantly reduced, resulting in much less computational time and memory requirements. The proposed models were compared with a GA-based weighted-sum model on a test system with 15 existing power plants for a six-year planning horizon divided into three equal sub-periods. Both models produced the Pareto-optimal front in a single simulation run and in considerably less time than the baseline model.

4. Uncertainty Handling

The GEP models examined to this point are deterministic in the sense that they use best available predicted values of parameters and input data, overlooking uncertainties that inexorably arise in the real world. Long-term planning of power systems have always been characterised by uncertainties. Traditionally, they were associated with parameters of the models such as the forecasted load, cost and availability of fuel, economic growth of the country, plant construction time, generation outages and regulatory policies. Figure 4 summarises the conventional uncertainties in GEP. The new paradigm in power systems planning, driven by growing environmental concerns, has introduced additional uncertainties, including the uncontrollability of intermittent renewable energy resources, governmental regulations for emissions, the response of customers to DSM programmes and advances in generation technologies. The large number of uncertainties further exacerbates the complexity in GEP, due to additional computational power requirements along with the difficulty in modelling the combination of their occurrences. Consequently, they have a profound effect on optimal decision making for power system planners. It is therefore imperative to integrate a systematic and consistent treatment of the various sources of uncertainty in the decision-making process so as to mitigate risks [7]. For this purpose, methodologies have been developed to address uncertainties in GEP in a computationally tractable manner. The most commonly used ones are scenario analysis, sensitivity analysis and probabilistic analysis [44]. These techniques have been derived from deterministic models and adapted to take uncertainties into account. Robustness and flexibility are the metrics that evaluate the effectiveness of the models to withstand uncertainties. The former pertains to the degree to which a plan is affected by changes in parameters while the latter is the inherent capability to modify a plan so as to accommodate and successfully adapt to such changes [45].

Scenario analysis generates a range of potential futures, referred to as scenarios, by making different assumptions about the future with varying forecasts for key uncertain variables. An expansion plan for the planning horizon is then generated for each scenario. This technique enables the DM to anticipate a broad range of realistic futures and to identify promising generation technology options that appear in many scenarios. However, a comprehensive discrimination of alternative plans would require that weights be assigned to individual scenarios to represent their perceived likelihood of occurrence and that the scenarios be mutually exclusive and exhaustive [46]. An alternative to scenarios is offered in the sensitivity analysis technique, which identifies sensitivities or areas of vulnerability in a problem. Initially, several optimal plans are developed on the basis of some assumptions. Subsequently, some key uncertain parameters are varied and the performance of each plan is studied under the new conditions. This technique is an appropriate tool for identifying the model parameters that have most impact on the output variables and for determining the parameter ranges over which the solutions remain optimal. A major shortcoming of scenario and sensitivity analyses is that they do not provide much information on the flexibility and robustness of the plans [46]. Moreover, they generate evidence on the extent of the consequences of changes in variables, but overlook the likelihoods of these changes. Probabilistic analysis address these limitations by allocating probabilities for the occurrence of uncertain variables and then determining the optimal output through a range of analytical approaches like Monte Carlo simulation and stochastic programming. The latter technique represents the uncertain data by scenarios generated in advance. In its elementary form, stochastic programming finds an optimal solution that produces the best weighted average objective function value over all scenarios. In realistic applications where multi-period planning is performed, the number of scenarios increases exponentially with the number of periods. To keep the problem tractable, scenario sampling is used [47,48]. More advanced versions include risk considerations such as penalties for constraint violation and probabilistic guarantees [49].

5. Integration of Intermittent Renewable Energy

RE sources have been the predominant drivers of the green revolution during the last decade, spurred by a combination of technological developments, innovation, decline in costs and government policies. In addition to offering emission-free electricity, RE ensures long-term energy security to countries. For these reasons and in the face of stringent carbon emission policies, many countries are considering the adoption of a larger share of renewables in their electricity mix. A series of compelling governmental actions are commonly applied to foster the development of RE. These include carbon taxes applicable to GHG emissions, feed-in tariffs guaranteeing lucrative wholesale prices for RE and tax credits for renewable electricity generation. The International Energy Agency (IEA) forecasts that the worldwide shares of RE technologies will increase to 57% of the load served by 2050 [50]. Intermittent RE sources, notably wind and solar, are expected to account for an overwhelming majority of this share. Nevertheless, operation and planning of existing power systems have traditionally centred on fossil fuel generation that can be adjusted as required by varying fuel inputs to match variability on the load side. Integrating intermittent RE generation in the power system brings variability on the supply side as well. These technologies are characterised by fluctuations in the power output that can neither be fully anticipated nor controlled by the operator. Fluctuations in the RE resource availability can be cyclical, where they are related to diurnal and annual cycles or stochastic, where fluctuations cannot be forecasted based on historical data. Consequently, the integration of RE in the generation mix introduces more uncertainty in the power expansion problem. The task of balancing the supply and the load becomes more challenging. Likewise, ensuring supply adequacy so that there is enough generating capacity installed to satisfy peak load requirements plus a reserve margin turns out to be more complex. In-depth reviews of studies that determine the feasibility of integrating large amounts of wind power in power systems and the resulting operational impacts have been performed [51,52].

5.1 Power supply adequacy

Probabilistic metrics can provide meaningful insight into supply adequacy. Loss of Load Probability (LOLP) and LOLE measure the probability and number of days respectively, on average per given period, that the available capacity is likely to fall short of demand [53]. Besides these two capacity-related indices, EENS or expected unserved energy (EUE) evaluates the extent of power failure by conveying the expected amount of energy not supplied by the system over a specified time period. Conventional generation units are dispatchable, implying that they can be turned on and off or their outputs can be adjusted at will to match the load. Notwithstanding some mean outage rate, these units can rely on their full capacity when planning the generation capacity needs of a power system. In contrast, the intermittent nature of wind and solar energy makes them non-dispatchable and unable to count on their full rated capacity for capacity planning. Proper GEP must therefore determine the effective contribution of variable power sources to the overall system capacity. Capacity value or capacity credit of a generation unit is often used by planners to determine the firm capacity it adds to the grid. It quantifies how much extra load can be served by the power system due to the addition of the unit while maintaining existing levels of reliability. It is defined as the ratio of the conventional capacity displaced to the rated capacity of the variable unit. The extra load that can be accommodated in the system due to the intermittent unit is termed as the effective load carrying capacity (ELCC). Figure 5 shows a graphical illustration of ELCC, where the addition of a new generation plant allows the power system to service an additional load of 400 MW while keeping the LOLE unchanged at 1 day in 10 years [53]. Several reviews of the different techniques to evaluate the capacity credit of RE sources exist in literature [53–56]. The most commonly used methods are briefly described here.

One of the first attempts to devise a probabilistic method to compute capacity credit of future wind power plants was performed by Van Wijk et al. [57]. The LOLE of a baseline power system which excluded the wind power plant is first calculated. Then, the LOLE for the power system with the wind power plant is computed after subtracting the predicted hourly wind power generation from the projected hourly load. Conventional capacity is then removed iteratively until the initial LOLE is achieved. The difference between the conventional capacities found in the two cases represents the ELCC of the proposed wind power plant. It was found that the capacity credit decreased with increasing wind power penetration, expressed as a percentage of the projected peak load. For example, 100 MW of installed wind power, corresponding to a penetration level of 0.9%, would have a capacity credit of 28%. In contrast, 2000 MW of installed wind power representing an 18% penetration level would result in a capacity credit of 13.6%. It was also shown that dispersing the wind turbines over a large geographical area improves the capacity credit. A slightly modified version of the methodology proposed by Van Wijk et al. [57] was recommended as the preferred method to determine capacity credit by a task force on "Capacity Value of Wind" set up by the IEEE Power and Energy Society [58]. Again, the power system without wind power is considered first. The capacity and forced outage rate of each generator is convoluted through an iterative algorithm to generate the capacity outage probability table (COPT) of the power system. The probabilities from this table are combined with the hourly load profile of the system to produce the hourly LOLPs, from which the annual LOLE can be easily derived. The loads can be adjusted to ensure that the LOLE meets the reliability standards. The same procedure is followed to find the LOLE for the power system with wind capacity by treating the wind power as a negative load in the hourly load time series. The load data is increased incrementally across all hours using an iterative process until the initial LOLE is reached. The net increase in peak load then corresponds to the ELCC. The task force highlighted the importance of using reliable hourly wind and load data from the same years so that the methodology captures the underlying correlation between wind and load. This observation was corroborated by the task force set up by the North American Electric Reliability Corporation (NERC) to investigate the integration of variable generation. In [59], the task force stated that ELCC calculations must be based on long-term variable generation output data just like LOLP calculations for conventional plants depend upon accurate long-term performance data. It is also important that all wind and solar data relating to variable generation is synchronised with each other and with the load data as they are dependent on the weather. Use of asynchronous data will miss the relationship between the variable resources and the load leading to erroneous results.

The multi-state model is an approximate calculation method for capacity credit that adopts a probabilistic representation of the intermittent generation plant. The approach is inspired from the two-state model of a conventional generation unit which can be either on or off depending whether there is an outage or not. D'Annunzio and Santoso [60] adopted this approach by considering wind generation in the calculation of the COPT as a multi-state unit that can exist in one or more partial capacity outage states with some individual probability. A histogram of the wind output power, obtained from historical resource profile and generation data, is segmented into different generation capacity bands with each band representing a state. The probability of partial capacity outage for each state is then found. A parameter is also determined from a graph depicting the dependence of LOLE on the load. A mathematical function finally combined the probabilities with the parameter to compute the ELCC. Strbac et al. [61] studied the impact of wind energy on the UK electricity market using a modified version of the multi-state method. It was observed that wind power displaced conventional generation capacity only to a modest extent, with capacity credits ranging from 34% for 5 GW of installed wind power to 20% for 25 GW. Calculation of capacity credit was based on an LOLP of 0.09 corresponding to the established capacity reserve margin of 24%. The intermittent behaviour of wind was derived from the frequency distribution of wind generation obtained from the past annual 0.5-hourly data of various wind farms. The authors noted that the LOLP-based capacity credit calculation does not provide any information about the frequency and duration of potential power shortages. To incorporate these parameters, a Markov Chain model was used to compute the transition rates and frequencies of departures for each generation capacity state of all units. The results showed that significant reductions in wind capacity credit are expected due to low wind conditions. Thus, a single day of no wind generation availability across the entire wind source would reduce the capacity credit of wind by 20%. These factors suggested that large conventional back-up capacities must be retained in the system to maintain the same level of supply security. The IEEE task force emphasised on the shortfall of information regarding wind-load correlation in the multi-state model [58]. Applying the model in regions marked by major seasonal and diurnal fluctuations in wind energy availability and demand can result in substantial inaccuracies in the computation of capacity credit of wind power.

Brouwer et al. [62] conducted a review of the literature on the impacts of power generation from intermittent renewable sources and noted that most studies performed after 2005 report a capacity credit ranging from 8% to 28% at 10% penetration level of intermittent energy sources. It was noticed that these values are generally lower than those reported in studies carried out before 2005, where the capacity credits exceed 15% at 10% penetration level. The authors suggested that the divergence may arise from the calculation methodology applied in older methods which for example, used time steps larger than 1 hour. It was also observed that studies conducted in large interconnected areas, such as Europe, reported higher capacity credits and that multiple years of data are necessary for an accurate quantification of capacity credit.

5.2 Operational flexibility

At high levels of intermittent generation penetration, it becomes imperative for GEP process to ensure not only that there is adequacy of generation capacity to meet the demand at all times but also that there is sufficient operational flexibility in the power system. The latter refers to the ability of the power system to quickly adjust supply to match predicted and unpredicted fluctuations in net load, where net load represents the remaining demand that must be supplied by the conventional generation fleet if all of intermittent energy is to be utilised [63]. At small levels of variable RE penetration, the power system is able to absorb fluctuations in renewable output because these fluctuations will be dwarfed by those commonly encountered on the demand side [64]. At higher penetration levels however, the extent and frequency of variability in net load escalates. As clearly illustrated in Figure 6, high variable RE penetration is usually marked by steeper ramps, shorter peaks and lower turn-downs [65]. Accordingly, the generation fleet of the power system must be endowed with conventional resources that possess the following crucial technical requirements to be able to follow the net load adequately: fast cycling and ramping capabilities, efficient partial load operation as well as sufficient reserve capacity. The cycling capability of a generator is its ability to start-up and shutdown frequently and rapidly [66]. Ramping capability refers to the speed at which a generating unit can change its output while partial loading efficiency pertains to the efficiency of the generator when it is operated at various output levels lower than its rated capacity [66]. Reserve capacity was already needed in traditional GEP to handle the possibility of insufficient supply capability due to unforeseen increase in demand or unexpected unavailability of some generation capacity. Increasing the share of RE in the grid calls for additional reserve requirements to cater for the enhanced uncertainty in the net load arising from inaccurate forecasting of the RE output. In many cases, DSM programmes have proved to be effective as a source of supplemental reserves in response to unexpected outage of a large generation unit or substantial decrease in intermittent generation within a short period. In large geographical areas, the availability of interconnections to adjacent power systems can provide additional flexibility to export excess or import supplementary power. In light of these requirements, simply having the required generation capacity may not be adequate for system security if that capacity is not flexible enough to respond to system variability [67]. It is important to note that operational flexibility should not be confused with uncertainty flexibility mentioned in Section 4, which relates to the power system's ability to adapt to changes in uncertain parameters.

Contemporary GEP therefore needs to assess whether the power system is flexible enough to successfully integrate renewable generation targets at all stages of the planning horizon. Inadequate flexibility may force power system operators to frequently curtail intermittent generation, thereby decreasing revenues and making it more difficult to meet emissions targets. There is currently a lack of established metrics and methods to perform tasks involved in GEP with high levels of RE integration: to quantify flexibility and its associated cost, to determine the degree of flexibility required, and to find the optimal generation mix in order to meet the targeted degree of flexibility. More specifically, GEP studies that delve into large-scale integration of intermittent generation considering adequacy of both generation capacity and generation flexibility are practically non-existent.

One of the early methods that provided an indication of operational flexibility in a power system was by determining the reserve capacity. Several methods have been devised to evaluate its optimal value for varying degrees of RE integration. Söder [68] found the margins of instantaneous, slow and fast reserves available on an hourly basis in the daily operation planning of a wind-hydro-thermal power system. The reserve margins were computed from the standard deviation of the system load and wind speed forecast errors and ramp rates of thermal units. Doherty and O'Malley [69] combined uncertainty in load and wind power forecasts with outage probability to calculate reserve margin requirements for a desired level of system reliability defined by the acceptable number of load shedding events annually. Ela et al. [70] broadly reviewed other studies to quantify reserve needs for power system with high RE penetration. Many of them used a two-stage stochastic programming model whereby numerous wind generation scenarios were simulated and unit commitment solutions were obtained reliably for each of the scenarios.

Several factors affect the degree of operational flexibility of the grid. They include the level of penetration of intermittent generation sources in the grid, the correlation between intermittent generation and total load and the outage rate of conventional generation resources [71]. All these dependent parameters contribute to the increased uncertainty and difficulty in flexibility computations. A classification into three categories of increasing complexity was proposed in a state-of-the-art review of existing metrics for flexibility assessment [65]. Metrics in the first category provide a glimpse of the system flexibility. In this regards, Yasuda [72] developed a flexibility chart that presents an easy and non-technical way to identify potential flexibility resources in a power system at a glance. The chart indicates the percentage of installed capacity of five potential sources of flexibility, namely pumped hydro, hydro, combined heat and power, combined cycle gas turbine and interconnection, relative to peak demand. Nevertheless, this method is indicative only as it does not allow computation of the overall power system flexibility. Besides, capacity is not a good pointer to flexibility.

The second category of metrics takes into account the time-specific nature of flexibility to provide a more meaningful appraisal of the system response to supply-demand imbalances [65].The IEA devised the Flexibility Assessment Tool (FAST) to provide a measure of the flexibility requirements and resources in different areas of a power system with varying levels of RE integration [64]. FAST has the benefit of being computationally simple as it basically consists of a four-step procedure that relates to key questions pertaining to the resources of the power system. Initially, the ramping capabilities of four already present flexible resources, namely dispatchable plants, interconnection, storage and DSM, are assessed over four different balancing time frames ranging from 15 minutes to 36 hours. Then, the extent to which aspects of the power system will limit the availability of the four flexible resources is determined. Thirdly, the maximum flexibility need of the system is computed from various parameters including the fluctuations and forecast errors in demand, variable generation output and unexpected outages. Finally, the availability of flexible resources is compared with the flexibility needs of the system to establish the extent to which intermittent RE capacity can be reliably balanced by the current. The IEA presented a refined version of their flexibility assessment tool in 2014, FAST2. It enables flexibility assessment on many timescales by processing synchronised historic time series of variable generation output and load data within an interactive environment [73]. FAST2 requires additional data such as flexibility features of conventional units together with interconnection and DSM information. It evaluates the power system flexibility by determining the maximum change in supply/demand balance that the system can meet at a given instant [65]. It also has the capability of computing the level of intermittent RE penetration at which additional flexibility will most likely be needed [73].

The third category of flexibility assessment tools adopts a holistic approach of the power system to incorporate its physical, institutional and interconnection characteristics in the evaluation [65]. The complexity of the analysis implies that data requirements for this category of metrics are substantial. Ma et al. [74] devised an “offline” flexibility metric that estimates the flexibility level of the overall power system along with those of individual generators in the system. The flexibility of each generator is calculated using its ramp rate and adjustable capacity given by the difference between its maximum and minimum generation levels. It is then normalised with respect to the maximum capacity of the plant. The flexibility index of the whole system is obtained from the weighted sum of the indices of individual generators.

Some flexibility metrics have been derived from techniques applied to obtain established generation adequacy indices. Thus, a task force set up by the NERC to study flexibility in power systems used the ELCC methodology to propose an Effective Ramping Capability (ERC) metric [59]. Just like ELCC estimates the contribution of a new unit to the overall firm capacity of a power system, ERC approximates the contribution of a unit to the overall ramping capacity of the power system. ERC basically specifies the ability of a generation unit to ramp in a given direction over various time scales. Its computation follows that of ELCC except for two things. Firstly, the highest ramp in a given direction and time scale is considered rather than the maximum rated output of the unit. Secondly, the ramping availability rate of the unit replaces its forced outage rate to represent the probability that it will be able to supply its maximum ramp at any instant. It is calculated from historical dispatch data at a small resolution.

Lannoye et al. [75] recommended insertion of a flexibility evaluation stage following the capacity adequacy assessment step in long-term GEP of power systems with a high share of intermittent RE. To this end, the authors drew on the LOLE methodology to devise the insufficient ramping resource expectation (IRRE) metric. The latter quantifies the risk that the power system will face a shortage of ramping resources to follow changes in net load over various time horizons. Adequacy of ramping resources can only be assessed if an appropriate unit commitment mechanism is applied to dispatch the resources in the system. This facilitates the comparison of the extent of ramping capability available in the power system with the ramping requirement at different time steps. Time series data of conventional and variable RE generation synchronised with load data for selected time horizons are processed to get time series data about net load ramping requirements. In a similar way to the creation of a COPT for LOLE calculation, an available flexibility distribution (AFD) is then generated for all upward and downward ramping resources from plant operational characteristics for each time horizon. By comparing the AFD with the net load ramp requirements, the probability that the power system lacks flexibility to meet each positive or negative ramp over each time horizon is computed and summed to obtain the overall system IRRE. The algorithm was tested on a 6-unit power system to underline the time horizons when the system is more vulnerable to deficiencies in ramping ability and to reveal the effect of increased variable RE penetration on overall system flexibility. In view of the substantial data and computational complexity involved in IRRE computation, a high-level methodology was subsequently proposed by the same authors to make the IREE calculation more manageable for stakeholders with limited exposure to RE integration [76]. Simplicity of the power system operations is achieved by assuming that units are dispatched on the basis of energy cost merit order. As a result, data requirements are constrained to synchronised time series of load and variable RE production for the smallest time horizon considered together with the features of individual flexible resource units. Once time series of the available flexibility are calculated from this data, the ability of the system to follow net load ramps can be determined. Hence, a period of flexibility deficit (PFD) metric can be deduced to give an indication of the number of periods when the system experiences a flexibility deficit within a given time horizon.

The Electric Power Research Institute (EPRI) elaborated an integrated long-term planning framework for power systems consisting of four levels of flexibility assessment that may arise at different stages of the planning process [86]. A multi-level assessment tool, InFLEXion, was developed to facilitate understanding of flexibility needs of the power system by decision-makers through four different metrics. Besides IRRE and PFD, expected unserved ramping (EUR) and well-being assessment are used to appraise flexibility issues in planning decisions. EUR is analogous to the EUE index used in quantifying capacity adequacy in the sense that it refers to the total magnitude of the flexibility shortage instead of its total duration. It represents the aggregate ramping deficits over a specific time horizon based on large ramps up to a certain percentile. Well-being analysis, first coined by Billinton and Fotuhi-Firuzabad [87], combined probabilistic and deterministic indices to express the well-being of a power system into one of three states: healthy, marginal or at risk. In a similar way, InFLEXion maps the frequency and magnitude of flexibility shortages over a particular period through PFD and EUR respectively, to determine whether a system is in a user-defined safe, warning, or dangerous state [86].

Hargreaves et al. [88] explored a novel stance on the flexibility problem. The authors observed that previous studies had focused mostly on characterising operating issues of the power system and did not address the cost implications of adding flexibility resources to the system. Consequently, a stochastic production simulation model, known as Renewable Energy Flexibility (REFLEX), was developed. It tracks the distribution of system load, dispatch, generation, outage and ramping conditions using synchronised historical data to capture unit commitment, forecast errors and ramping requirements. Various reliability and flexibility metrics, including EUR, EUE and Expected Overgeneration (EOG) are derived to characterise expected system flexibility and adequacy shortages. Penalty values are assigned to each violation based on the value of unserved energy for upward violations and excess generation for downward violations. REFLEX then performs an economic analysis to evaluate optimal flexible capacity investments by trading off the cost of new flexible resources against the gain achieved by avoiding flexibility violations. The proposed framework enables power system planners to evaluate the integrity of their power system in the face of challenges introduced by intermittent RE integration and to determine the least-cost capacity planning strategy to meet these challenges in various timescales.

5.3 Recent long-term capacity planning models

In the wake of the increased integration of intermittent RE sources in the electricity grid, it is essential for the new long-term GEP paradigm to capture the operational characteristics of the generation fleet and gain insight into the actual dispatch practices in order to integrate flexibility issues. As observed throughout this paper, traditional GEP models used to simply ignore short-term system operational details or account for them by using highly simplified assumptions. For example, cycling and load following features of individual power plants are often overlooked and the chronology of demand is entirely absent in the load duration curve used to approximate the annual load profile. Recent literature has mostly been directed towards finding ways to incorporate short-term power system operational details in GEP while ensuring that the problem remains computationally tractable. Typically, methods developed for this purpose integrate unit commitment and dispatch processes within the existing GEP models. Ma et al. [77] proposed a Unit Construction and Commitment (UCC) algorithm to find the optimal generation portfolio that satisfies the flexibility requirements at a given wind penetration level. The UCC algorithm represents one of the first efforts to capture flexibility within GEP by integrating short-term operational decisions in the long-term planning. Rather than considering a fixed set of existing generating units and their operational costs as traditionally done in unit commitment planning, the UCC has the possibility of adding new generation plants along with their associated investment costs. Limitations of this work include the use of a deterministic methodology to model stochastic wind energy output and inability to study intra-hour variations in intermittent generation and demand. Palmintier and Webster [84] merged GEP with unit commitment planning in another study to capture the influence of flexibility on long-term capacity planning. Computational tractability is ensured by clustering generators that share the same technical characteristics in terms of ramp rates, heat rate as well as minimum and maximum operating levels. A one-year simulation conducted at an hourly resolution on a 205-unit power system indicates not only that flexibility significantly affects generation mixes but also that ignoring flexibility can lead to generation portfolios that are infeasible to operate. A major drawback of this methodology relates to its deterministic approach to reserves. Once reserve constraints are satisfied, the model does not investigate scenarios where reserves may be inadequate due to capacity outages and forecast errors. Batlle and Rodilla [78] incorporated the cycling features of thermal units in a traditional least-cost optimisation GEP model. The unit scheduling process considered start-up times and minimum generation levels of units together with usual cost functions in determining the most appropriate technologies to provide power at various intervals of the planning horizon. The main problems of this method relate to its unique economic objective function and the absence of uncertainties in its formulation. Jin et al. [79] attended to the issue of uncertainties by proposing a stochastic GEP model where long-term uncertainty in the wind resource is introduced by using multiple scenarios consisting of weekly time series of hourly wind power output data. On the other hand, short-term errors in wind forecast are compensated by a calculated amount of operating reserves. Power plant operational details are included through a simple unit dispatch model regulated by economic aspects and constrained by ramping characteristics of generators. However, due to the computational complexity, the model can handle only a subset of weekly wind power scenarios. Other shortcomings pertain to the relatively basic treatment of short-term wind forecast errors and to the representation of operational constraints of generating units by ramp rates only. Flores-Quiroz et al. [80] reduced the computation complexity by using a decomposition technique that allows for the inclusion of integer variables in the various stages of the GEP. A wide range of unit operational characteristics appear as constraints in the model. The main deficiencies of this method are concerned with the sequential approach to its multi-stage solution and its deterministic nature that prevents it from handling uncertainties adequately. Koltsaklis and Georgiadis [79] implemented a mixed integer linear programming model that also makes investment decisions based on short-term operational constraints of energy planning. Computational tractability has been preserved by taking a typical day to represent each month over a long period to determine the optimal generation mix and energy planning details of the power system. One common drawback of all these studies is that they focused solely on thermal generating units for flexibility provision and did not consider alternative sources of flexibility. Moreover, the models apply long temporal resolutions, in order to avoid the prohibitive computational complexity associated with smaller temporal resolutions. Such high resolutions are not able to fully capture the intricacies of the generator operations.

In recent years, a rational strategy that has been widely applied to represent operational details in GEP is the soft-linking of two commercially available energy modelling tools [81–86]. A first tool is selected to implement traditional long-term capacity planning by optimising the generation portfolio while a second one executes short-term modelling of the resulting power system in terms of unit commitment and dispatch. The second tool thus transposes short-term operational dynamics of the power system to the generation mix resulting from the high-level optimisation procedure of the first tool. The two tools are usually applied iteratively in order to verify the operational feasibility of the expansion plan. The wide acceptance of this hybrid framework stems from its simplicity, computational tractability and use of well-known commercial modelling packages. Nevertheless, several limitations of the soft-linking approach have been reported. The fact that the two tools use overlapping but different sets of input parameters could lead to hidden input data inconsistency [85]. Additionally, it is unlikely that investment decisions on new power plants will be guided predominantly by short-term operational constraints of the power system. Moreover, since most applications of the hybrid model use long time steps in the capacity expansion tool, they are unable to directly include flexibility constraints in it [87]. Another weakness is the single least-cost minimisation objective function used in most studies which dictates that other potential objectives are converted into constraints.

6. Summary And Research Questions

The power generation industry has been subjected and forced to constant evolution since its inception. Among other things, this review has shown that power system DMs have had to continuously adjust their long-term planning models in order to fully capture changes in policies and technological progress. During the last two decades in particular, a major transition has occurred in power systems characterised by the rising influx of RE sources in the generation mix. This shift is motivated by environmental, energy security and sustainability concerns. The salient modifications in GEP modelling in response to this transformation in the electricity industry have been highlighted chronologically in this paper. More recently, the increased integration of intermittent RE sources in the electricity grid has presented several new challenges to long-term energy planning. In particular, the dynamics and variability of these resources on small timescales must be considered to verify the feasibility of capacity expansion plans. Conventional GEP models have ignored or considerably simplified operational details of the power system at the level of individual generating plants and focused on ensuring that the planned generation capacity is sufficient to meet the forecasted demand. Guaranteeing the required generation capacity is no longer adequate for system security if that capacity is not flexible enough to respond to supply and demand variability. Key state-of-the-art models that have been devised to depict the dynamics experienced in actual operations to some extent have been discussed critically in this paper. The discussion has enabled the identification of gaps that offer interesting opportunities for further research, as iterated below:

Operational flexibility: During this review, we have established that generation portfolios with high shares of variable RE must have sufficient operational flexibility in order to meet larger and more frequent fluctuations in net load. For this purpose, several metrics of varying complexity have been developed to evaluate the flexibility requirements of power systems and the flexibility availability in power systems. It is essential to capture both types of metrics in GEP to shed light on the feasibility of the generation plans. As explained in sections 5.2 and 5.3, most efforts in this direction have used less data-intensive metrics that provide a high-level representation of flexibility in the planning process. Investigating the coupling of accurate flexibility metrics with

GEP will provide a more detailed and realistic overview of operations. Such metrics, however, rely on detailed simulations of extensive historical load and generation time-series data. Future research efforts could focus on developing computationally tractable algorithms to deal with the enhanced complexity. Another issue that requires immediate attention of researchers is the economic value associated with operational flexibility. Improving the flexibility availability within the power system entails additional costs. Although some studies have attempted to estimate the cost of flexibility provision through solar and wind power [88–90], a collective framework is required to harmonize the inherent differences among various power systems and the features that are considered in the economic evaluation. Costs associated with provision of flexibility are of prime importance to DMs in their selection of the optimal expansion plan. The literature survey has also revealed that GEP studies incorporating flexibility mostly consider conventional power plants as the sole source of flexibility. Future works need to account for other sources of flexibility in the power system, including sort-term DSM programmes, storage devices and interconnection with neighbouring networks, in order to provide a holistic view into the real potential of the system to cope with variable RE. Methods to assess the flexibility provision by these sources need to be devised. A crucial gap in present knowledge relates to determining the minimum level of flexibility that a power system must possess in order to accept a given share of intermittent RE. Along the same lines, it is presently impossible to evaluate precisely the additional amount of variable renewables that the grid can take even if its flexibility resources are known. Again, such information is vital for DMs before undertaking new RE obligations.

Treatment of uncertainties: Measures taken to decarbonize the electricity grid have contributed to an escalation of uncertainties in energy planning and heightened the complexity of GEP. Models have strived to incorporate the uncertainties caused by variations in RE output and demand separately in GEP [91–93]. However, simplistic formulations are applied to represent uncertainties in both RE output and load in the modelling process to ensure its computational tractability. Future load is usually estimated through one or more of the following factors: projected population, economic state and technological progress. The effects of diurnal, weekly, and seasonal patterns on demand could be combined with the aforementioned factors. Similarly, uncertainties in intermittent RE output is commonly represented by the average annual output. In this context, capacity credit and ELCC computation could be introduced in GEP to convincingly represent the firm contribution of wind and solar energy outputs to the grid. The geographical availability of variable RE resources could also be incorporated in the formulation. Moreover, given that both demand and variable RE output depend on climatic conditions, the correlation between them and its effect on the generation mix could be investigated in GEP. Variable RE sources also introduce uncertainties in short-term operational details. Current unit commitment models used in GEP attempt to forego its traditional deterministic nature by considering a few cycling and ramping constraints of individual plants. The actual operations of units could be more accurately captured by integrating a whole range of technical characteristics of generators in the model. Furthermore, unit commitment and dispatch can be simulated more effectively by incorporating forecasting algorithms that anticipate wind and solar resources in GEP models. Until now, forecasting techniques have hardly been considered but their potential to mitigate reliability and resource overscheduling risks can be valuable in capacity planning models.

Smart grid technologies: The impact of smart grid technologies on GEP is likely to intensify in the future as more variable renewables are added to the grid. The main reason for their growing influence stems from their ability to decrease the variability in the power system by facilitating the supply-demand balance through DSM programmes, modern information and communication technologies, advanced metering infrastructure, sensor networks and enhanced grid management and control. Future research efforts in GEP should therefore optimally involve these smart technologies in a rational way. Notably, the performance of smart grid technologies from operational and economic perspectives could feature in upcoming GEP models by analysing the benefits and problems associated with them. Most of the existing literature on the impacts of smart grid technologies on GEP has focused on DSM programmes. Other emerging alternatives that help in maintaining the grid demand-supply balance, such as distributed energy resources and plug-in electric vehicles, could also be investigated.

Finally, it is important to note that the suggested future research directions will add new dimensions to GEP, thereby exacerbating the complexity of an already convoluted problem. More sophisticated techniques, tools and algorithms will inevitably be needed to cope with the additional computational requirements. More often than not, GEP model developers will be faced with the delicate task of making trade-offs between the level of granularity implemented in their models and the computational complexity.

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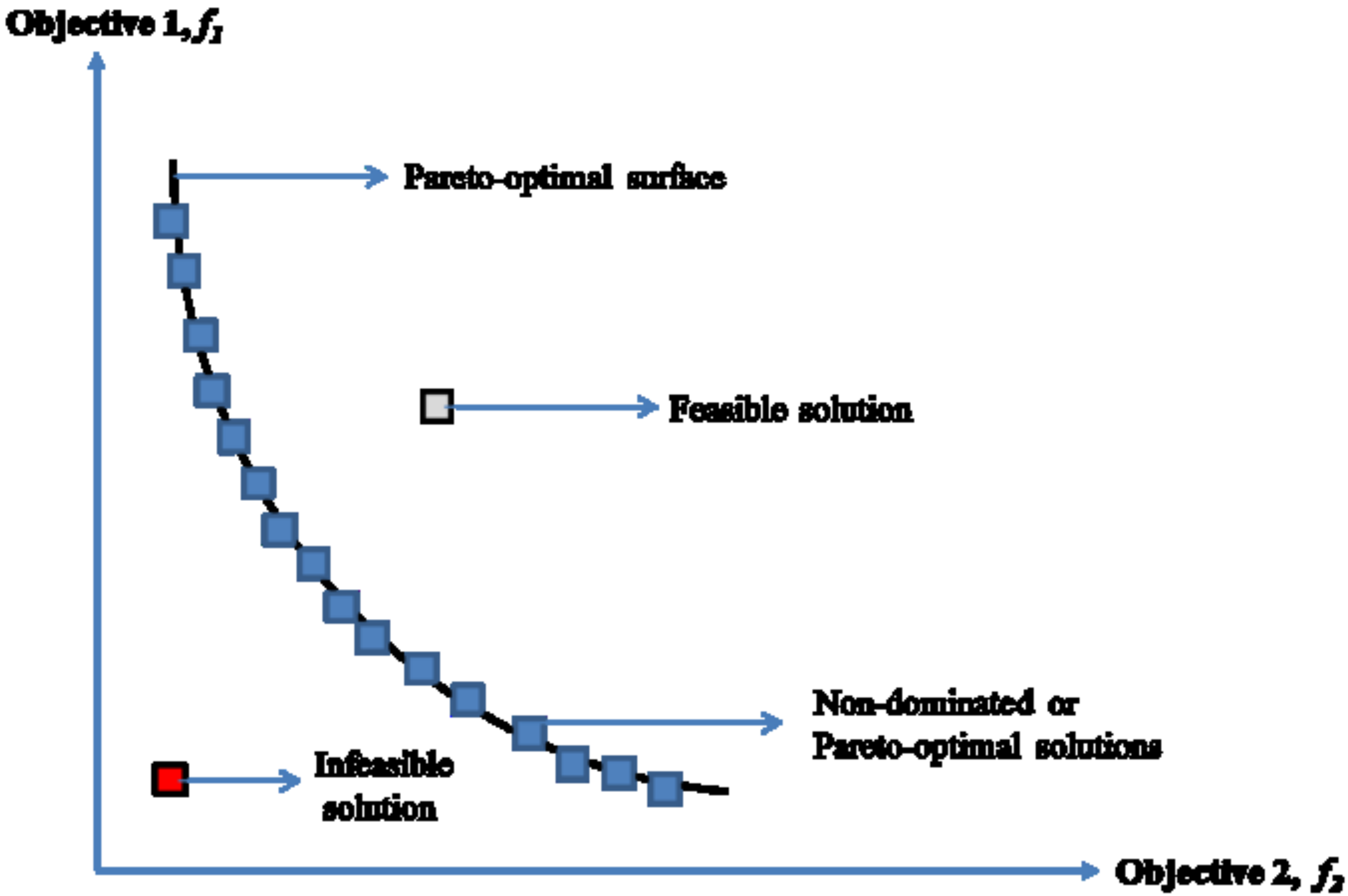

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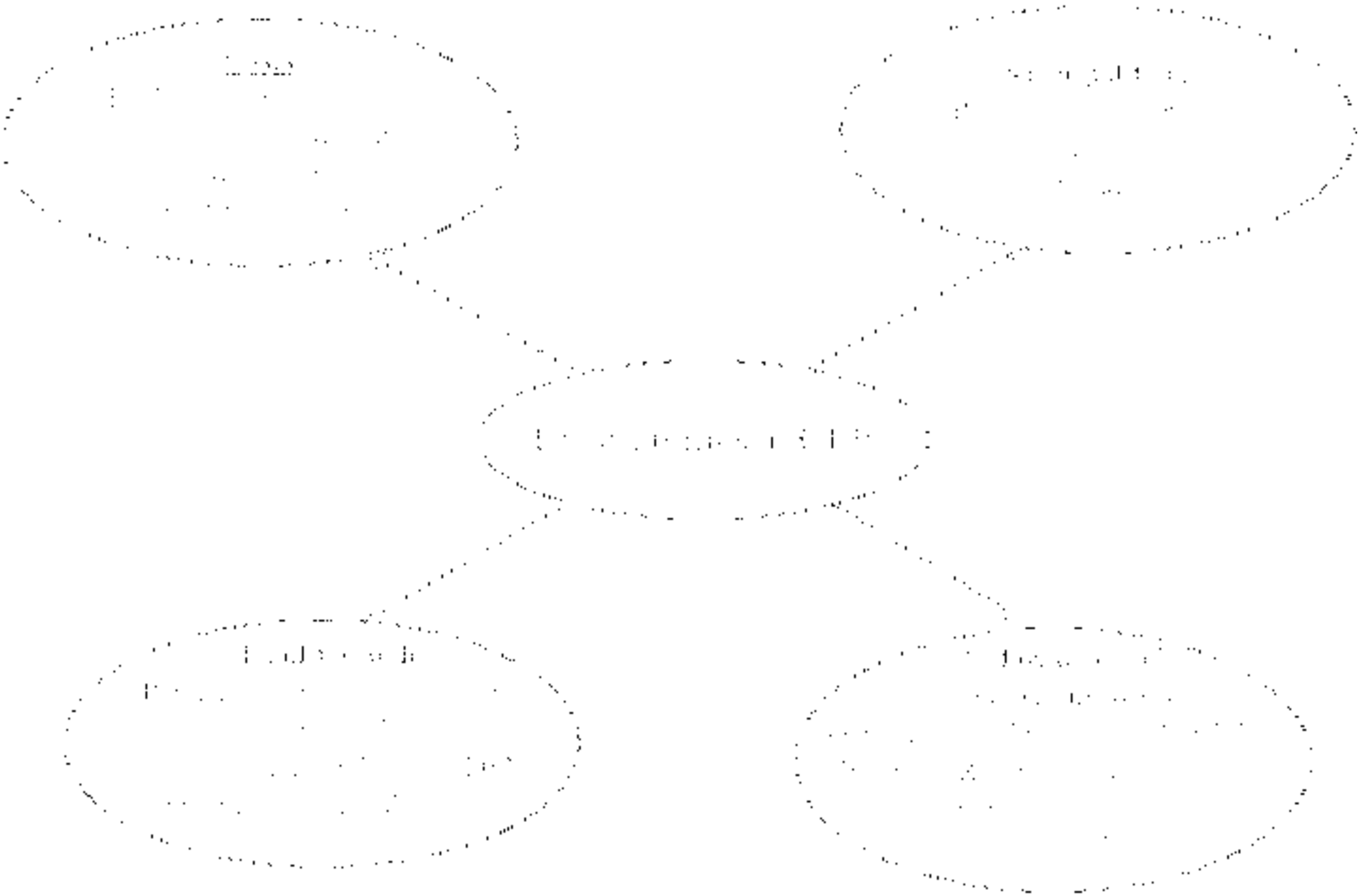

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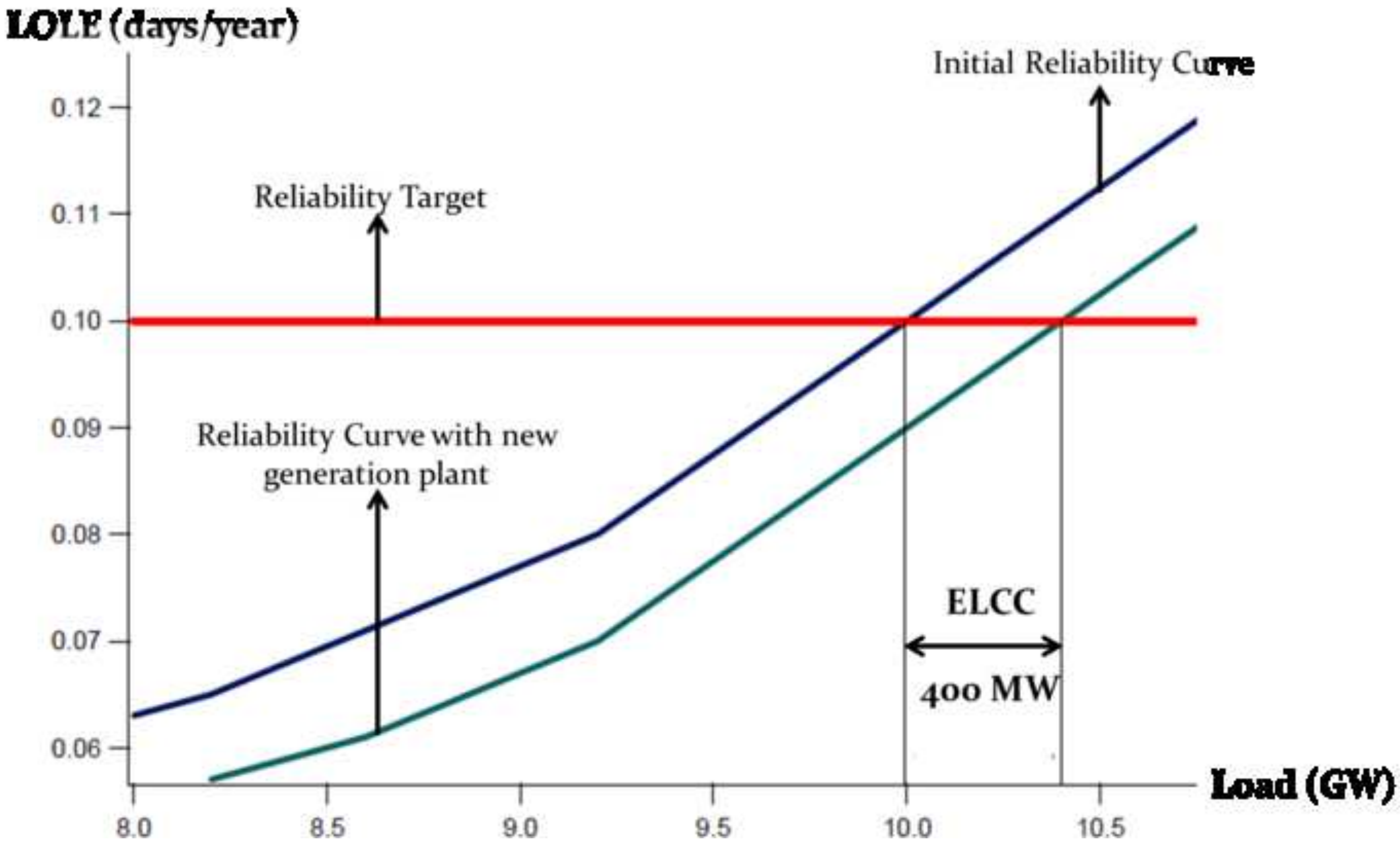

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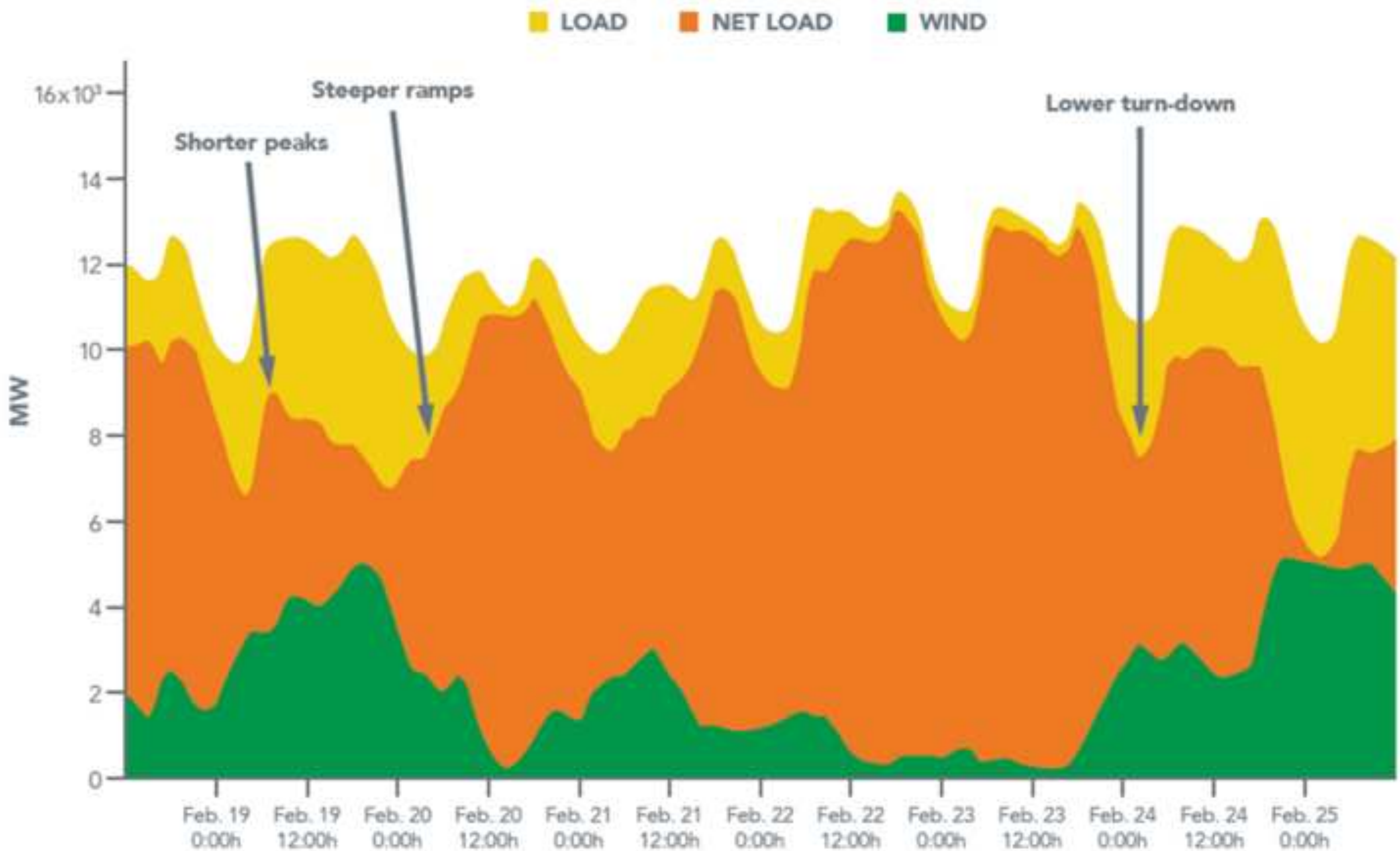

Figure Captions

Figure 1: External costs associated with a coal-fired generation plant.

Figure 2: Classification of Multi-Attribute Decision Making methods.

Figure 3: Pareto-optimal surface for a problem with two objectives.

Figure 4: Traditional uncertainties considered in GEP.

Figure 5: Example illustrating the concept of ELCC of an additional power plant [53].

Figure 6: Variability in wind generation, demand and net load during a one-week period [65].