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5 1                   **Generation expansion planning optimisation with renewable energy**  
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10 4                   Vishwamitra Oree<sup>1</sup>, Sayed Z. Sayed Hassen<sup>2</sup>, Peter J. Fleming<sup>3</sup>  
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5 1 **Generation expansion planning optimisation with renewable energy**  
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10 4 **Abstract**  
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12 5 Generation expansion planning consists of finding the optimal long-term plan for the  
13 6 construction of new generation capacity subject to various economic and technical constraints. It  
14 7 usually involves solving a large-scale, non-linear discrete and dynamic optimisation problem in a  
15 8 highly constrained and uncertain environment. Traditional approaches to capacity planning have  
16 9 focused on achieving a least-cost plan. During the last two decades however, new paradigms for  
17 10 expansion planning have emerged that are driven by environmental and political factors. This has  
18 11 resulted in the formulation of multi-criteria approaches that enable power system planners to  
19 12 simultaneously consider multiple and conflicting objectives in the decision-making process.  
20 13 More recently, the increasing integration of intermittent renewable energy sources in the grid to  
21 14 sustain power system decarbonisation and energy security has introduced new challenges. Such a  
22 15 transition spawns new dynamics pertaining to the variability and uncertainty of these generation  
23 16 resources in determining the best mix. In addition to ensuring adequacy of generation capacity, it  
24 17 is essential to consider the operational characteristics of the generation sources in the planning  
25 18 process. In this paper, we first review the evolution of generation expansion planning techniques  
26 19 in the face of more stringent environmental policies and growing uncertainty. More importantly,  
27 20 we highlight the emerging challenges presented by the intermittent nature of some renewable  
28 21 energy sources. In particular, we discuss the power supply adequacy and operational flexibility  
29 22 issues introduced by variable renewable sources as well as the attempts made to address them.  
30 23 Finally, we identify important future research directions.

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36 24 **Keywords:** Multi-criteria decision making; multi-objective optimisation; generation expansion  
37 25 planning; intermittent renewable energy resources; operational flexibility.  
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41 26 **1. INTRODUCTION**

42 27 Relentless increase in electricity demand calls for new investments in generation capacity on a  
43 28 regular basis. Efficient planning of new generation units is an optimisation problem that entails  
44 29 answering the following four basic questions so as to ensure that the installed generation capacity  
45 30 adequately meets the forecasted demand growth over a medium to long-term planning horizon:  
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- 48 31 i. WHAT - the types of generation technologies that will be added to the grid  
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50 32 ii. HOW MUCH - the size of each new generation plant  
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52 33 iii. WHERE - the location of these plants  
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54 34 iv. WHEN - the stage of the planning horizon when the new units must be implemented.  
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56 35 Generation Expansion Planning (GEP) has been the focus of active research since the 1950s  
57 36 when linear programming (LP) models were successfully used to approximate the objective  
58 37 function and the constraints to linear functions, starting with the work of Masse and Gibrat [1].  
59 38 However, the complexity associated with GEP has risen dramatically due to the variety of  
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1 generation technology options available to the planners, the numerous stakeholders involved and  
2 the diversity of constraints derived from limitations imposed by physical processes, generation  
3 capacity, reliability of electrical supply, resource availability and economic considerations,  
4 among others. Initially, the aim of GEP was to search for the most economical scheme that could  
5 provide an adequate supply of electricity to meet the projected demand growth subject to a set of  
6 constraints over a planned period of time. The cost function typically included investment, fuel,  
7 and generation costs over the entire planning period. LP models cannot deal satisfactorily with  
8 the large number of constraints inherent to a realistic GEP problem. Furthermore, the need for  
9 greater accuracy in the modelling uncovered non-linear relationships among the decision  
10 variables and the objective function. To overcome this problem, a variety of mathematical  
11 optimisation methods was developed and applied to the GEP problem including non-linear  
12 programming (NLP) [2], mixed integer programming [3], dynamic programming [4] and  
13 decomposition techniques [5–7]. Moreover various approximations and assumptions were made  
14 on the model to keep the optimisation problem computationally tractable. For example, aspects  
15 of the real-time operations of the power system were often neglected and parameters like  
16 spinning reserves and variable heat rates were rarely considered.

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

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4 1 Over the last two decades, concerns about the likelihood of fossil fuel prices soaring in the long-  
5 2 term, geopolitical changes, energy security and the environmental impact of the fossil fuels have  
6 3 resulted in concerted efforts to reduce greenhouse gas (GHG) emissions worldwide.  
7 4 Consequently, interest in harnessing renewable energy (RE) resources has intensified. In  
8 5 particular, the consistent growth of intermittent RE resources, mainly sun and wind, has been key  
9 6 to the energy transition. In addition to mitigation of pollutant emissions, the integration of  
10 7 variable renewables in the electricity grid caused the emergence of other crucial aspects in the  
11 8 energy planning scenario such as the reliability, flexibility and efficiency of the power system.  
12 9 This paper evaluates different models that have been applied to account for the push towards a  
13 10 carbon-constrained power system. It reports a wide range of research papers relevant to this topic  
14 11 chronologically, starting from the early minor improvements made to existing models, to state-  
15 12 of-the-art models that deal with contemporary challenges. This review also attempts to propose a  
16 13 classification of approaches adopted in this field. In this context, the paper has been divided into  
17 14 four distinct sections to demarcate different approaches that have been employed to address the  
18 15 needs of decision-makers in response to additional requirements of GEP following the  
19 16 integration of RE in the electricity grid. They are as follows:

- 20 17
- 21 18 • traditional methods of integrating environmental considerations as constraints or external  
22 19 costs in GEP
- 23 20 • formulation of GEP as a multiple-objective optimisation problem whereby the ecological  
24 21 footprint is considered as one of the objectives
- 25 22 • techniques used for the inclusion of additional uncertainties in the planning process  
26 23 brought by variable RE sources
- 27 24 • new dynamics introduced by increased integration of intermittent RE resources in the  
28 25 power system and associated challenges experienced by power system planners
- 29 26

30 27 The intricacies of the models as well as their strengths and limitations are highlighted. In  
31 28 addition to methodological contributions, we elaborate on future research with new questions  
32 29 that are being asked by planners working in GEP and the corresponding paradigms that must be  
33 30 captured within the planning models to answer these questions.

## 31 32 **2. EARLY ENVIRONMENTAL CONSIDERATIONS**

33 34 Initially, environmental impacts were handled as constraints imposed on the operation of the  
34 35 power grid by setting tolerance thresholds for the maximum acceptable emission rates. Another  
35 36 common approach integrated the external costs associated to environmental impacts of energy  
36 37 production by the various power plants in the system.

### 37 38 **2.1 ENVIRONMENTAL CONSTRAINTS**

38 39 Sirikum and Techanitisawad [8] added air pollutant emission and concentration limits to the  
39 40 usual capacity, power balance, reliability, location and resource availability constraints of their  
40 41 mixed integer non-linear programming (MINLP) model. The authors appended environmental  
41 42 and investment costs in demand side management (DSM) programmes and outage costs into the  
42 43 objective function. The complex MINLP task was decomposed into two parts. Firstly, a  
43 44 combinatorial problem is solved by GA search to determine a feasible generation mix

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4 1 considering only reserve margin, reliability and location constraints. Then, an optimum level of  
5 2 power generation is found by a continuous LP method under demand, capacity and emission  
6 3 constraints. The proposed technique was validated on seven different case studies of a scaled-  
7 4 down model of the Thailand power system with different planning periods and problem sizes.  
8 5 Chen et al. [9] reported a GEP model that integrates a series of low-carbon factors in the  
9 6 objective function, decision variables and constraints. Additional decision variables are used to  
10 7 indicate the level of retrofit of conventional coal plants with carbon capture and storage (CCS)  
11 8 technologies, the implementation of new low-carbon technology plants and the overall CO<sub>2</sub>  
12 9 traded allowance. In addition to the usual cost components, the economic objective function  
13 10 consisted of income from CO<sub>2</sub> trading mechanisms, CO<sub>2</sub> emission penalty and CCS retrofit  
14 11 expenses. Limits are imposed on the total CO<sub>2</sub> emission levels and on the overall tradable CO<sub>2</sub>  
15 12 allowance. The model was tested on the power system of China to reveal the prospects of CO<sub>2</sub>  
16 13 mitigation measures until 2030. Both [8] and [9] considered only thermal power plants and  
17 14 limited scenarios in their analysis.  
18 15

19 16 Cormio et al. [10] applied a linear programming optimisation procedure based on the energy  
20 17 flow optimisation model (EFOM) to support regional energy planning in Apulia located in  
21 18 southern Italy. The total cost of the entire energy system was minimised by a LP procedure over  
22 19 a time horizon of some decades. A financial estimation of the burdens incurred to the  
23 20 environment as a result of the setting up and operation of the electrical power plants was  
24 21 included in the cost objective. Two scenarios that consider different regional economic and  
25 22 environmental policies were simulated. The results showed that the regional policy, aimed at  
26 23 meeting heat and energy loads by various end-use sectors through cleaner technologies, can rely  
27 24 heavily on combined cycle power plants with less contribution from wind power, waste-to-  
28 25 energy, biomass and industrial cogeneration systems. Mejia-Giraldo et al. [11] formulated a  
29 26 linear optimisation model for the GEP where CO<sub>2</sub> emission tax formed part of the cost function  
30 27 to be minimised and annual CO<sub>2</sub> emission reductions were enforced as one of the constraints.  
31 28 When the model was applied to a simplified 11-region representation of the US power system,  
32 29 considering ten candidate generation technologies over a planning period of twenty years, it was  
33 30 found that polluting technologies were largely rejected by the optimisation process. Karaki et al.  
34 31 [12] used tunnel DP to minimise either the cost or the environmental impact or some weighted  
35 32 function of these two functions in the GEP problem. The environmental impact is integrated in  
36 33 the objective function by appending the cost of cleaning the pollutants emitted by the additional  
37 34 generation units. The algorithm divides the problem into stages, where each sub-period of the  
38 35 planning horizon represents a stage having several expansion options. At each stage, the  
39 36 algorithm determines the feasible expansion options of the next stage by adding generation units  
40 37 to the options of the present stage. The number of options is kept within manageable limits by  
41 38 applying tunnel-heuristic rules. A probabilistic production costing simulation is run to determine  
42 39 the expected energy not served (EENS) and the total cost incurred up to that stage for each  
43 40 remaining option. Generation units were added to the power system only if the EENS exceeded a  
44 41 pre-determined threshold.  
45 42

## 46 43 2.2 INTERNALISATION OF EXTERNAL COSTS

47 44 While models considering environmental impacts as constraints in the form of emission taxes  
48 45 and penalties have the advantage of simplicity as they use existing deterministic models, their  
49 46 main limitation is that they assume a constant average emission level for each generation

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4 1 technology. In doing so, they preclude the impact that operating conditions of thermal power  
5 2 plants have on pollutant emission levels [13]. Another alternative is to consider environmental  
6 3 and health impacts of energy generation, whose costs are generally not directly borne by  
7 4 consumers. For example, every stage in the generation of electricity from coal-fired power plants  
8 5 releases harmful emissions that contribute to environmental and health degradation in the long  
9 6 term as illustrated in Figure 1. However, the low price of coal-generated electricity does not  
10 7 account for the real cost that society ultimately pays. Internalisation of external costs refers to the  
11 8 integration of the environmental and health adverse effects into the decision-making process.  
12 9 Several authors have applied existing energy models to study the internalisation of external costs  
13 10 of power production in GEP. A robust and exhaustive quantification of external costs is required  
14 11 to evaluate, in monetary terms, the impact of emissions from power plants on the environment  
15 12 and the human health [14]. Energy models are ideal tools for such analysis as they are based on  
16 13 strong economic foundations that use rigorous mathematical formulations to process quantitative  
17 14 data and provide numerical solutions related to economics and the environment [15].  
18 15

19 16 Nguyen [16] used MARKAL, a dynamic and multi-period LP model that adopts a bottom-up  
20 17 approach to a generalised energy system, to devise a capacity expansion plan for Vietnam over a  
21 18 20-year period. The damage costs of CO<sub>2</sub>, NO<sub>x</sub>, SO<sub>2</sub> and particulate matter (PM) emissions for  
22 19 every generation technology were estimated on the basis of the outcomes of the European  
23 20 Commission ExternE Project [14]. This project tracked the ecological and social footprints of  
24 21 pollution produced during the whole lifecycle of each generation technology. The external costs  
25 22 were then incorporated in the model as an externality tax for conventional fuels and as part of the  
26 23 variable costs for RE technologies. When minimising the overall cost of the expansion plan, it  
27 24 was found that inclusion of external costs caused an increase in the share of RE, natural gas  
28 25 combined cycle and advanced coal-based technologies in the generation mix. The results further  
29 26 indicated that the drop in external costs resulting from the reduction in emissions would be  
30 27 higher than the rise in the generation cost of electricity induced by the adoption of cleaner  
31 28 generation technologies. Rafaj and Kypreos [17] considered the cost of environmental and health  
32 29 damages in GEP for five regions of the world with the Global Multiregional MARKAL model  
33 30 over successive ten-year periods starting in 1990. External costs were derived from the ExternE  
34 31 project and scaled by factors needed by the model, such as regional population density, fuel  
35 32 quality, conversion efficiency and compliance of the technologies with emission control  
36 33 schemes. Modelling results indicated that internalising the external costs of SO<sub>2</sub> and NO<sub>x</sub>  
37 34 favoured low-emission technologies and emission control systems in the generation mix. When  
38 35 external costs of CO<sub>2</sub> were introduced in the model, fossil fuel-based generation plants were  
39 36 clearly restrained and RE along with fuel cells were more competitive. Klaasen and Riahi [18]  
40 37 analysed the impacts of internalising the external costs of electricity generation using a  
41 38 combination of three models: MESSAGE, a bottom-up LP model to find the best expansion plan  
42 39 by tracking energy flows through the system; MACRO, a top-down macroeconomic model that  
43 40 evaluates a series of economic parameters required to assess the impact of the external costs on  
44 41 the gross domestic product of the regions under consideration; and SG, a scenario generation  
45 42 model consisting of extensive economic and energy historical datasets for various regions that  
46 43 help in the formulation of different potential scenarios. Like in the previous two studies, it is  
47 44 noted that internalising the external costs of energy production fostered the use of technologies  
48 45 such as clean coal, natural gas combined cycles, fuel cells, wind and biomass in the generation  
49 46 mix instead of conventional fuels. Yet another energy model, WASP-IV, was employed by  
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4 1 Becker and al. [19] to assess the impact of environmental externalities on capacity expansion  
5 2 planning in Israel over the period 2011-2025. Although the objective was to minimise the overall  
6 3 costs subject to several technological and demand constraints, each of the pollutants considered  
7 4 in the study was treated as a separate objective because their valuations could not be integrated  
8 5 into a single function. A wide range of scenarios was simulated by varying the weights assigned  
9 6 to the tax rate for each pollutant. Seven scenarios were shortlisted as potentially providing the  
10 7 best results in terms of pollution reduction-cost ratio for consideration by policy-makers.

### 15 8 **3. MANAGING CONFLICTING OBJECTIVES**

16 9 Although accounting for the environmental impact of power plants from a financial perspective  
17 10 enabled a more holistic approach to GEP by capturing the indirect costs borne by society on  
18 11 power system expansion, these models had several drawbacks. The methods and the scientific  
19 12 data commonly used to elicit the monetary valuation of the impact are devised on the basis of a  
20 13 wide range of assumptions. It is obvious that uncertainties abound when estimating the costs  
21 14 associated to externalities in the long term. Evaluating the extent of the uncertainties is complex  
22 15 and requires changes to the traditional planning models. Moreover, these models still employ  
23 16 much simplified operating constraints to depict the operational characteristics of the power  
24 17 system. More importantly, as the environmental impacts of power generation became  
25 18 increasingly critical, it was essential to expand GEP beyond an absolute economic analysis  
26 19 exercise. Consequently, the classical formulation of the least-cost GEP was no longer suitable as  
27 20 realistic generation expansion models had to incorporate distinct evaluation attributes as  
28 21 incommensurable objective functions rather than aggregating them in a single economic  
29 22 objective function [20]. Multi-Criteria Decision Making (MCDM) methods enable power system  
30 23 planners to make decisions in the presence of multiple and conflicting objectives that have to be  
31 24 considered simultaneously. These methods help the decision-maker (DM) in identifying the most  
32 25 satisfactory alternative from a set of feasible solutions.

#### 38 26 3.1 MULTI-ATTRIBUTE DECISION MAKING

39 27 One popular approach used to solve MCDM problems is multi-attribute decision making  
40 28 (MADM), in which a discrete, predefined set of alternatives is compared and evaluated against a  
41 29 set of decision attributes or criteria. The output will usually consist of ranking the alternatives in  
42 30 terms of their total preferences when all the decision criteria are considered simultaneously.  
43 31 Diakoulaki et al. [21] stated that the main strength of MADM models is their ability to structure  
44 32 problems that are not clearly defined and to provide a good understanding of their components.  
45 33 Their popularity also stems from their simplicity. They further make the task of the DM more  
46 34 comfortable by presenting a set of detailed alternatives with an order of precedence as opposed  
47 35 to models where complex mathematical functions are involved. In addition, these methods have  
48 36 the ability to consider both quantitative and qualitative criteria simultaneously. In his literature  
49 37 review of MADM methods applied to energy planning, Løken [22] distinguished between three  
50 38 types of MADM models. The classification is summarised in Figure 2.

51 39  
52 40 Value measurement methods assign a numerical score to the alternatives so as to arrange them in  
53 41 an order of merit. The two most common value measurement models are Multi-Attribute Utility  
54 42 Theory (MAUT) and Analytical Hierarchy Process (AHP). MAUT aggregates the criteria into a  
55 43 utility function that scales the importance of each criterion from 0 to 1 based on the preferences  
56 44 of the DM. It then evaluates the alternatives and assigns weights with the purpose of trade-off



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4 1 between attributes [23]. The alternative with the best value of the aggregated function is  
5 2 considered as the optimal one. MAUT has not been extensively applied to the energy planning  
6 3 field mainly due to the requirement of the DM to interact dynamically with the model as well as  
7 4 the complexity of computing some parameters involved in the algorithm [24,25]. AHP has been  
8 5 widely applied to decompose the GEP problem into a hierarchy with objectives occupying the  
9 6 top position, criteria and sub-criteria at levels and sub-levels, and decision alternatives at the  
10 7 bottom of the hierarchy [25–28]. The hierarchical tree is used to weigh the relative importance of  
11 8 the criteria using an assessment scale. The alternatives are then scored and ranked based on the  
12 9 subjective criteria.

13 10  
14 11 Goal programming (GP) uses mathematical algorithms to find alternatives that are closest to  
15 12 achieving predefined goals for each objective function. In many cases, GP is applied as the first  
16 13 step in a multi-criteria process involving numerous alternatives to eliminate the most unsuitable  
17 14 ones in an efficient way [22]. Two GP techniques have been commonly applied to solve energy  
18 15 planning problems: Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) and  
19 16 step method. TOPSIS compares alternative solutions with two artificial ideal and worst solutions.  
20 17 It then selects the alternative that is closest to the ideal solution and furthest to the worst solution  
21 18 in terms of Euclidean distances [25]. Kaya and Kahraman [29] proposed a modified fuzzy  
22 19 TOPSIS approach to find the most appropriate energy technology based on various technical,  
23 20 economic, environmental and social criteria. The weights of the selection criteria were  
24 21 determined using a fuzzy AHP. The stem method uses an ideal point as a goal and then applies  
25 22 the Tchebycheff norm as a distance metric to minimise the maximum distance from the goal  
26 23 [30]. Once the best alternatives for the objective functions are obtained, the DM can formulate  
27 24 preferences. According to Pokharel and Chandrashekar [31], the step method allows direct  
28 25 comparison among alternate solutions, thereby helping DMs to experience the impact of their  
29 26 preference for an objective function on the solution. Nevertheless, they should be able to  
30 27 articulate their goals precisely at each iteration.

31 28  
32 29 The final type of MADM model, known as outranking models, compare the alternatives among  
33 30 each other with respect to each attribute in order to determine the best alternative for each pair  
34 31 [25]. They do not output a single best alternative but the degree of dominance of one alternative  
35 32 over another. Two outranking approaches, Preference Ranking Organisation METHod for  
36 33 Enrichment Evaluation (PROMETHEE) and Elimination Et Choix Traduisant la Réalité  
37 34 (ELECTRE), have been successfully applied to many GEP studies. In both methods, a pairwise  
38 35 comparison between the alternatives is performed to identify and retain the non-dominated  
39 36 alternatives on the basis of the selected criteria. PROMETHEE additionally considers the degree  
40 37 to which the non-dominated alternative is better and uses this piece of information to rank  
41 38 alternatives. Newer versions of PROMETHEE and ELECTRE with improved features were  
42 39 subsequently developed. Pohekar and Ramachandran [25] reviewed more than 90 published  
43 40 papers that dealt with the application of MADM techniques to sustainable energy planning. The  
44 41 authors observed that AHP is the most popular method followed by outranking techniques,  
45 42 PROMETHEE and ELECTRE. Wang et al. [32] performed a thorough review of the published  
46 43 literature on MADM applications in sustainable energy systems focusing on the different criteria  
47 44 considered in the formulation of the problem. Løken [22] illustrated that a multitude of MADM  
48 45 techniques have been used to solve energy planning problems. Each method has its own  
49 46 advantages and drawbacks and the choice of the methodology used depends on the DM. The

1 author asserted that ‘black-box’ models should be avoided as they are poorly understood by  
2 DMs. Several studies have also combined two or more methods to exploit the strengths of each  
3 algorithm.

### 4 3.2 MULTI-OBJECTIVE DECISION MAKING (MODM)

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

23  
24 One of the earliest efforts to consider multiple objectives simultaneously in GEP was performed  
25 by Climaco et al. [35]. The model optimised three objective functions in the form of total  
26 expansion costs, reliability and environmental impacts subject to load requirements, operational  
27 capacity and fund availability constraints. The authors used an interactive tri-criteria LP tool,  
28 TRIMAP, to help the DM in progressively learning the set of non-dominated solutions. TRIMAP  
29 allows the DM to grasp in an interactive way, the boundaries of the non-dominated surface so  
30 that he can guide the model to focus on the regions where the solutions better relate to his  
31 preferences. The results demonstrated that among the three generation technologies investigated,  
32 minimum cost was achieved with a mix of nuclear and coal units, whereas the minimum  
33 environmental impact occurred when additional units were oil-based. Martins et al. [36]  
34 extended the interactive multi-objective LP model based on TRIMAP by integrating DSM as a  
35 separate power generation group defined by the same type of parameters as the other generation  
36 alternatives. Three objective functions were considered: the total expansion cost, the  
37 environmental impact associated with the additional installed capacity during the planning period  
38 and the environmental externalities associated with the energy output. Five sets of constraints  
39 dealing with the reliability of the supply system, the generating capacity of power plants and the  
40 DSM unit, the total new generation capacity, and pollutant emissions were imposed on the  
41 system. When the model was simulated with realistic data, the resulting expansion plans  
42 exhibited a high diversity of generation technologies.

43  
44 Chattopadhyay et al. [37] evaluated the benefits of integrating DSM options in capacity  
45 expansion planning considering the annual system cost, the CO<sub>2</sub> emissions and the reliability of  
46 the system in terms of loss-of-load expectation (LOLE), as its three objective functions. The

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4 1 model adopted a compromise programming approach deriving optimal solutions in which the  
5 2 distance of each objective from its ideal value was minimised. Depending on the type of savings  
6 3 achieved, each DSM option was categorised as one of four possible supply-side resources. The  
7 4 methodology was validated on an Indian utility over the 1990-2000 planning horizon. Linares  
8 5 and Romero [38] integrated decision-makers' preferences into a GEP problem featuring an  
9 6 overarching cost objective along with several environmental objectives subject to various power  
10 7 flow, generation capacity and resource availability constraints. The economic objective  
11 8 comprised of investment, decommissioning, operation and maintenance costs while the  
12 9 environmental objectives aimed at minimising the emissions of CO<sub>2</sub>, SO<sub>2</sub>, NO<sub>x</sub> and radioactive  
13 10 wastes. The authors formulated a compromise programming model based on preferential weight  
14 11 elicitation by the decision-makers using AHP. When tested on the Spanish electrical power  
15 12 network with a planning horizon extending until 2030, the best compromise solutions involved a  
16 13 higher share of renewable and gas-based technologies with coal and nuclear technologies  
17 14 accounting for less than 10% of the generating mix.

18 15  
19 16 Unlike the previous attempts to solve the GEP problem that were LP-based and used continuous  
20 17 variables, Antunes et al. [20] adopted a multi-objective mixed integer linear programming  
21 18 (MOMILP) model which integrates the discrete nature of the additional generation capacity  
22 19 required for each technology during the planning horizon. An interactive approach, whereby the  
23 20 DM intervenes to direct the computation phase towards his preferences, is applied to cater for the  
24 21 increased computational complexity resulting from considering the modular capacities of  
25 22 generation units. The same three objectives used by Martins et al. [36] were considered. DSM  
26 23 programmes implementing peak demand shaving were modelled as an equivalent DSM  
27 24 generating unit. As such, investment and operating costs as well as loss of revenues due to  
28 25 decrease in sales of electricity resulting from DSM programmes are included in the cost  
29 26 objective function. Mavrotas et al. [39] claimed that applying an interactive procedure as a  
30 27 strategy to solve MOMILP problems does not generate the entire set of efficient solutions, even  
31 28 for small-scale problems. To curb this shortcoming, the authors suggested a mixed 0-1 multi-  
32 29 objective LP model based on modified version of the branch and bound algorithm. It has the  
33 30 ability to generate the whole set of efficient solutions by implicitly enumerating all potentially  
34 31 efficient solutions and then eliminating the non-efficient ones through pairwise comparison.  
35 32 Annual electricity production cost and yearly SO<sub>2</sub> emissions were minimised by the model  
36 33 subject to capacity, minimum load requirements, demand satisfaction, natural gas supply and  
37 34 reserve margin constraints.

38 35  
39 36 Aghaei et al. [34] formulated a MOMILP model to simultaneously optimise five objectives: total  
40 37 costs, CO<sub>2</sub> emissions, fuel consumption, fuel price risk and system reliability. Total costs is an  
41 38 all-encompassing objective function that involves cost of DSM programmes, benefits of RE  
42 39 generation and cost of wind intermittency in addition to the usual investment, operation and  
43 40 maintenance costs. Outage cost is used as a metric to represent the reliability of the system and is  
44 41 evaluated using the EENS index. Simulations carried out on three cases with different sets of  
45 42 weights for objective functions showed better results as compared to conventional and  
46 43 augmented  $\epsilon$ -constraints methods. The authors proposed another multi-objective model for multi-  
47 44 period GEP problems based on a Corrected Normal Boundary Intersection (CNBI) method to  
48 45 minimise the total cost and the amount of CO<sub>2</sub> emissions and maximise the reliability of the  
49 46 system [40]. The latter objective function is evaluated using an analytical probabilistic method

1 that computes Z values which are associated to the expected surplus of available generation. The  
2 CNBI method outputs efficient solutions that are evenly spread on the Pareto front while  
3 ensuring that dominated solutions are not produced. The efficiency of the model was  
4 demonstrated on three test cases with seven types of generating technologies in a 6-year planning  
5 horizon consisting of three 2-year stages and produced reliable portfolios of resources.

### 6 3.3 HEURISTIC ALGORITHMS

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

21  
22 Kannan et al. [42] analysed two different formulations for the GEP problem using the elitist  
23 Non-dominated Sorting Genetic Algorithm Version II (NSGA-II). Each formulation contained  
24 two objective functions. The first one aimed at minimising both the total cost and the sum of  
25 normalised constraint violations while the second one was designed to minimise investment costs  
26 and maximise the system reliability. NSGA-II implements elitism so as to retain all non-  
27 dominated solutions and preserves diversity among the solutions through an explicit mechanism  
28 based on the crowding distance [43]. The authors encountered convergence problems when  
29 implementing the standard NSGA-II algorithm on the GEP problem. The overall additional  
30 generation capacity required by an expansion plan was found to be excessively sensitive to small  
31 changes in the decision vector. A Virtual Mapping Procedure (VMP) was introduced to modify  
32 the solution representation into dummy decision variable which ranks the candidate solutions  
33 according to their additional generation capacity in ascending order. In doing so, the number of  
34 decision variables was significantly reduced, resulting in much less computational time and  
35 memory requirements. The proposed models were compared with a GA-based weighted-sum  
36 model on a test system with 15 existing power plants for a six-year planning horizon divided into  
37 three equal sub-periods. Both models produced the Pareto-optimal front in a single simulation  
38 run and in considerably less time than the baseline model.

## 39 4. UNCERTAINTY HANDLING

40 The GEP models examined to this point are deterministic in the sense that they use best available  
41 predicted values of parameters and input data, overlooking uncertainties that inexorably arise in  
42 the real world. Long-term planning of power systems have always been characterised by  
43 uncertainties. Traditionally, they were associated with parameters of the models such as the  
44 forecasted load, cost and availability of fuel, economic growth of the country, plant construction

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4 1 time, generation outages and regulatory policies. Figure 4 summarises the conventional  
5 2 uncertainties in GEP. The new paradigm in power systems planning, driven by growing  
6 3 environmental concerns, has introduced additional uncertainties, including the uncontrollability  
7 4 of intermittent renewable energy resources, governmental regulations for emissions, the response  
8 5 of customers to DSM programmes and advances in generation technologies. The large number of  
9 6 uncertainties further exacerbates the complexity in GEP, due to additional computational power  
10 7 requirements along with the difficulty in modelling the combination of their occurrences.  
11 8 Consequently, they have a profound effect on optimal decision making for power system  
12 9 planners. It is therefore imperative to integrate a systematic and consistent treatment of the  
13 10 various sources of uncertainty in the decision-making process so as to mitigate risks [7]. For this  
14 11 purpose, methodologies have been developed to address uncertainties in GEP in a  
15 12 computationally tractable manner. The most commonly used ones are scenario analysis,  
16 13 sensitivity analysis and probabilistic analysis [44]. These techniques have been derived from  
17 14 deterministic models and adapted to take uncertainties into account. Robustness and flexibility  
18 15 are the metrics that evaluate the effectiveness of the models to withstand uncertainties. The  
19 16 former pertains to the degree to which a plan is affected by changes in parameters while the latter  
20 17 is the inherent capability to modify a plan so as to accommodate and successfully adapt to such  
21 18 changes [45].  
22 19

23 20 Scenario analysis generates a range of potential futures, referred to as scenarios, by making  
24 21 different assumptions about the future with varying forecasts for key uncertain variables. An  
25 22 expansion plan for the planning horizon is then generated for each scenario. This technique  
26 23 enables the DM to anticipate a broad range of realistic futures and to identify promising  
27 24 generation technology options that appear in many scenarios. However, a comprehensive  
28 25 discrimination of alternative plans would require that weights be assigned to individual scenarios  
29 26 to represent their perceived likelihood of occurrence and that the scenarios be mutually exclusive  
30 27 and exhaustive [46]. An alternative to scenarios is offered in the sensitivity analysis technique,  
31 28 which identifies sensitivities or areas of vulnerability in a problem. Initially, several optimal  
32 29 plans are developed on the basis of some assumptions. Subsequently, some key uncertain  
33 30 parameters are varied and the performance of each plan is studied under the new conditions. This  
34 31 technique is an appropriate tool for identifying the model parameters that have most impact on  
35 32 the output variables and for determining the parameter ranges over which the solutions remain  
36 33 optimal. A major shortcoming of scenario and sensitivity analyses is that they do not provide  
37 34 much information on the flexibility and robustness of the plans [46]. Moreover, they generate  
38 35 evidence on the extent of the consequences of changes in variables, but overlook the likelihoods  
39 36 of these changes. Probabilistic analysis address these limitations by allocating probabilities for  
40 37 the occurrence of uncertain variables and then determining the optimal output through a range of  
41 38 analytical approaches like Monte Carlo simulation and stochastic programming. The latter  
42 39 technique represents the uncertain data by scenarios generated in advance. In its elementary  
43 40 form, stochastic programming finds an optimal solution that produces the best weighted average  
44 41 objective function value over all scenarios. In realistic applications where multi-period planning  
45 42 is performed, the number of scenarios increases exponentially with the number of periods. To  
46 43 keep the problem tractable, scenario sampling is used [47,48]. More advanced versions include  
47 44 risk considerations such as penalties for constraint violation and probabilistic guarantees [49].  
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## 60 45 **5. INTEGRATION OF INTERMITTENT RENEWABLE ENERGY**

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

## 5.1 POWER SUPPLY ADEQUACY

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

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4 1 evaluate the capacity credit of RE sources exist in literature [53–56]. The most commonly used  
5 2 methods are briefly described here.  
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7 3  
8 4 One of the first attempts to devise a probabilistic method to compute capacity credit of future  
9 5 wind power plants was performed by Van Wijk et al. [57]. The LOLE of a baseline power  
10 6 system which excluded the wind power plant is first calculated. Then, the LOLE for the power  
11 7 system with the wind power plant is computed after subtracting the predicted hourly wind power  
12 8 generation from the projected hourly load. Conventional capacity is then removed iteratively  
13 9 until the initial LOLE is achieved. The difference between the conventional capacities found in  
14 10 the two cases represents the ELCC of the proposed wind power plant. It was found that the  
15 11 capacity credit decreased with increasing wind power penetration, expressed as a percentage of  
16 12 the projected peak load. For example, 100 MW of installed wind power, corresponding to a  
17 13 penetration level of 0.9%, would have a capacity credit of 28%. In contrast, 2000 MW of  
18 14 installed wind power representing an 18% penetration level would result in a capacity credit of  
19 15 13.6%. It was also shown that dispersing the wind turbines over a large geographical area  
20 16 improves the capacity credit. A slightly modified version of the methodology proposed by Van  
21 17 Wijk et al. [57] was recommended as the preferred method to determine capacity credit by a task  
22 18 force on “Capacity Value of Wind” set up by the IEEE Power and Energy Society [58]. Again,  
23 19 the power system without wind power is considered first. The capacity and forced outage rate of  
24 20 each generator is convoluted through an iterative algorithm to generate the capacity outage  
25 21 probability table (COPT) of the power system. The probabilities from this table are combined  
26 22 with the hourly load profile of the system to produce the hourly LOLPs, from which the annual  
27 23 LOLE can be easily derived. The loads can be adjusted to ensure that the LOLE meets the  
28 24 reliability standards. The same procedure is followed to find the LOLE for the power system  
29 25 with wind capacity by treating the wind power as a negative load in the hourly load time series.  
30 26 The load data is increased incrementally across all hours using an iterative process until the  
31 27 initial LOLE is reached. The net increase in peak load then corresponds to the ELCC. The task  
32 28 force highlighted the importance of using reliable hourly wind and load data from the same years  
33 29 so that the methodology captures the underlying correlation between wind and load. This  
34 30 observation was corroborated by the task force set up by the North American Electric Reliability  
35 31 Corporation (NERC) to investigate the integration of variable generation. In [59], the task force  
36 32 stated that ELCC calculations must be based on long-term variable generation output data just  
37 33 like LOLP calculations for conventional plants depend upon accurate long-term performance  
38 34 data. It is also important that all wind and solar data relating to variable generation is  
39 35 synchronised with each other and with the load data as they are dependent on the weather. Use of  
40 36 asynchronous data will miss the relationship between the variable resources and the load leading  
41 37 to erroneous results.  
42 38

43 39 The multi-state model is an approximate calculation method for capacity credit that adopts a  
44 40 probabilistic representation of the intermittent generation plant. The approach is inspired from  
45 41 the two-state model of a conventional generation unit which can be either on or off depending  
46 42 whether there is an outage or not. D’Annunzio and Santoso [60] adopted this approach by  
47 43 considering wind generation in the calculation of the COPT as a multi-state unit that can exist in  
48 44 one or more partial capacity outage states with some individual probability. A histogram of the  
49 45 wind output power, obtained from historical resource profile and generation data, is segmented  
50 46 into different generation capacity bands with each band representing a state. The probability of  
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1 partial capacity outage for each state is then found. A parameter is also determined from a graph  
2 depicting the dependence of LOLE on the load. A mathematical function finally combined the  
3 probabilities with the parameter to compute the ELCC. Strbac et al. [61] studied the impact of  
4 wind energy on the UK electricity market using a modified version of the multi-state method. It  
5 was observed that wind power displaced conventional generation capacity only to a modest  
6 extent, with capacity credits ranging from 34% for 5 GW of installed wind power to 20% for 25  
7 GW. Calculation of capacity credit was based on an LOLP of 0.09 corresponding to the  
8 established capacity reserve margin of 24%. The intermittent behaviour of wind was derived  
9 from the frequency distribution of wind generation obtained from the past annual 0.5-hourly data  
10 of various wind farms. The authors noted that the LOLP-based capacity credit calculation does  
11 not provide any information about the frequency and duration of potential power shortages. To  
12 incorporate these parameters, a Markov Chain model was used to compute the transition rates  
13 and frequencies of departures for each generation capacity state of all units. The results showed  
14 that significant reductions in wind capacity credit are expected due to low wind conditions. Thus,  
15 a single day of no wind generation availability across the entire wind source would reduce the  
16 capacity credit of wind by 20%. These factors suggested that large conventional back-up  
17 capacities must be retained in the system to maintain the same level of supply security. The IEEE  
18 task force emphasised on the shortfall of information regarding wind-load correlation in the  
19 multi-state model [58]. Applying the model in regions marked by major seasonal and diurnal  
20 fluctuations in wind energy availability and demand can result in substantial inaccuracies in the  
21 computation of capacity credit of wind power.

22  
23 Brouwer et al. [62] conducted a review of the literature on the impacts of power generation from  
24 intermittent renewable sources and noted that most studies performed after 2005 report a  
25 capacity credit ranging from 8% to 28% at 10% penetration level of intermittent energy sources.  
26 It was noticed that these values are generally lower than those reported in studies carried out  
27 before 2005, where the capacity credits exceed 15% at 10% penetration level. The authors  
28 suggested that the divergence may arise from the calculation methodology applied in older  
29 methods which for example, used time steps larger than 1 hour. It was also observed that studies  
30 conducted in large interconnected areas, such as Europe, reported higher capacity credits and that  
31 multiple years of data are necessary for an accurate quantification of capacity credit.

## 32 33 5.2 OPERATIONAL FLEXIBILITY

34 At high levels of intermittent generation penetration, it becomes imperative for GEP process to  
35 ensure not only that there is adequacy of generation capacity to meet the demand at all times but  
36 also that there is sufficient operational flexibility in the power system. The latter refers to the  
37 ability of the power system to quickly adjust supply to match predicted and unpredicted  
38 fluctuations in net load, where net load represents the remaining demand that must be supplied  
39 by the conventional generation fleet if all of intermittent energy is to be utilised [63]. At small  
40 levels of variable RE penetration, the power system is able to absorb fluctuations in renewable  
41 output because these fluctuations will be dwarfed by those commonly encountered on the  
42 demand side [64]. At higher penetration levels however, the extent and frequency of variability  
43 in net load escalates. As clearly illustrated in Figure 6, high variable RE penetration is usually  
44 marked by steeper ramps, shorter peaks and lower turn-downs [65]. Accordingly, the generation  
45 fleet of the power system must be endowed with conventional resources that possess the  
46 following crucial technical requirements to be able to follow the net load adequately: fast cycling



1 and ramping capabilities, efficient partial load operation as well as sufficient reserve capacity.  
2 The cycling capability of a generator is its ability to start-up and shutdown frequently and rapidly  
3 [66]. Ramping capability refers to the speed at which a generating unit can change its output  
4 while partial loading efficiency pertains to the efficiency of the generator when it is operated at  
5 various output levels lower than its rated capacity [66]. Reserve capacity was already needed in  
6 traditional GEP to handle the possibility of insufficient supply capability due to unforeseen  
7 increase in demand or unexpected unavailability of some generation capacity. Increasing the  
8 share of RE in the grid calls for additional reserve requirements to cater for the enhanced  
9 uncertainty in the net load arising from inaccurate forecasting of the RE output. In many cases,  
10 DSM programmes have proved to be effective as a source of supplemental reserves in response  
11 to unexpected outage of a large generation unit or substantial decrease in intermittent generation  
12 within a short period. In large geographical areas, the availability of interconnections to adjacent  
13 power systems can provide additional flexibility to export excess or import supplementary  
14 power. In light of these requirements, simply having the required generation capacity may not be  
15 adequate for system security if that capacity is not flexible enough to respond to system  
16 variability [67]. It is important to note that operational flexibility should not be confused with  
17 uncertainty flexibility mentioned in Section 4, which relates to the power system's ability to  
18 adapt to changes in uncertain parameters.

19  
20 Contemporary GEP therefore needs to assess whether the power system is flexible enough to  
21 successfully integrate renewable generation targets at all stages of the planning horizon.  
22 Inadequate flexibility may force power system operators to frequently curtail intermittent  
23 generation, thereby decreasing revenues and making it more difficult to meet emissions targets.  
24 There is currently a lack of established metrics and methods to perform tasks involved in GEP  
25 with high levels of RE integration: to quantify flexibility and its associated cost, to determine the  
26 degree of flexibility required, and to find the optimal generation mix in order to meet the targeted  
27 degree of flexibility. More specifically, GEP studies that delve into large-scale integration of  
28 intermittent generation considering adequacy of both generation capacity and generation  
29 flexibility are practically non-existent.

30  
31 One of the early methods that provided an indication of operational flexibility in a power system  
32 was by determining the reserve capacity. Several methods have been devised to evaluate its  
33 optimal value for varying degrees of RE integration. Söder [68] found the margins of  
34 instantaneous, slow and fast reserves available on an hourly basis in the daily operation planning  
35 of a wind-hydro-thermal power system. The reserve margins were computed from the standard  
36 deviation of the system load and wind speed forecast errors and ramp rates of thermal units.  
37 Doherty and O'Malley [69] combined uncertainty in load and wind power forecasts with outage  
38 probability to calculate reserve margin requirements for a desired level of system reliability  
39 defined by the acceptable number of load shedding events annually. Ela et al. [70] broadly  
40 reviewed other studies to quantify reserve needs for power system with high RE penetration.  
41 Many of them used a two-stage stochastic programming model whereby numerous wind  
42 generation scenarios were simulated and unit commitment solutions were obtained reliably for  
43 each of the scenarios.

44  
45 Several factors affect the degree of operational flexibility of the grid. They include the level of  
46 penetration of intermittent generation sources in the grid, the correlation between intermittent

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

12  
13 The second category of metrics takes into account the time-specific nature of flexibility to  
14 provide a more meaningful appraisal of the system response to supply-demand imbalances  
15 [65].The IEA devised the Flexibility Assessment Tool (FAST) to provide a measure of the  
16 flexibility requirements and resources in different areas of a power system with varying levels of  
17 RE integration [64]. FAST has the benefit of being computationally simple as it basically  
18 consists of a four-step procedure that relates to key questions pertaining to the resources of the  
19 power system. Initially, the ramping capabilities of four already present flexible resources,  
20 namely dispatchable plants, interconnection, storage and DSM, are assessed over four different  
21 balancing time frames ranging from 15 minutes to 36 hours. Then, the extent to which aspects of  
22 the power system will limit the availability of the four flexible resources is determined. Thirdly,  
23 the maximum flexibility need of the system is computed from various parameters including the  
24 fluctuations and forecast errors in demand, variable generation output and unexpected outages.  
25 Finally, the availability of flexible resources is compared with the flexibility needs of the system  
26 to establish the extent to which intermittent RE capacity can be reliably balanced by the current.  
27 The IEA presented a refined version of their flexibility assessment tool in 2014, FAST2. It  
28 enables flexibility assessment on many timescales by processing synchronised historic time  
29 series of variable generation output and load data within an interactive environment [73]. FAST2  
30 requires additional data such as flexibility features of conventional units together with  
31 interconnection and DSM information. It evaluates the power system flexibility by determining  
32 the maximum change in supply/demand balance that the system can meet at a given instant [65].  
33 It also has the capability of computing the level of intermittent RE penetration at which  
34 additional flexibility will most likely be needed [73].

35  
36 The third category of flexibility assessment tools adopts a holistic approach of the power system  
37 to incorporate its physical, institutional and interconnection characteristics in the evaluation [65].  
38 The complexity of the analysis implies that data requirements for this category of metrics are  
39 substantial. Ma et al. [74] devised an “offline” flexibility metric that estimates the flexibility  
40 level of the overall power system along with those of individual generators in the system. The  
41 flexibility of each generator is calculated using its ramp rate and adjustable capacity given by the  
42 difference between its maximum and minimum generation levels. It is then normalised with  
43 respect to the maximum capacity of the plant. The flexibility index of the whole system is  
44 obtained from the weighted sum of the indices of individual generators.

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4 1 Some flexibility metrics have been derived from techniques applied to obtain established  
5 2 generation adequacy indices. Thus, a task force set up by the NERC to study flexibility in power  
6 3 systems used the ELCC methodology to propose an Effective Ramping Capability (ERC) metric  
7 4 [59]. Just like ELCC estimates the contribution of a new unit to the overall firm capacity of a  
8 5 power system, ERC approximates the contribution of a unit to the overall ramping capacity of  
9 6 the power system. ERC basically specifies the ability of a generation unit to ramp in a given  
10 7 direction over various time scales. Its computation follows that of ELCC except for two things.  
11 8 Firstly, the highest ramp in a given direction and time scale is considered rather than the  
12 9 maximum rated output of the unit. Secondly, the ramping availability rate of the unit replaces its  
13 10 forced outage rate to represent the probability that it will be able to supply its maximum ramp at  
14 11 any instant. It is calculated from historical dispatch data at a small resolution.  
15 12

16 13 Lannoye et al. [75] recommended insertion of a flexibility evaluation stage following the  
17 14 capacity adequacy assessment step in long-term GEP of power systems with a high share of  
18 15 intermittent RE. To this end, the authors drew on the LOLE methodology to devise the  
19 16 insufficient ramping resource expectation (IRRE) metric. The latter quantifies the risk that the  
20 17 power system will face a shortage of ramping resources to follow changes in net load over  
21 18 various time horizons. Adequacy of ramping resources can only be assessed if an appropriate  
22 19 unit commitment mechanism is applied to dispatch the resources in the system. This facilitates  
23 20 the comparison of the extent of ramping capability available in the power system with the  
24 21 ramping requirement at different time steps. Time series data of conventional and variable RE  
25 22 generation synchronised with load data for selected time horizons are processed to get time series  
26 23 data about net load ramping requirements. In a similar way to the creation of a COPT for LOLE  
27 24 calculation, an available flexibility distribution (AFD) is then generated for all upward and  
28 25 downward ramping resources from plant operational characteristics for each time horizon. By  
29 26 comparing the AFD with the net load ramp requirements, the probability that the power system  
30 27 lacks flexibility to meet each positive or negative ramp over each time horizon is computed and  
31 28 summed to obtain the overall system IRRE. The algorithm was tested on a 6-unit power system  
32 29 to underline the time horizons when the system is more vulnerable to deficiencies in ramping  
33 30 ability and to reveal the effect of increased variable RE penetration on overall system flexibility.  
34 31 In view of the substantial data and computational complexity involved in IRRE computation, a  
35 32 high-level methodology was subsequently proposed by the same authors to make the IREE  
36 33 calculation more manageable for stakeholders with limited exposure to RE integration [76].  
37 34 Simplicity of the power system operations is achieved by assuming that units are dispatched on  
38 35 the basis of energy cost merit order. As a result, data requirements are constrained to  
39 36 synchronised time series of load and variable RE production for the smallest time horizon  
40 37 considered together with the features of individual flexible resource units. Once time series of  
41 38 the available flexibility are calculated from this data, the ability of the system to follow net load  
42 39 ramps can be determined. Hence, a period of flexibility deficit (PFD) metric can be deduced to  
43 40 give an indication of the number of periods when the system experiences a flexibility deficit  
44 41 within a given time horizon.  
45 42

46 43 The Electric Power Research Institute (EPRI) elaborated an integrated long-term planning  
47 44 framework for power systems consisting of four levels of flexibility assessment that may arise at  
48 45 different stages of the planning process [86]. A multi-level assessment tool, InFLEXion, was  
49 46 developed to facilitate understanding of flexibility needs of the power system by decision-makers

1 through four different metrics. Besides IRRE and PFD, expected unserved ramping (EUR) and  
2 well-being assessment are used to appraise flexibility issues in planning decisions. EUR is  
3 analogous to the EUE index used in quantifying capacity adequacy in the sense that it refers to  
4 the total magnitude of the flexibility shortage instead of its total duration. It represents the  
5 aggregate ramping deficits over a specific time horizon based on large ramps up to a certain  
6 percentile. Well-being analysis, first coined by Billinton and Fotuhi-Firuzabad [87], combined  
7 probabilistic and deterministic indices to express the well-being of a power system into one of  
8 three states: healthy, marginal or at risk. In a similar way, InFLEXion maps the frequency and  
9 magnitude of flexibility shortages over a particular period through PFD and EUR respectively, to  
10 determine whether a system is in a user-defined safe, warning, or dangerous state [86].

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

### 27 28 5.3 RECENT LONG-TERM CAPACITY PLANNING MODELS

29 In the wake of the increased integration of intermittent RE sources in the electricity grid, it is  
30 essential for the new long-term GEP paradigm to capture the operational characteristics of the  
31 generation fleet and gain insight into the actual dispatch practices in order to integrate flexibility  
32 issues. As observed throughout this paper, traditional GEP models used to simply ignore short-  
33 term system operational details or account for them by using highly simplified assumptions. For  
34 example, cycling and load following features of individual power plants are often overlooked  
35 and the chronology of demand is entirely absent in the load duration curve used to approximate  
36 the annual load profile. Recent literature has mostly been directed towards finding ways to  
37 incorporate short-term power system operational details in GEP while ensuring that the problem  
38 remains computationally tractable. Typically, methods developed for this purpose integrate unit  
39 commitment and dispatch processes within the existing GEP models. Ma et al. [77] proposed a  
40 Unit Construction and Commitment (UCC) algorithm to find the optimal generation portfolio  
41 that satisfies the flexibility requirements at a given wind penetration level. The UCC algorithm  
42 represents one of the first efforts to capture flexibility within GEP by integrating short-term  
43 operational decisions in the long-term planning. Rather than considering a fixed set of existing  
44 generating units and their operational costs as traditionally done in unit commitment planning,  
45 the UCC has the possibility of adding new generation plants along with their associated  
46 investment costs. Limitations of this work include the use of a deterministic methodology to

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4 1 model stochastic wind energy output and inability to study intra-hour variations in intermittent  
5 2 generation and demand. Palmintier and Webster [84] merged GEP with unit commitment  
6 3 planning in another study to capture the influence of flexibility on long-term capacity planning.  
7 4 Computational tractability is ensured by clustering generators that share the same technical  
8 5 characteristics in terms of ramp rates, heat rate as well as minimum and maximum operating  
9 6 levels. A one-year simulation conducted at an hourly resolution on a 205-unit power system  
10 7 indicates not only that flexibility significantly affects generation mixes but also that ignoring  
11 8 flexibility can lead to generation portfolios that are infeasible to operate. A major drawback of  
12 9 this methodology relates to its deterministic approach to reserves. Once reserve constraints are  
13 10 satisfied, the model does not investigate scenarios where reserves may be inadequate due to  
14 11 capacity outages and forecast errors. Batlle and Rodilla [78] incorporated the cycling features of  
15 12 thermal units in a traditional least-cost optimisation GEP model. The unit scheduling process  
16 13 considered start-up times and minimum generation levels of units together with usual cost  
17 14 functions in determining the most appropriate technologies to provide power at various intervals  
18 15 of the planning horizon. The main problems of this method relate to its unique economic  
19 16 objective function and the absence of uncertainties in its formulation. Jin et al. [79] attended to  
20 17 the issue of uncertainties by proposing a stochastic GEP model where long-term uncertainty in  
21 18 the wind resource is introduced by using multiple scenarios consisting of weekly time series of  
22 19 hourly wind power output data. On the other hand, short-term errors in wind forecast are  
23 20 compensated by a calculated amount of operating reserves. Power plant operational details are  
24 21 included through a simple unit dispatch model regulated by economic aspects and constrained by  
25 22 ramping characteristics of generators. However, due to the computational complexity, the model  
26 23 can handle only a subset of weekly wind power scenarios. Other shortcomings pertain to the  
27 24 relatively basic treatment of short-term wind forecast errors and to the representation of  
28 25 operational constraints of generating units by ramp rates only. Flores-Quiroz et al. [80] reduced  
29 26 the computation complexity by using a decomposition technique that allows for the inclusion of  
30 27 integer variables in the various stages of the GEP. A wide range of unit operational  
31 28 characteristics appear as constraints in the model. The main deficiencies of this method are  
32 29 concerned with the sequential approach to its multi-stage solution and its deterministic nature  
33 30 that prevents it from handling uncertainties adequately. Koltsaklis and Georgiadis [79]  
34 31 implemented a mixed integer linear programming model that also makes investment decisions  
35 32 based on short-term operational constraints of energy planning. Computational tractability has  
36 33 been preserved by taking a typical day to represent each month over a long period to determine  
37 34 the optimal generation mix and energy planning details of the power system. One common  
38 35 drawback of all these studies is that they focused solely on thermal generating units for  
39 36 flexibility provision and did not consider alternative sources of flexibility. Moreover, the models  
40 37 apply long temporal resolutions, in order to avoid the prohibitive computational complexity  
41 38 associated with smaller temporal resolutions. Such high resolutions are not able to fully capture  
42 39 the intricacies of the generator operations.

43 40  
44 41 In recent years, a rational strategy that has been widely applied to represent operational details in  
45 42 GEP is the soft-linking of two commercially available energy modelling tools [81–86]. A first  
46 43 tool is selected to implement traditional long-term capacity planning by optimising the  
47 44 generation portfolio while a second one executes short-term modelling of the resulting power  
48 45 system in terms of unit commitment and dispatch. The second tool thus transposes short-term  
49 46 operational dynamics of the power system to the generation mix resulting from the high-level

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4 1 optimisation procedure of the first tool. The two tools are usually applied iteratively in order to  
5 2 verify the operational feasibility of the expansion plan. The wide acceptance of this hybrid  
6 3 framework stems from its simplicity, computational tractability and use of well-known  
7 4 commercial modelling packages. Nevertheless, several limitations of the soft-linking approach  
8 5 have been reported. The fact that the two tools use overlapping but different sets of input  
9 6 parameters could lead to hidden input data inconsistency [85]. Additionally, it is unlikely that  
10 7 investment decisions on new power plants will be guided predominantly by short-term  
11 8 operational constraints of the power system. Moreover, since most applications of the hybrid  
12 9 model use long time steps in the capacity expansion tool, they are unable to directly include  
13 10 flexibility constraints in it [87]. Another weakness is the single least-cost minimisation objective  
14 11 function used in most studies which dictates that other potential objectives are converted into  
15 12 constraints.

## 13 6. SUMMARY AND RESEARCH QUESTIONS

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

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

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4 1 GEP will provide a more detailed and realistic overview of operations. Such metrics, however,  
5 2 rely on detailed simulations of extensive historical load and generation time-series data. Future  
6 3 research efforts could focus on developing computationally tractable algorithms to deal with the  
7 4 enhanced complexity. Another issue that requires immediate attention of researchers is the  
8 5 economic value associated with operational flexibility. Improving the flexibility availability  
9 6 within the power system entails additional costs. Although some studies have attempted to  
10 7 estimate the cost of flexibility provision through solar and wind power [88–90], a collective  
11 8 framework is required to harmonize the inherent differences among various power systems and  
12 9 the features that are considered in the economic evaluation. Costs associated with provision of  
13 10 flexibility are of prime importance to DMs in their selection of the optimal expansion plan. The  
14 11 literature survey has also revealed that GEP studies incorporating flexibility mostly consider  
15 12 conventional power plants as the sole source of flexibility. Future works need to account for  
16 13 other sources of flexibility in the power system, including short-term DSM programmes, storage  
17 14 devices and interconnection with neighbouring networks, in order to provide a holistic view into  
18 15 the real potential of the system to cope with variable RE. Methods to assess the flexibility  
19 16 provision by these sources need to be devised. A crucial gap in present knowledge relates to  
20 17 determining the minimum level of flexibility that a power system must possess in order to accept  
21 18 a given share of intermittent RE. Along the same lines, it is presently impossible to evaluate  
22 19 precisely the additional amount of variable renewables that the grid can take even if its flexibility  
23 20 resources are known. Again, such information is vital for DMs before undertaking new RE  
24 21 obligations.

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34 22 *Treatment of uncertainties:* Measures taken to decarbonize the electricity grid have contributed  
35 23 to an escalation of uncertainties in energy planning and heightened the complexity of GEP.  
36 24 Models have strived to incorporate the uncertainties caused by variations in RE output and  
37 25 demand separately in GEP [91–93]. However, simplistic formulations are applied to represent  
38 26 uncertainties in both RE output and load in the modelling process to ensure its computational  
39 27 tractability. Future load is usually estimated through one or more of the following factors:  
40 28 projected population, economic state and technological progress. The effects of diurnal, weekly,  
41 29 and seasonal patterns on demand could be combined with the aforementioned factors. Similarly,  
42 30 uncertainties in intermittent RE output is commonly represented by the average annual output. In  
43 31 this context, capacity credit and ELCC computation could be introduced in GEP to convincingly  
44 32 represent the firm contribution of wind and solar energy outputs to the grid. The geographical  
45 33 availability of variable RE resources could also be incorporated in the formulation. Moreover,  
46 34 given that both demand and variable RE output depend on climatic conditions, the correlation  
47 35 between them and its effect on the generation mix could be investigated in GEP. Variable RE  
48 36 sources also introduce uncertainties in short-term operational details. Current unit commitment  
49 37 models used in GEP attempt to forego its traditional deterministic nature by considering a few  
50 38 cycling and ramping constraints of individual plants. The actual operations of units could be  
51 39 more accurately captured by integrating a whole range of technical characteristics of generators  
52 40 in the model. Furthermore, unit commitment and dispatch can be simulated more effectively by

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4 1 incorporating forecasting algorithms that anticipate wind and solar resources in GEP models.  
5 2 Until now, forecasting techniques have hardly been considered but their potential to mitigate  
6 3 reliability and resource overscheduling risks can be valuable in capacity planning models.  
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9 4 *Smart grid technologies:* The impact of smart grid technologies on GEP is likely to intensify in  
10 5 the future as more variable renewables are added to the grid. The main reason for their growing  
11 6 influence stems from their ability to decrease the variability in the power system by facilitating  
12 7 the supply-demand balance through DSM programmes, modern information and communication  
13 8 technologies, advanced metering infrastructure, sensor networks and enhanced grid management  
14 9 and control. Future research efforts in GEP should therefore optimally involve these smart  
15 10 technologies in a rational way. Notably, the performance of smart grid technologies from  
16 11 operational and economic perspectives could feature in upcoming GEP models by analysing the  
17 12 benefits and problems associated with them. Most of the existing literature on the impacts of  
18 13 smart grid technologies on GEP has focused on DSM programmes. Other emerging alternatives  
19 14 that help in maintaining the grid demand-supply balance, such as distributed energy resources  
20 15 and plug-in electric vehicles, could also be investigated.  
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22 16 Finally, it is important to note that the suggested future research directions will add new  
23 17 dimensions to GEP, thereby exacerbating the complexity of an already convoluted problem.  
24 18 More sophisticated techniques, tools and algorithms will inevitably be needed to cope with the  
25 19 additional computational requirements. More often than not, GEP model developers will be  
26 20 faced with the delicate task of making trade-offs between the level of granularity implemented in  
27 21 their models and the computational complexity.  
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## Figure 1

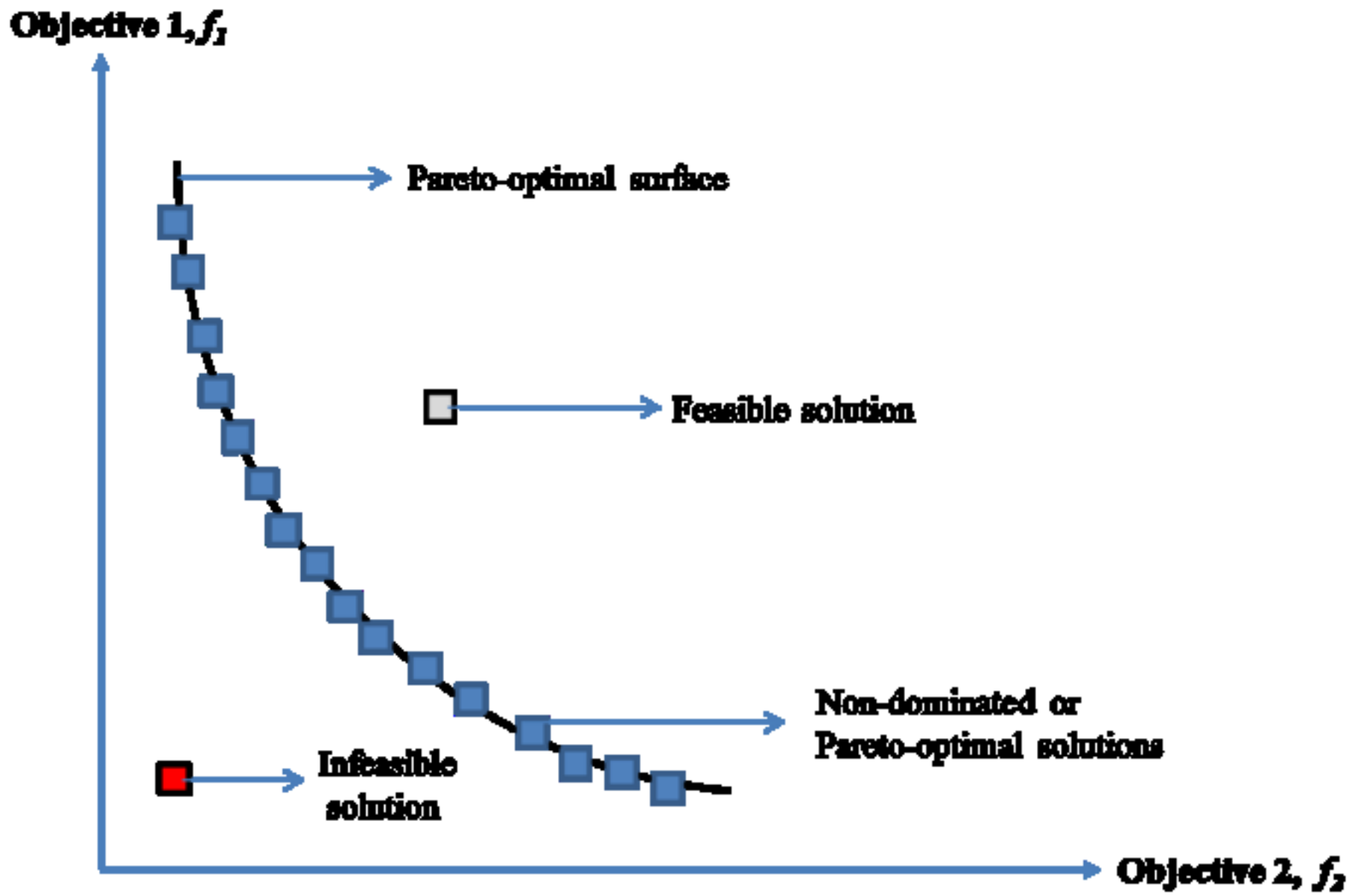
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## Figure 2

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Figure 3  
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**Figure 4**  
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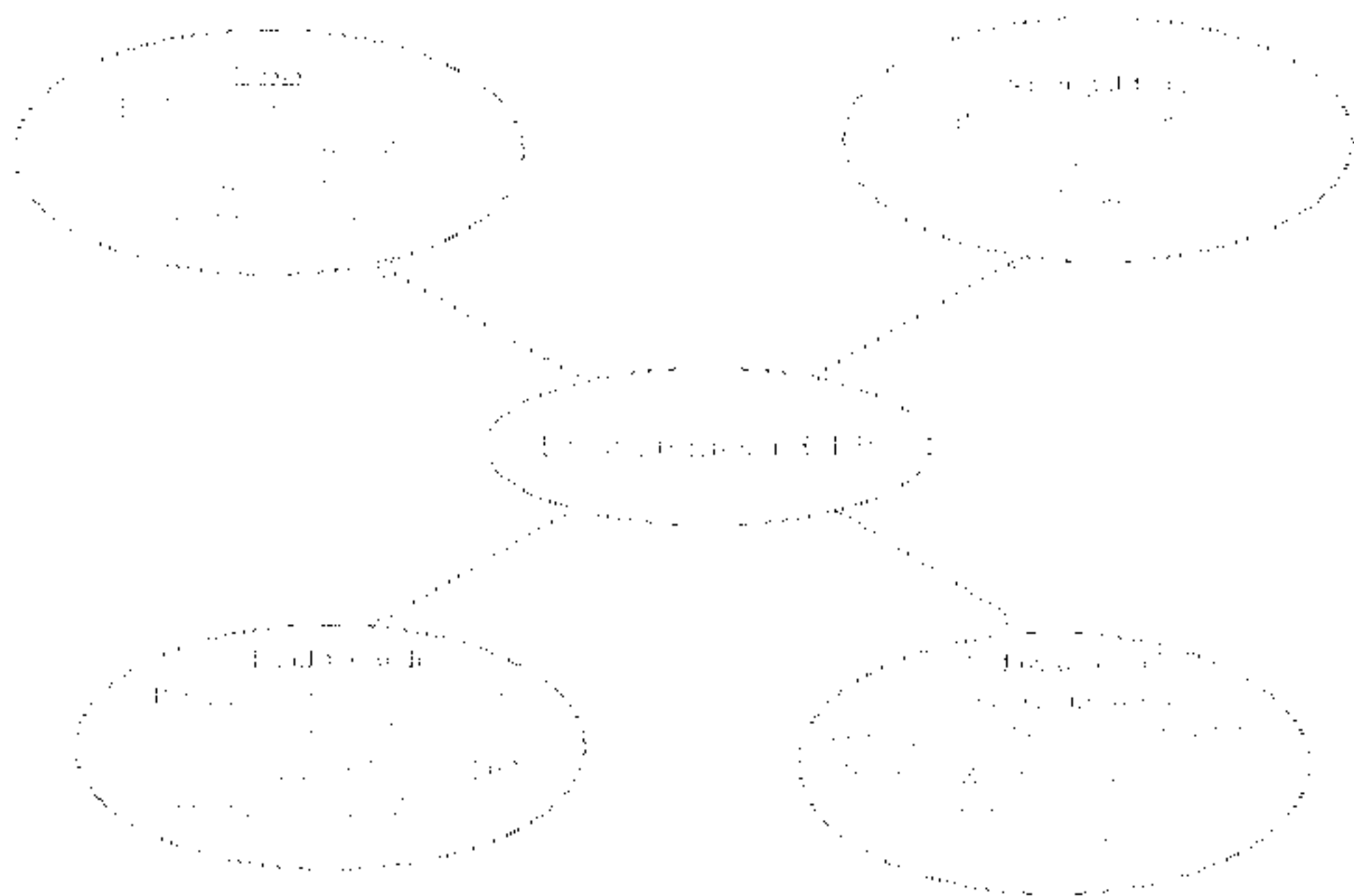


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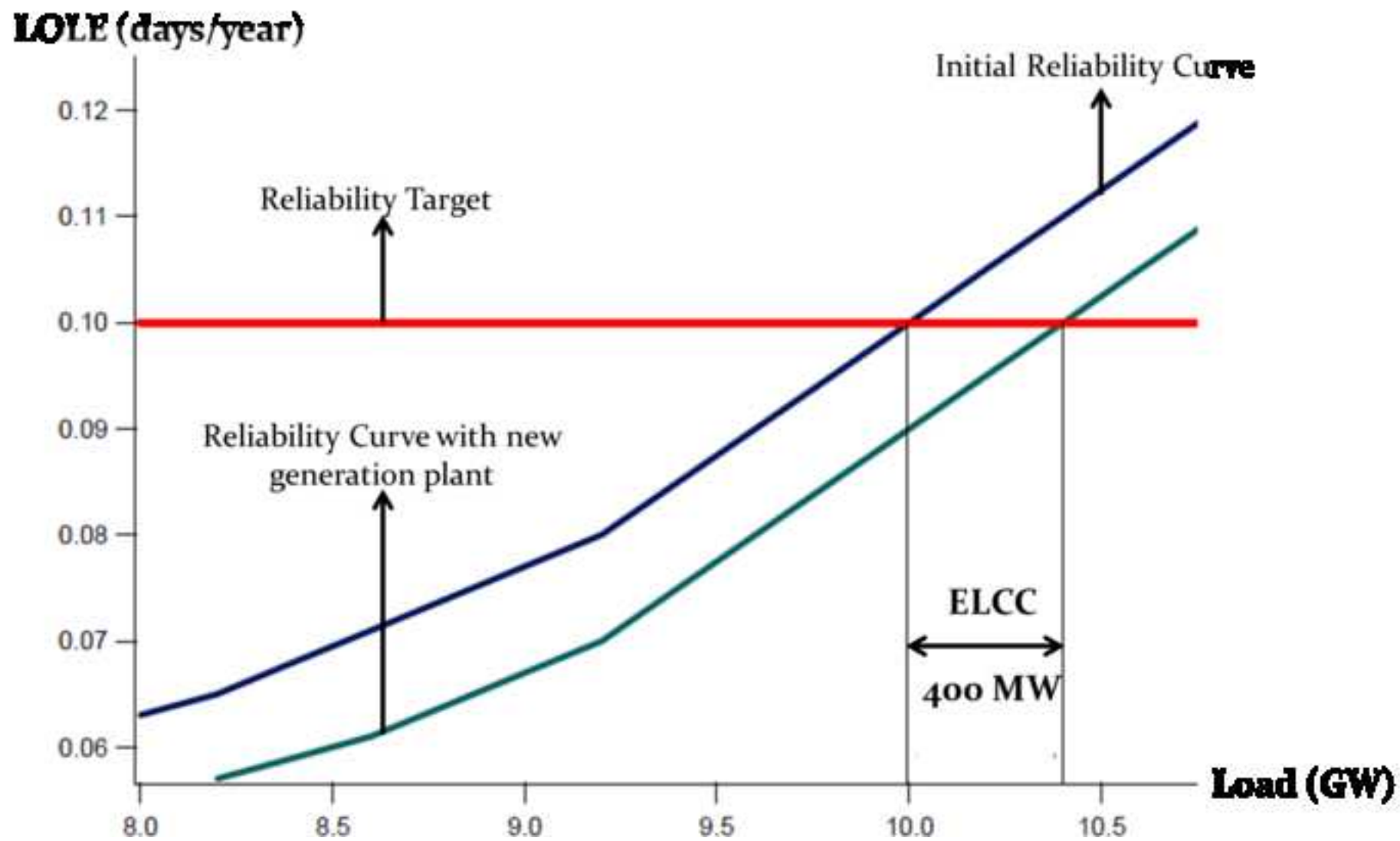
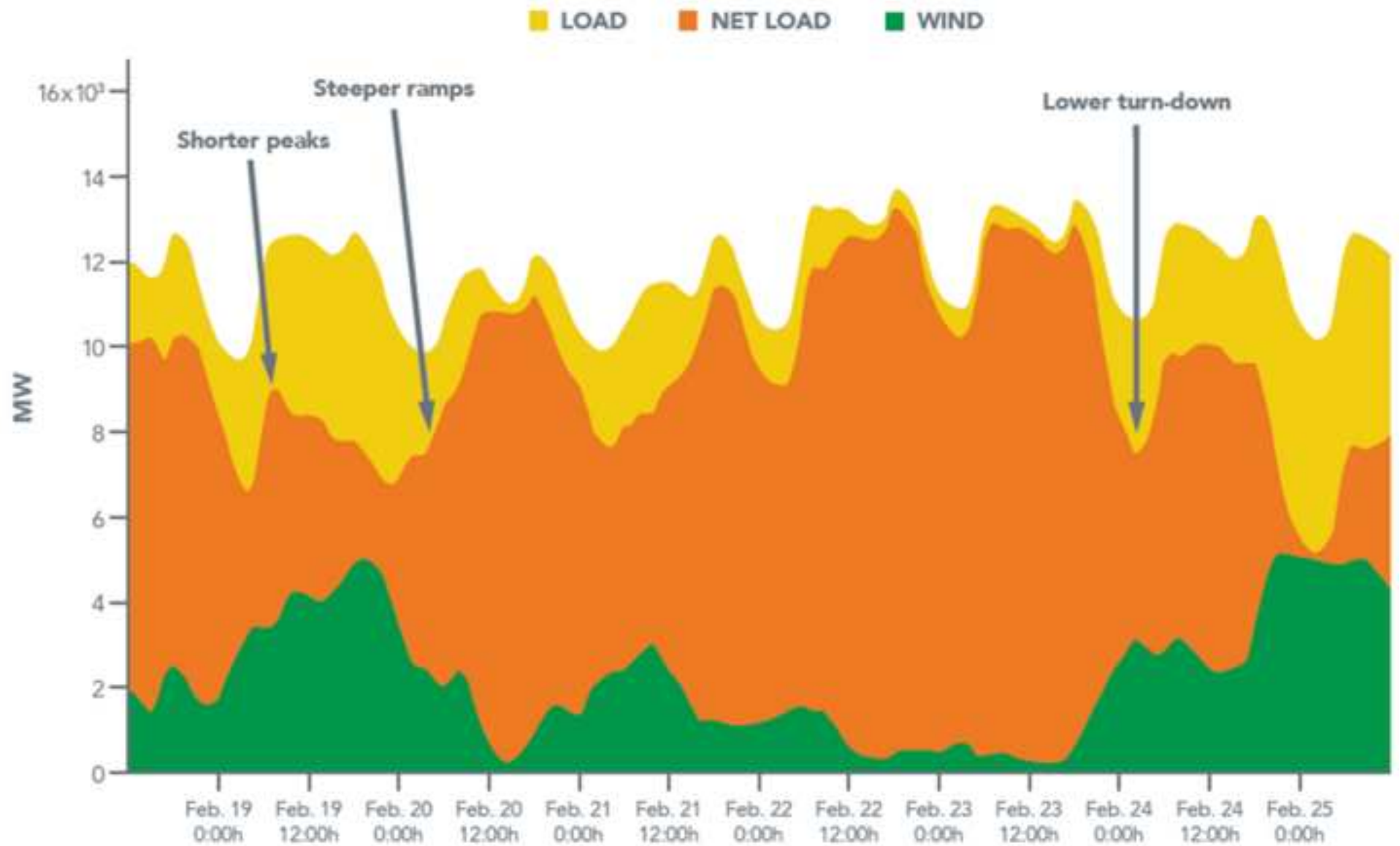


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### **Figure Captions**

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].