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A multi-objective framework for long-term generation expansion planning with variable renewables

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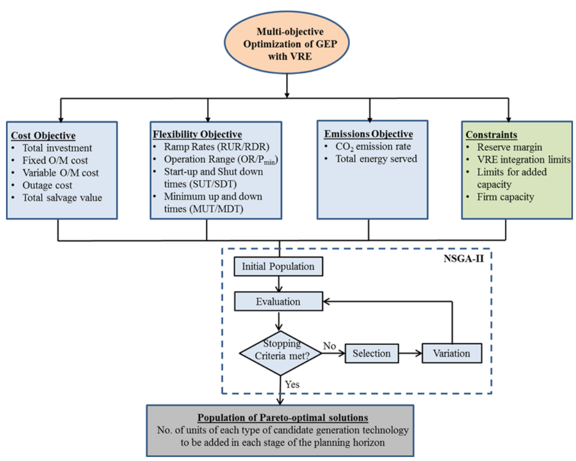
HIGHLIGHTS

- Framework considers flexibility, cost and CO_2 emissions as separate objectives.
- Overlooking flexibility in generation planning gives rise to infeasible portfolios.
- Analysis of Pareto-optimal solutions reveals potential correlations among objectives.
- Unit commitment validates evaluation of flexibility in generation plans by model.
- Parallel coordinates plots help in the selection of preferred investment plan.

GRAPHICAL ABSTRACT



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ABSTRACT

The growing importance of operational flexibility in generation expansion planning with increased integration of variable renewables has been regularly highlighted in recent research. Yet, operational flexibility has been largely overlooked in order to reduce the prohibitive problem size that results when operational details at small timescales are included in this long-term exercise. In this work, we present a multi-objective optimization framework that effectively and tractably incorporates flexibility screening of candidate generation portfolios in long-term generation expansion planning. Operational flexibility is considered as a separate objective along with the traditional economic and environmental objectives. The ability of the proposed methodology to provide valuable insights into the correlations between flexibility, total costs and carbon emissions is demonstrated using a case study. The results clearly reveal that omission of flexibility from the framework gives rise to deficient generation mixes that are unable to match the more frequent and steeper variations in net load. A high-level evaluation of the flexibility needed in generation portfolios to balance net loads with different degrees of variability is also provided. Finally, a procedure is proposed to support the decision-making process for selecting the most appropriate investment plan among the many solution options provided by the multi-objective optimization framework.

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Nomenclature

Acronyms

AHP	Analytical Hierarchy Process
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CFM	Composite Flexibility Metric
DM	Decision-Maker
EENS	Expected Energy Not Served
FOR	Forced Outage Rate
GEP	Generation Expansion Planning
IEA	International Energy Agency
LOLP	Loss of Load Probability
MDT	Minimum Down Time
MOO	Multi-Objective Optimization
MUT	Minimum Up Time
NSGA-II	Non-dominated Sorting Genetic Algorithm Version II
OCGT	Open Cycle Gas Turbine
O&M	Operation and Maintenance
OR	Operating Range
P_{min}	Minimum Stable Generation Level
PV	Photovoltaic
RDR	Ramp-Down Rate
RE	Renewable Energy
RTS-96	Reliability Test System 1996
RUR	Ramp-Up Rate
SDT	Shut Down Time
SPC	Supercritical Pulverized Coal
SUT	Start Up Time
UC	Unit Commitment
VRE	Variable Renewable Energy

Sets and indices

t, T	set of periods within the planning horizon
g, G	set of existing generation technology types
n, N	set of candidate generation technology types
k, K	set of generation technology types ($K = G + N$)
i, I	set of VRE technology types ($I \subset N$)
z, Z	set of flexibility indicators of a generator unit

Parameters

r	yearly discount rate
α	yearly discount factor = $1/(1 + r)$
y	number of consecutive years constituting a period
$U_{n,max}^t$	maximum number of units of n allowed in t
U_g^t	number of units of g available at start of t
Cap_g	capacity of unit of g (MW)
Cap_n	capacity of unit of n (MW)
I_n	investment cost for n ($/MW)
F_g	annual fixed O&M cost for g ($/MW)
F_n	annual fixed O&M cost for n ($/MW)
V_g	variable O&M cost for g ($/MWh)
V_n	variable O&M cost for n ($/MWh)
C_{EENS}	cost of lost load ($/MWh)
δ_n	salvage factor for unit of n
Emi_g	CO_2 emissions generated by g ($kgCO_2e/MWh$)
Emi_n	CO_2 emissions generated by n ($kgCO_2e/MWh$)
Dem^t	peak demand during t (MW)
R_{min}^t	minimum reserve margin during t (% of Dem^t)
R_{max}^t	maximum reserve margin during t (% of Dem^t)
VRE_{min}^t	minimum % generation from units of i during t
VRE_{max}^t	maximum % generation from units of i during t
x_z	value assigned to flexibility indicator z
W_z	weight of flexibility indicator z in CFM
$\min(x_z)$	minimum value of x_z among units of k
$\max(x_z)$	maximum value of x_z among units of k

Variables:

U_n^t	num. of units of n added in time periods until t
U_n^T	total num. units of n added in planning horizon.
E_g^t	total energy served by units of g during t (MWh)
E_n^t	total energy served by units of n during t (MWh)
C_{inv}^t	total investment cost during t ($).
C_{OMF}^t	total fixed O&M cost during t ($/kW-yr)
C_{OMV}^t	total variable O&M cost during t ($/MWh).
C_{out}^t	total outage cost during t ($)
C_{sal}^t	total salvage value of units of n during t ($)
$TCap_n^t$	total capacity of n added in time periods until t (MW)
$EENS_t$	expected energy not served during t (MWh)
$x_{z,k}$	value of flexibility indicator z for unit of k
$I_{z,k}$	normalized value of $x_{z,k}$
r_{xy}	Pearson correlation coefficient between a pair of flexibility indicators x and y
$Flex_k$	CFM index of unit of k
$Flex_g$	CFM index of unit of g
$Flex_n$	CFM index of unit of n

1. Introduction

In recent years, new paradigms for generation expansion planning (GEP) have emerged that are mainly driven by commitments to decarbonize power systems. The increased integration of wind and solar energy in the electricity grid has compelled power system planners to focus their attention on the operational challenges associated with the uncertain output of these variable renewable energy (VRE) sources. With higher levels of VRE penetration, the magnitude and frequency of the fluctuations in net load intensify. The conventional generation fleet requires increased operational flexibility to quickly adjust its supply to match these variations [1]. Present-day GEP models with increased VRE integration must therefore ensure that the optimal generation portfolios are flexible enough to satisfy the renewable energy targets set during the various stages of the planning horizon [2]. Overlooking flexibility in such planning models will inevitably result in sub-optimal or infeasible capacity addition [3]. While the critical importance of flexibility in capacity planning with renewables has been widely acknowledged, very few attempts have been made to integrate it in the planning process [4]. The main issue is that traditional GEP for vertically integrated power systems is already a complex problem. It involves multi-period, non-linear, mixed-integer, dynamic and stochastic optimization in a highly constrained and uncertain environment [5]. Capturing flexibility would entail considering operational details at a sub-hourly timescale, generally through the unit commitment (UC) problem, within a GEP exercise that usually spans over decades [6]. UC formulations merge many binary and real-valued decisions regarding the commitment and dispatch levels of generating units respectively. Moreover, many complex time-related constraints are associated with each generating unit [7]. As a result, combined GEP-Flexibility models present considerable complexity and computational tractability challenges [8].

An initial approach to the GEP-Flexibility problem applied a two-stage technique [9,10]. In the first stage, future generation portfolios are obtained using conventional generation planning models. In the second stage, the operational dynamics of a sample of generation mixes selected from the outcome of the first stage are examined in detail [9].

This technique usually employs common energy planning models such as TIMES for the long-term generation planning and EnergyPLAN for the short-term operational model [10]. The main issue with this approach is that ignoring operational details in the generation planning model during the first stage will likely result in generation mixes that are operationally or economically infeasible [11]. In addition, the two stages use different sets of input parameters that could lead to hidden input data inconsistency [11].

A second approach extended the traditional screening curves technique to develop heuristic-based models [12,13]. The latter represent the cycling operation of thermal units in capacity planning with VRE. Basically, these models first apply a UC model that considers some operational constraints to determine how generating units will be dispatched. The implications of the dispatch order on the total costs are then computed and the screening curve is adjusted accordingly. Although this method provides solutions within a reasonable time, it does not ensure their global optimality and omits many operational constraints of thermal generators. Furthermore, it does not model the discrete generator sizes, leading to a very optimistic UC schedule for all generating technologies [14].

Several GEP models have curtailed the computational burden of integrating short-term operational dynamics by applying variants of the UC formulation. One common technique involves the judicious selection of representative days or weeks to simulate UC during the planning horizon. Usually, one week of chronological load and wind data is used to represent each season in a planning horizon of one year [15]. The planning horizon can be extended beyond one year while maintaining the computational efficiency by selecting one representative day of each month over a number of years [16]. A limitation of this technique relates to the difficulty in selecting representative periods that can accurately model highly stochastic VRE resource patterns over much longer time periods [17]. Moreover, some operational constraints are typically simplified to reduce the computational complexity.

During the last few years, a new modeling methodology has scaled down the dimension of the UC problem by aggregating groups of generating units with similar characteristics into clusters [5]. Consequently, a reduced set of integer variables per cluster replaces a much larger set of binary commitment variables for each individual unit [18]. Likewise, the clustered formulation deals with significantly fewer constraints that are imposed on clusters of generators rather than on individual generators [19]. The problem size can be further reduced by ignoring a few UC constraints for each cluster. This approach has been successful in reducing run times considerably while upholding reasonable accuracy in the results [20]. However, when applying the clustered UC formulation in the long-term planning exercise, a series of approximations are often required to keep computation time within limits. For example, most clustered approaches use representative weeks of demand and VRE outputs. Furthermore, while it is expected that errors are introduced into such formulations for clusters of heterogeneous generating units, it has been demonstrated that even clusters of identical units can lead to errors under certain power system operating conditions [21].

In this work, we present a novel multi-objective optimization framework that effectively and tractably incorporates flexibility screening of candidate generation portfolios in long-term generation expansion planning. The key contributions of this work are:

(i) One common feature of the foregoing GEP-Flexibility models is that they all minimize a single cost objective subject to several constraints. This cost function aggregates all cost components associated with capacity investment. They include fixed operation and maintenance costs, UC costs as well as miscellaneous costs such as penalties for CO_2 emissions, load shedding and VRE curtailment. Yet, many components of this cost objective are conflicting in nature. Besides, GEP and UC are non-commensurable processes and the intricacies of the UC problem cannot be readily converted to monetary terms. In this paper, a multi-objective optimization (MOO) approach is used to provide an appropriate way to deal with these conflicting, non-commensurable and non-monetary outcomes [22].

(ii) The proposed framework meets the needs and expectations of contemporary GEP. It searches for minimal cost investment plans while also considering capacity adequacy, compliance with environmental obligations and flexibility preparedness to match increased net load variability. The latter is implemented by the explicit inclusion of flexibility as an objective in a multi-objective formulation. This represents the first attempt to consider flexibility as a separate objective in GEP. The decision is justified by the well-documented prominence of flexibility in present-day power system planning, as detailed in Section 3.2.

(iii) Existing combined models tend to examine limited planning horizons to prevent exceedingly long run times. Attempting to simulate a typical long-term GEP problem with these models will be computationally prohibitive. The proposed model is not only developed for long planning horizons but also allows the latter to be broken down into stages. This enables modification of parameters for each stage to reflect changes in the energy market.

(iv) It has been largely reported that large-scale integration of VRE sources calls for higher amounts of flexibility in the generation portfolio in order to maintain reliability of supply. The current work contributes to the growing body of knowledge on this topic. The economic and environmental impacts of embedding flexibility in the GEP exercise can be visualized within the proposed framework. More importantly, the results provide clear evidence that ignoring flexibility in GEP leads to generation mixes that are infeasible during operations.

The rest of the paper is structured as follows. Section 2 describes the MOO algorithm used. Section 3 details the objectives and constraints of the MOO formulation, with particular emphasis on the flexibility objective function that is central to this study. Section 4 presents the results for a test system and discusses the impact of flexibility on investment and operational costs. It also elaborates on the decision-making process. Section 5 demonstrates the effectiveness of the methodology to appropriately represent the operational behavior of the power system in the proposed framework using a UC model. Section 6 provides a summary and concluding remarks.

2. Multi-objective optimization algorithm

Early GEP models aimed at finding the most economical generation plan that could provide an adequate supply of electricity. As power systems evolved, GEP models needed to consider a wide range of aspects besides the traditional least-cost objective. In particular, environmental, technical, operational, regulatory and social considerations became important [3]. An initial approach for handling these additional potential objectives consisted of expressing them as constraints imposed on the GEP model. For example, environmental impacts were often tackled by setting tolerance thresholds for the maximum acceptable emission rates during the planning horizon. Alternatively, other objectives were converted into cost or penalty functions that were subsequently incorporated into the least-cost objective function. While models considering additional objectives, either as constraints or from a financial perspective, are simple, they provide a single solution as a result of the search process. This implies that trade-offs between different components of the cost objective must be established in advance of the solution, thereby limiting considerably the decision-making process [23]. No single solution can be claimed as being optimal in problems involving multiple conflicting objectives [24]. In addition, the ongoing low-carbon transition of the power sector has bolstered the importance of environmental and operational objectives in GEP. These conflicting and non-commensurate objectives must be optimized simultaneously. GEP models become more realistic when distinct evaluation criteria are explicitly considered as objective functions rather than performing an absolute economic analysis exercise [25,26].

The aim of the proposed MOO model is to yield optimal generation mixes that are resilient to the unexpected nature of future net loads in the grid while satisfying the traditional economic and environmental objectives. Problems involving multiple conflicting criteria do not have a unique optimal solution but a set of alternatives, known as Pareto-optimal or non-dominated solutions, which represent trade-offs among the various criteria [27]. Evolutionary algorithms are well suited for solving problems of this nature for several reasons [28]. Firstly, they have the inherent ability to search for multiple Pareto-optimal solutions concurrently in a single simulation run. Also, unlike exact optimization methods, evolutionary algorithms have robust and powerful search mechanisms that allow them to handle the large and complex search spaces commonly associated with real-world optimization problems [28]. They further enable the decision-maker (DM) to refine and adjust preferences in the search for a compromise solution in a limited amount of time [29]. Among the many existing multi-objective evolutionary approaches, the Non-dominated Sorting Genetic Algorithm Version II (NSGA-II) has been successfully applied to several disciplines [30], including the traditional GEP problem [24]. It has been demonstrated that NSGA-II outperforms a number of contemporary MOO evolutionary algorithms in finding a diverse set of solutions for problems with a maximum of three objectives [27].

Since its inception in 2002, the NSGA-II has become pervasive in finding multiple Pareto-optimal solutions in MOO problems. Its widespread use is attributed to the application of three distinctive features, namely, an elitism strategy, an explicit diversity preserving mechanism, and a focus on non-dominated solutions [27]. The NSGA-II algorithm for one iteration is illustrated in Fig. 1. An offspring population Q_j is generated from the parent population P_j, each of size S, using typical evolutionary operators. The two populations are subsequently merged together to form an intermediate population R_j of size $2S$. The fitness of all individuals in R_j are evaluated and the solutions are then sorted on the basis of their non-dominance. In other words, all non-dominated solutions are assigned rank 1 and grouped in Pareto Front 1. Those that are dominated only by rank 1 individuals are ascribed rank 2 and classified in Pareto Front 2, etc. The new population for the next iteration P_{j+1} is constituted by considering individuals from the Pareto Fronts in increasing order, one at a time. Once the S places in P_{j+1} are filled, the remaining fronts are discarded. If all individuals of the last front admitted cannot be accommodated in the new population as shown in Fig. 1, then selection is made based on the diversity of the solutions. For this purpose, an operator is used to determine the crowding distance d_u of each solution u in the last front. The crowding distance d_u estimates the density of solutions in the objective space around u. To maintain diversity in the population, individuals from the least crowded regions are chosen to fill up the remaining places in P_{j+1}.

3. GEP-flexibility formulation

Since long-term GEP is considered here, the planning horizon is broken down into T stages consisting of y consecutive years each. There are G existing generation technologies at the start of the planning horizon and N candidate generation technologies available for expansion purposes. The outcome of the optimization problem is provided through a decision variable vector representing the number of units of each type of candidate generation technology to be added to the power system in each stage of the planning horizon. In addition, the three objective functions are evaluated at the end of each stage.

Fig. 2 illustrates the general flowchart of the MOO framework for long-term GEP with increased integration of VRE sources. The objectives and constraints of the formulation are described in this section.

3.1. Cost objective function

The traditional cost objective ensures that electricity is supplied to customers at an affordable and reasonable cost. The total cost is calculated as the cumulative sum of the costs related to the investment in new generating units, fixed and variable operation and maintenance of existing and newly introduced units, and the unmet demand costs in each period less the salvage value associated with candidate units committed during each period. All future costs are discounted with a discount factor α to yield their net present value.

Minimize cost objective O_1:

$$O_1 = \sum_{t=1}^{T} C_{inv}^t + C_{OMF}^t + C_{OMV}^t + C_{out}^t - C_{sal}^t \tag{1}$$

The various components of the cost objective for each period t are detailed below.

3.1.1. Investment costs

It is assumed that investments in candidate units of technology n are made at the start of any period t. However, additional generation capacity from these units is available only in future periods to account for inevitable construction lead times:

$$C_{inv}^t = \alpha^{[y(t-1)]} \sum_{n=1}^{N} I_n U_n^t Cap_n \tag{2}$$

It follows that the additional generation capacity available in the next period $t + 1$ is given by:

$$TCap_n^{t+1} = \sum_{n=1}^{N} U_n^t Cap_n \quad t = 1, \cdots, T-1 \tag{3}$$

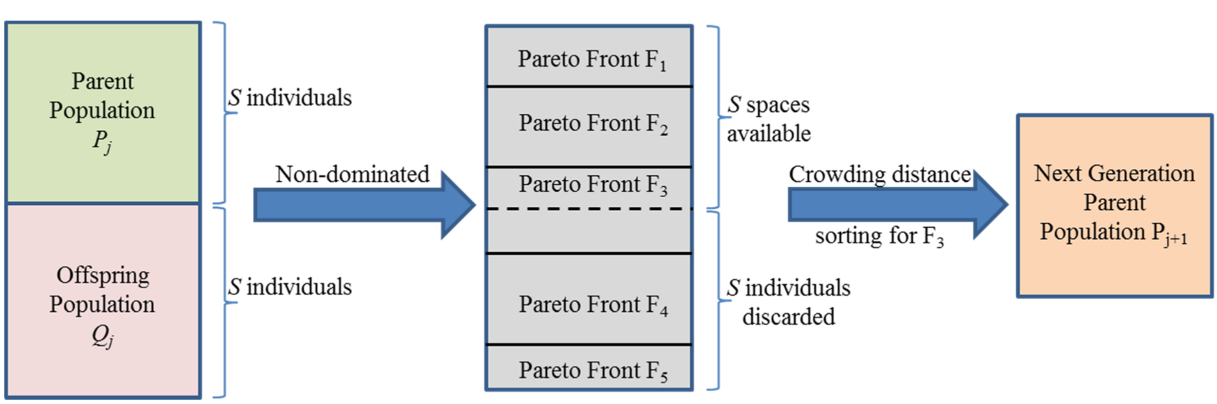

Fig. 1. Mechanisms involved in the NSGA-II algorithm (adapted from [27]).

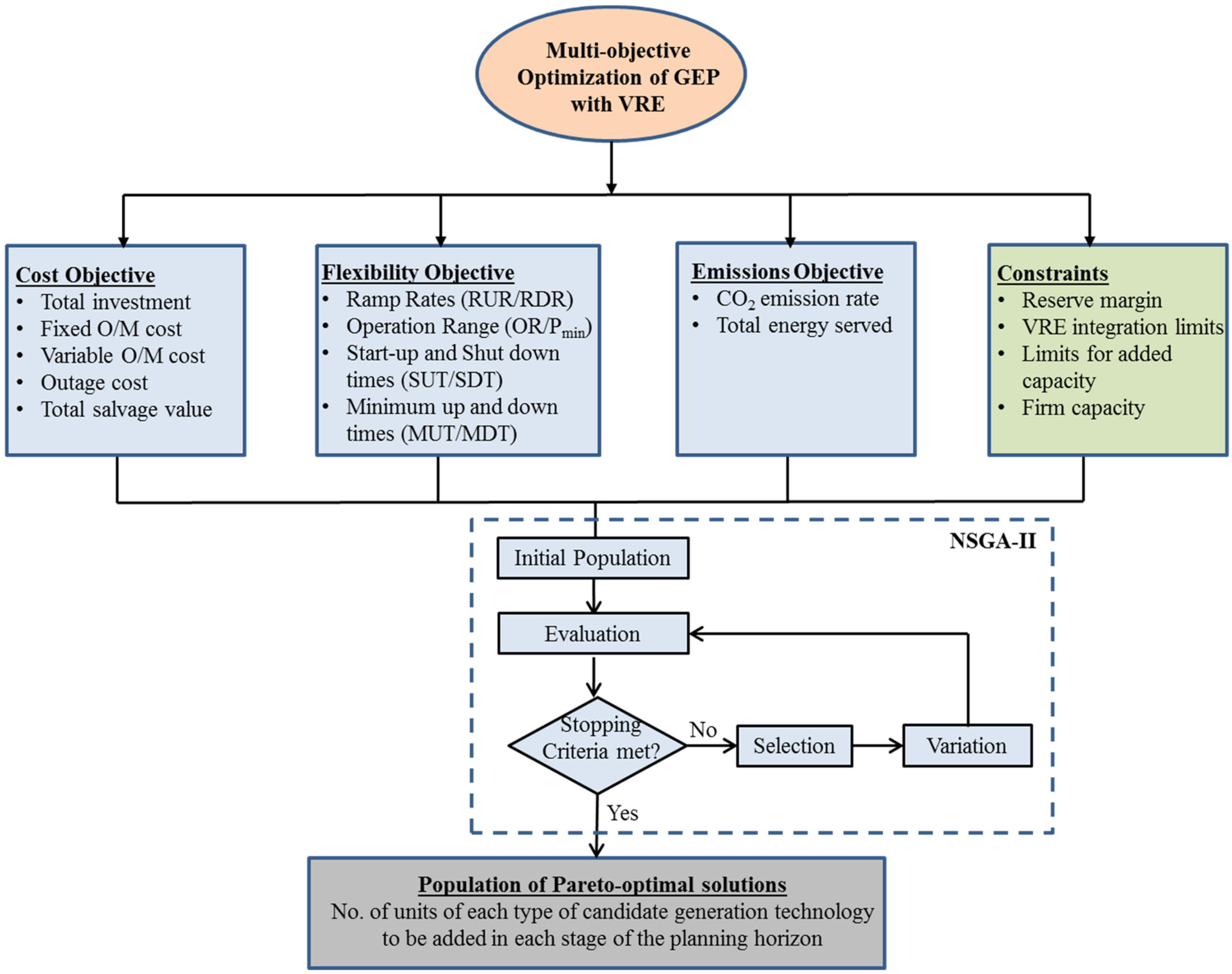

Fig. 2. General flowchart of the proposed multi-objective optimization framework.

3.1.2. Unmet demand cost

Reliability is another primary objective of GEP as the power system must adequately meet the demand for electrical power. However, the number of objectives is restricted to three in this study in order to avoid degradation in effectiveness of conventional Pareto-based evolutionary algorithms when tackling many-objective optimization problems [31]. In this context, system reliability is implicitly maximized by minimizing the costs associated with the unmet demand in the overarching cost function. The Expected Energy Not Served (EENS) index is used to calculate the unmet demand costs. It is the most direct method to financially quantify the cost of outages when comparing potential investments that will meet power system adequacy targets [32]. It is evaluated using an analytical probabilistic approach based on the Loss of Load Probability (LOLP) [23]. The outage costs are computed mid-year.

$$C_{out}^{t} = \sum_{j=1}^{y} \alpha^{[(j-0.5)+y(t-1)]} EENS^{t} C_{EENS} \tag{4}$$

3.1.3. Operation and Maintenance (O&M) costs

O&M costs are divided into fixed and variable components and are both accounted for in the middle of each year. The former, C_{OMF}^{t}, is dependent on the plant capacity whereas the latter, C_{OMV}^{t}, is proportional to the annual generation volume and includes fuel costs.

$$C_{OMF}^{t} = \begin{cases} \sum_{j=1}^{y} \alpha^{[(j-0.5)+y(t-1)]} \sum_{g=1}^{G} F_g Cap_g U_g^t, & t = 1 \\ \sum_{j=1}^{y} \alpha^{[(j-0.5)+y(t-1)]} \left[\sum_{g=1}^{G} F_g Cap_g U_g^t + \sum_{n=1}^{N} F_n Cap_n U_n^{t-1} \right], & t = 2, \cdots, T \end{cases} \tag{5}$$

$$C_{OMV}^{t} = \begin{cases} \sum_{j=1}^{y} \alpha^{[(j-0.5)+y(t-1)]} \sum_{g=1}^{G} V_g E_g^t, & t = 1 \\ \sum_{j=1}^{y} \alpha^{[(j-0.5)+y(t-1)]} \left[\sum_{g=1}^{G} V_g E_g^t + \sum_{n=1}^{N} V_n E_n^t \right], & t = 2, \cdots, T \end{cases} \tag{6}$$

E_g^t and E_n^t for each unit is determined by comparing the unserved energy with and without that specific unit.

3.1.4. Salvage cost

The salvage value is considered in the cost objective to represent the monetary value of added generating units at the end of the planning horizon. It is calculated at the end of the overall planning horizon using a salvage factor that is dependent on the operational life of the unit:

$$C_{sal}^{t} = (\alpha)^{(yT)} \sum_{n=1}^{N} I_n U_n^t Cap_n \delta_n^{[y(T-t+1)]} \tag{7}$$

3.2. Flexibility objective function

The flexibility needs of power systems to enable efficient integration of VRE were recognized as early as 2005 [33]. Since then, a substantial body of work has highlighted the increasing significance of flexibility in future low-carbon power systems. In this context, a report analyzing the needs of European power systems in 2030 observed that many countries "will strive to draw 32–34% of their electricity from wind and solar by 2030, making increased system flexibility ***crucial***" [34]. In a recent report, the International Energy Agency (IEA) stressed that "power system flexibility has become a ***global priority***" [35]. An IEA working group on high penetration of PV systems in electricity grids further pointed out that "flexibility resources are gaining ***more and more importance***" [36]. There is general agreement that flexibility is becoming absolutely critical to ensure reliable operations in power systems with high VRE levels. As such, flexibility has become an important factor to take into account in the planning of future low-carbon power systems and its explicit inclusion as a separate objective is considered in this work.

Defining flexibility as an objective in a MOO formulation poses a huge challenge for planners to evaluate its availability in candidate generation mixes. In particular, the computational complexity should not be too high because the flexibility evaluation process needs to be run many times. For example, 5000 evaluations will be required if 100 generations of populations consisting of 50 candidate generation mixes each are selected for the NSGA-II. The low modeling effort prerequisite precludes flexibility assessment approaches based on highly complex operational models [37,38]. Likewise, probabilistic metrics that use data-intensive methods to evaluate the duration, frequency or likelihood that the power system has insufficient ramping capability to cope with net load fluctuations cannot be considered [19,39,40].

Less data-intensive metrics have also been developed to provide a representation of the flexibility characteristics inherent to the power system resources. In spite of their simplicity, they offer a good insight into the flexibility of generating units through their technical and operational constraints. Hence, these screening-level metrics are convenient for assessing the flexibility of generation mixes in the multi-objective GEP model. Ma et al. [15] proposed a promising "offline" flexibility index that estimates the individual contribution of generating units to the overall system flexibility based on ramp rates and operating range. Oree and Sayed Hassen [41] formulated a more comprehensive metric, termed the composite flexibility metric (CFM). It takes into account the eight most cited technical flexibility characteristics of generating units as indicators: operating range (*OR*), minimum stable generation level (P_{min}), ramp-up rate (*RUR*), ramp-down rate (*RDR*), start-up time (*SUT*), shut-down time (*SDT*), minimum-up time (*MUT*) and minimum-down time (*MDT*). The sequence of steps involved in the construction of the CFM is illustrated in Fig. 3. Using the min-max normalization method, all indicators are first converted to an identical range between 0 and 1 as follows:

$$I_{z,k} = \frac{x_{z,k} - \min(x_z)}{\max(x_z) - \min(x_z)} \tag{8}$$

where $x_{z,k}$ is the value of indicator z for generating unit k, $I_{z,k}$ is its normalized equivalent, while $\min(x_z)$ and $\max(x_z)$ are the minimum and maximum values of indicator z across all generating units. An Analytic Hierarchy Process (AHP) is then applied to qualitatively assign weights that reflect the relative importance of indicators in determining flexibility availability in generator units. For this purpose, pairwise comparisons of indicators are performed to express the intensity of importance of one indicator with respect to another in influencing the flexibility of a generating unit. The Pearson correlation coefficient r_{xy} between each pair of indicators x and y is also computed to determine whether any pair has a high degree of correlation as it may induce an element of double counting in the CFM:

$$r_{xy} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{(p-1)\sigma_x\sigma_y} \tag{9}$$

where there are p values of indicators x and y, with their means being $\bar{x}$ and $\bar{y}$ and their standard deviations σ_x and σ_y respectively. Subsequently, all indicators are aggregated linearly to give a measure of the flexibility availability from individual generating units. The CFM index of each generating unit k is obtained by:

$$Flex_k = \sum_{z=1}^{8} (I_{z,k} \times W_z) \tag{10}$$

subject to $\sum_z W_z = 1$and $0 \le W_z \le 1$, where W_z is the weight assigned to indicator z.

The overall flexibility available from all constituent generating units of a power system can thus be computed. Obviously, since the output of a VRE unit is non-dispatchable, its associated CFM index is 0. Besides considering a comprehensive range of technical and operational constraints, the CFM has two other distinctive features that make it well suited for the GEP-Flexibility problem. Firstly, it can be used to intuitively compare the flexibility availability in different candidate generation mixes [41]. Secondly, rather than assigning a constant flexibility index to a particular generating unit irrespective of the generation portfolio in which it participates, the CFM automatically adapts to the flexibility characteristics of other units. In other words, the same generating unit will have a lower CFM when present in a highly flexible generation mix than in one composed of less flexible units, as in actual power system operations [41].

The CFM index of each Pareto-optimal expansion plan at the end of the planning horizon is determined by adding the CFM indices of all of its constituent generating units.

Maximize flexibility objective O_2:

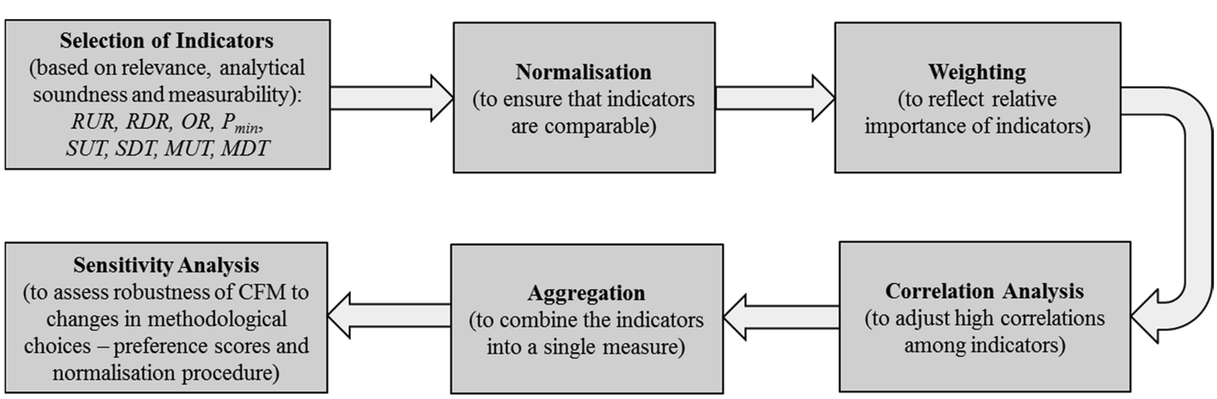

Fig. 3. Methodology for constructing the composite flexibility metric [41].

$$O_2 = -\left[\left(\sum_{g=1}^{G} Flex_g U_g^1\right) + \left(\sum_{n=1}^{N} Flex_n U_n^T\right)\right] \tag{11}$$

where $U_n^T = (\sum_{t=2}^{T} U_n^t)$. The negative sign in Eq. (11) indicates that this objective is maximized as opposed to the other two objectives that are minimized in the framework.

3.3. CO_2 emissions objective function

In order to highlight the growing importance of environmental considerations in GEP and in line with the commitments taken by many countries during successive United Nations Climate Change conferences, minimization of CO_2 emissions is considered as the third objective. Evaluation of this objective is based on the emission rates for generating units of different technologies.

Minimize CO_2 emissions objective O_3:

$$O_3 = \sum_{t=1}^{T}\sum_{g=1}^{G} E_g^t Emi_g + \sum_{t=2}^{T}\sum_{n=1}^{N} E_n^t Emi_n \tag{12}$$

3.4. Constraints

Classical GEP formulations consider some capacity, reliability and operational constraints on the power system. The proposed GEP-Flexibility model is subject to the following constraints:

3.4.1. Reserve margin

This constraint requires that the total capacity available in the power system during any period t should be sufficient to meet the demand plus a prescribed amount of reserves.

$$(1 + R_{min}^t)\cdot Dem^t \le \sum_{j=2}^{t} TCap_n^t + \sum_{g=1}^{G} Cap_g U_g^t \le (1 + R_{max}^t)\cdot Dem^t \tag{13}$$

3.4.2. Upper and lower bounds for VRE integration

This constraint not only ensures minimum generation from VRE technologies based on targets set by policy-makers but also enforces upper limits that will preserve the stability of the power system.

$$VRE_{min}^t \le \sum_{j=2}^{t}\sum_{i=1}^{I} Cap_i U_i^t \Big/ \left(\sum_{j=2}^{t} TCap_n^t + \sum_{g=1}^{G} Cap_g U_g^t\right) \le VRE_{max}^t \tag{14}$$

3.4.3. Upper bound on candidate technology capacity

In order to ensure diversity in the generation expansion mixes, a constraint is imposed to limit the added capacity of each candidate technology type in each period.

$$0 \le U_n^t \le U_{n,max}^t \tag{15}$$

4. Results and discussion

The proposed MOO GEP-Flexibility model was implemented on a personal computer with a 3.2 GHz quad-core CPU and 16 GB of RAM in MATLAB version 9.2. Its performance was evaluated on the IEEE Reliability Test System (RTS-96) without hydro units. Three different formulations were applied to explore correlations between the flexibility, economic and environmental objectives by analyzing trade-offs among the Pareto-optimal generation mixes:

(i) GEP-CFE incorporates all three objectives,
(ii) GEP-CF considers the flexibility and cost objectives, and
(iii) GEP-CE is the traditional multi-objective GEP model that takes into account the cost and CO_2 emissions objectives.

4.1. Test system

The IEEE RTS-96 consists of 26 generating units of 8 different generation technologies with a combined generating capacity of 3105 MW [42]. This test system was chosen because it is well documented and all eight flexibility characteristics of its constituent units used in the CFM computation have been provided in the literature. The important parameters of the generating units are summarized in Table 1. Flexibility characteristics are taken from [42]. Fixed and variable O&M costs of the IEEE RTS-96 have been updated to present-day values in this study [43]. The CFM indices presented in Table 1 are those of each generator unit within the IEEE RTS-96 system [41]. Due to the adaptive nature of the CFM highlighted in Section 3.2, the CFM indices will change as new generating units are added to the system during the GEP exercise.

4.2. Model parameters

The performance of the proposed model is demonstrated by considering a 12-year planning horizon, divided into 4 stages of 3 years each. A load profile similar to that of IEEE RTS-96 is used, with a peak load of 3000 MW at the start of the planning period. It is assumed that the peak load increases at a yearly rate of 7.5%. Future costs are discounted to yield net present values using an annual interest rate of 8.5%.

Five candidate technologies are considered as expansion options for the GEP: supercritical pulverized coal (SPC), open cycle gas turbine (OCGT), combined cycle gas turbine (CCGT), wind and solar photovoltaic (PV). They represent a good mix of VRE, flexible and more efficient conventional technologies to support both growing load and increasing integration of VRE during the planning horizon. None of the existing technologies are considered as candidates for expansion. Technical and economic parameters of all candidate generating units are given in Table 2 and the flexibility characteristics of the thermal units are provided in Table 3 [44,45].

VRE integration targets are assumed to grow progressively from stage 2 to 4 as follows: 5–10%, 10–15% and 15–25%. Accordingly, the planning reserve margin increases gradually to ensure system reliability

Table 1
Parameters of generating units of IEEE RTS-96 [40–42].

Unit Type	No. of Units	Size (MW)	FOR (%)	$O\&M_{var}$ (\$/MWh)	$O\&M_{Fix}$ (\$/kW-yr)	Emi ($KgCO_2e$ /MWh)	Initial CFM index
Oil/Steam	5	12	2	42.74	13.17	320.87	0.589
Oil/CT	4	20	10	71.92	7.04	302.00	0.643
Coal/Steam	4	76	2	14.93	51.4	396.37	0.559
Oil/Steam	3	100	4	42.74	13.17	320.87	0.537
Coal/Steam	4	155	4	14.93	51.4	396.37	0.425
Oil/Steam	3	197	5	42.74	13.17	320.87	0.481
Coal/3Steam	1	350	8	14.93	51.4	396.37	0.424
Nuclear	2	400	12	4.60	93.3	0.00	0.498

Table 2
Parameters of candidate generating units.

Unit Type	Size (MW)	FOR (%)	$O\&M_{var}$ ($/MWh)	$O\&M_{Fix}$ ($/kW-yr)	Inv. costs ($/kW)	Emi ($kgCO_2e$/ MWh)	Life (yrs)
SPC	250	9.7	3.1	38.85	2215	743	50
CCGT	130	8	5.4	7.69	840	349	40
OCGT	176	7.5	7.7	3.08	558	515	30
Wind	100	7.3	10	34.62	1962	0	20
Solar PV	100	5.9	0	19.23	1808	0	25

as more VRE resources, typified by low capacity values, are added to the system. Thus, the lower limits for reserve margin are taken as 120%, 130% and 140% of their respective peak demands for stages 2, 3 and 4 respectively while the upper limit is constrained at 150%. Unserved energy is penalized at a rate of $5/kWh. The maximum number of units that can be added during each stage is limited to 5 for the VRE technologies and 3 for the other technologies.

A salient feature of NSGA-II is that, unlike many contemporary evolutionary MOO algorithms, it does not require any additional parameters beyond standard parameters such as population size, number of generations, crossover probability and mutation probability [46]. Its outcome is therefore less sensitive to user-defined parameter values. 20 independent test runs were conducted with different combinations of parameters to determine the most appropriate combination. Subsequently, the NSGA-II was run for 100 generations of population size 50 along with a simulated binary crossover probability of 0.833 and a polynomial mutation probability of 0.067. Recognizing the stochastic nature of the NSGA-II algorithm, multiple runs of the simulation for the GEP-CFE, GEP-CF and GEP-CE formulations were carried out and the results presented in this section represent the typical non-dominated solutions for one run.

4.3. Optimal expansion plans

A broad overview of the differences in optimal expansion plans obtained from the three formulations is first discussed. Table 4 summarizes the ranges of the objective function values for the non-dominated solutions output by each model. There are widespread differences between the ranges depending on the objective functions involved. Applying the additional flexibility objective to the traditional GEP-CE model expands the total cost range while scaling the CO_2 emissions range marginally. On the other hand, replacing the CO_2 emissions objective in GEP-CE by flexibility considerably reduces both limits of the total cost range, suggesting that integrating flexibility in GEP can significantly alter optimal generation portfolios and lower total costs.

The tractability of the proposed approach is evidenced by the relatively short solution times of 3595, 3761 and 3841 s for GEP-CE, GEP-CF and GEP-CFE respectively compared to those of combined GEP-UC formulations covered in Section 1, which often take several days.

4.4. Decision-making

There is no single optimal solution to a multi-objective optimization problem when at least one of the objectives is in conflict with another of the objectives, as is the case here. Instead, a family of solutions is sought. This Pareto-optimal set of solutions is one in which each solution is considered as equally good mathematically. Improving one such solution in any one objective inevitably results in degrading at least one of the remaining two objectives. If a DM is not involved to articulate additional preference information, it is difficult to choose a particular compromise solution as none of the Pareto-optimal solutions can be said to be inferior to the others. Determining the most preferred solution requires DMs to have a good knowledge of the problem at hand. Moreover, they must have a good understanding of the correlations among the objectives and decision variables. With all this information in mind, they will be in a position to elicit preferences with respect to the importance that they assign to the objectives. At the same time, they can gather valuable insights from the interdependencies among the objectives revealed by the proposed framework to refine their choice. Thus, using these insights and their domain-specific knowledge, they are able to determine which solution offers the best compromise with respect to the competing objectives.

Table 4
Range of objective function values for pareto-optimal solutions for the three models.

	GEP-CFE	GEP-CE	GEP-CF
Total Cost ($10^9 \times$ $)	9.63–15.12	10.35–14.59	9.60–11.91
CO_2 emissions ($10^{10} \times kgCO_2e$)	1.60–2.45	1.57–2.41	
Flexibility (CFM)	20.16–27.60		25.29–27.77

The GEP-CFE formulation is used as an example to illustrate how DMs could proceed to select the most appropriate investment plan from the set of non-dominated solutions. Table 5 presents four solutions selected from the GEP-CFE Pareto-optimal solution set. Solutions 1, 2 and 3 represent investment plans that have the best values for the objective functions total cost, CO_2 emissions and flexibility, respectively. It implies that solution 1, with a total cost of 9.63 ($\times 10^9$$), is an appropriate solution if cost is a critical concern for DMs. Similarly, solution 2 is suitable if the country has set very stringent emission targets over the planning horizon, although its cost is significantly higher than that of solution 1. The underlying principle of Pareto-optimality is also clearly evidenced by these three solutions. Thus, any investment plan cannot be improved in one objective without making it worse in at least one of the two remaining objectives. A comparison of solutions 1 and 2 shows that curtailing the CO_2 emissions drastically from 2.45 to 1.60 ($\times 10^{10}$ $kgCO_2e$) results in a substantial rise in the total cost from 9.63 to 14.60 ($\times 10^9$$), while simultaneously lowering the flexibility index of the generation portfolio considerably from 25.29 to 22.52. A similar cause-effect pattern is noted when solutions 2 and 3 are contrasted. A large improvement in the CFM from 22.52 to 27.60 leads to a deterioration in the CO_2 emissions from 1.60 to 1.95 ($\times 10^{10}$ $kgCO_2e$) and a small benefit in total cost from 14.60 to 13.63 ($\times 10^9$$).

Therefore, choosing one of these three solutions ensures that the

Table 3
Flexibility characteristics of candidate units.

Unit Type	P_{min} (%)	OR (MW)	RUR (MW/h)	RDR (MW/h)	SUT (h)	SDT (h)	MUT (h)	MDT (h)
SPC	0.4	250	180	180	3	2	6	4
CCGT	0	130	130	130	1	1	4	2
OCGT	0	176	176	176	0	0	0.5	0.5

Table 5
Objective function values of four solutions selected from the GEP-CFE Pareto-optimal set.

Solution no.	Total Cost ($10^9 \times \$$)	CO_2 Emissions ($10^{10} \times kgCO_2e$)	Flexibility (CFM)
1	9.63	2.45	25.29
2	14.60	1.60	22.52
3	13.63	1.95	27.60
4	12.82	1.90	25.06

DMs get the best out of one objective at the expense of at least one of the remaining objectives. As illustrated in this case, when the other objectives are conflicting with the favored one, the former are adversely affected to a large extent. Hence, DMs must analyze trade-offs among the objectives to assist them in the selection of a compromise solution. Typically, the DMs will be aware of the emission reduction commitments along with the RE integration targets set by the policy-makers over the GEP horizon. In addition, they will be well informed about the financial resources and priorities of the utility over the planning period. Using this knowledge, DMs can differentiate among the solutions and choose the one that has the best potential to fulfill the emission and RE obligations while staying within a reasonable budgetary envelope. For example, if DMs are looking for a solution whose emission and flexibility values are closer to the best values among all solutions but with intermediate cost, solution 4 represents a suitable solution. It is a good compromise solution whose cost lies nearly midway between the limits of the total cost range (12.82 within a range of 9.63–15.12) while its CO_2 emissions are closer to the lower boundary of its overall solution range (1.90 within a range of 1.60–2.45) and its flexibility index lies in the superior segment of its overall solution range (25.06 within a range of 20.16–27.60). For solution 4, of course, an informed domain-expert DM will be best placed to make this choice.

4.5. Correlations among the objectives of GEP-CFE

Viewing and understanding interdependencies between two objectives can be readily done using scatter plots. However, extracting meaningful information from scatter plot representations with 3 or more objectives is extremely difficult, let alone reading the objective function values of the solutions. Parallel coordinates plots provide a more convenient way of visualizing and analyzing the solutions of such problems [47]. Rather than placing the objective axes orthogonally to each other as done in scatter plots, the parallel coordinates plot inserts them parallel to each other, mostly vertically and equidistant. Each solution in the non-dominated population set is then represented by joining its objective function values on each pair of axes by a line.

Fig. 4 shows the parallel coordinates plot of the non-dominated solutions for the GEP-CFE formulation. Each pair of connected lines denotes one solution. For example, the two pairs of connected blue lines represent the two investment plans with highest flexibility index of 27.60. Connected line pairs in green represent the remaining non-dominated solutions. A careful interpretation of the pattern of lines between two adjacent objective axes can reveal important information about any correlation between them. It may be necessary to re-order the axes in order to identify interdependencies between non-adjacent axes, such as the total cost and CO_2 emission axes in Fig. 4. Accordingly, Fig. 5 displays the same solution set but with the total cost and CO_2 emissions objective axes adjacent to each other. One easily identifiable characteristic from the parallel coordinates plot is the degree of conflict between two objectives. This is indicated by the number of intersecting lines between their axes. A large number of crossing lines points to heavy conflict. This is the case for the total cost and CO_2 emissions objectives in Fig. 5, implying that they are negatively correlated. Moreover, the lines intersect within a narrow band in the space between the two axes. This behavior suggests that the inverse relationship is consistent, even if it is not exactly linear. Therefore, higher investments are mostly associated with lower CO_2 emissions for this particular case study.

There are also several intersecting lines between the total cost and flexibility objectives in Fig. 4, although the number is lower than in the previous case. While this is not always the case, higher costs also generally translate into lower flexibility in the generation expansion portfolios for the IEEE RTS-96 system. Since the points of intersection occur along most of the flexibility axis length, the magnitude of this general negative correlation is variable. In contrast, the line crossing pattern is more erratic between the flexibility and CO_2 emission objectives. For this reason, no definite correlation between these two objectives can be inferred from parallel coordinates plots.

The four non-dominated GEP-CFE solutions that were presented in Table 5 are highlighted in Fig. 5. The parallel coordinates plot makes it

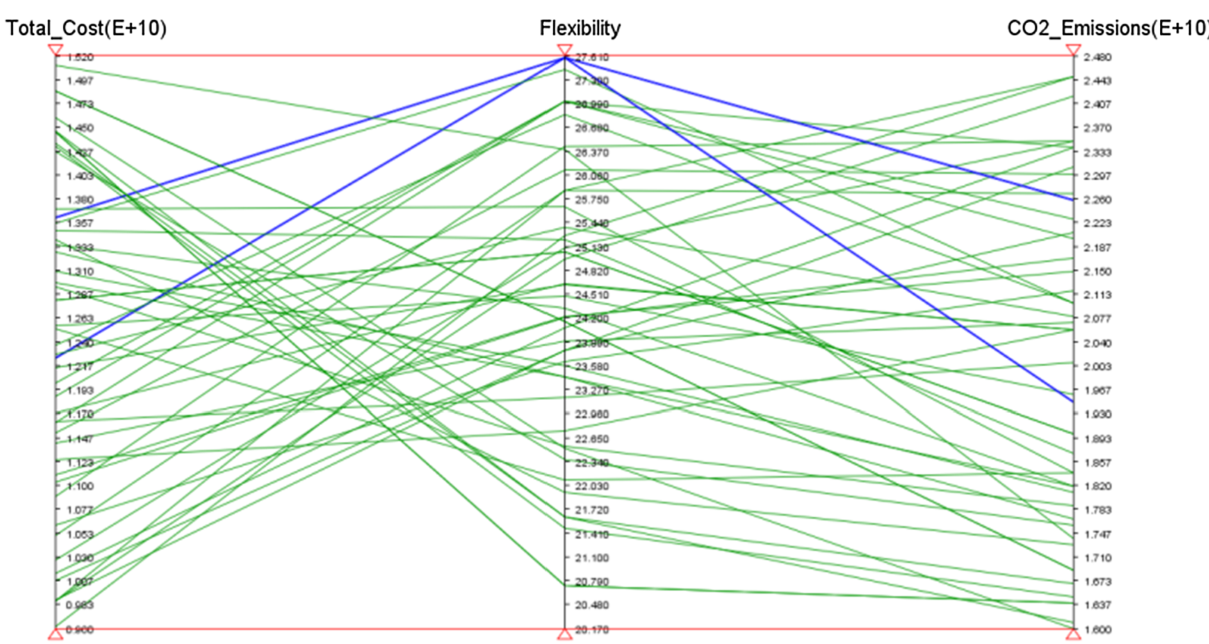

Fig. 4. Parallel coordinates plot of the GEP-CFE non-dominated solution set for objective order: Total cost, flexibility, CO_2 emissions.

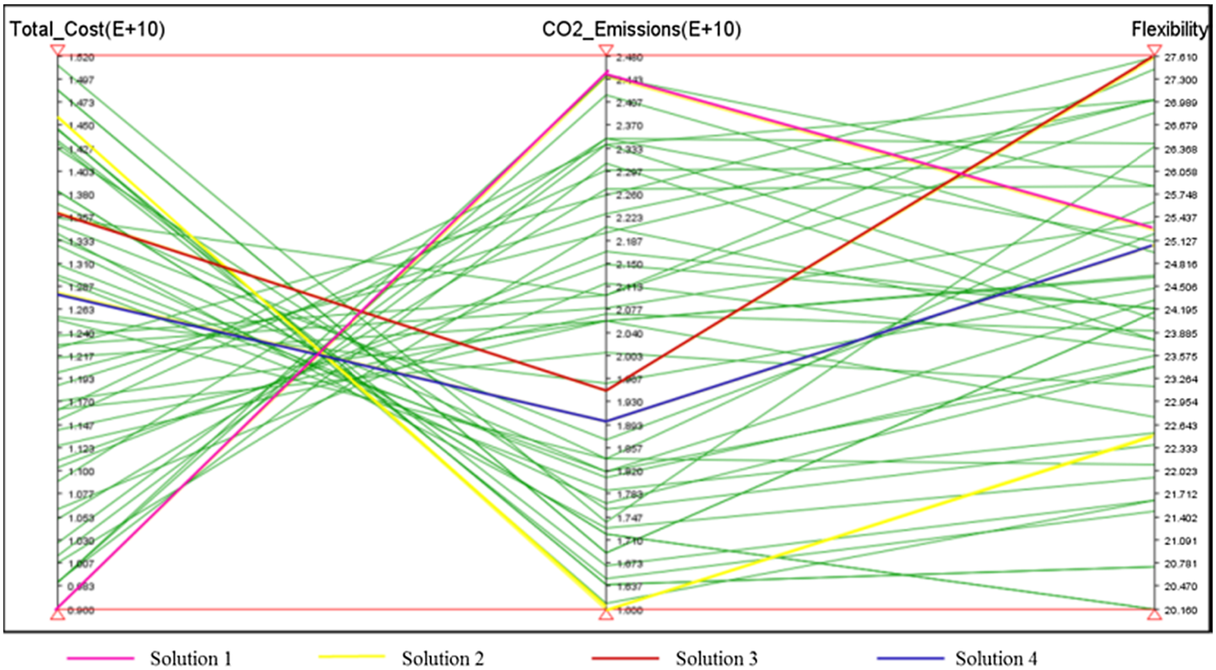

Fig. 5. Parallel coordinates plot of the GEP-CFE non-dominated solution set for objective order: Total cost, CO_2 emissions, flexibility.

easy for the DM to distinguish solutions with the best values in each objective function. Thus, solutions 1 and 2 that minimize total cost and CO_2 emissions respectively intersect the corresponding axes at the lowest point, that is 9.63×10^9\$ for total cost and 1.60×10^{10} kgCO_2e for CO_2 emissions. On the other hand, the flexibility axis is crossed at its highest point of 27.60 by solution 3 as it maximizes this objective. The parallel coordinates plot also simplifies trade-off analysis by enabling a quick assessment of the extent to which the other objectives are affected by favoring one objective in a particular solution. Solution 4, for example, illustrates an investment plan whose CO_2 emissions and flexibility are closer to the best values while its total cost is intermediate as explained in Section 4.4.

4.6. Impact of flexibility

To gain more insight into the impact of modeling flexibility explicitly as an objective on total cost and CO_2 emissions, a detailed analysis of the Pareto-optimal expansion plans is performed. The statistics of the constituent candidate generating units of all non-dominated generation mixes resulting from the three formulations are synthesized in the box-plot of Fig. 6. Some distinctive trends can be observed in the Pareto-optimal expansion plans, leading to some general observations for this specific IEEE RTS-96 case study. Notably, when generator operational constraints are omitted from the framework in the GEP-CE formulation, the optimal investment plans contain significantly more inflexible SPC units. Thus, GEP-CE solutions contained between 2 and 6 SPC units compared to 0 to 3 for GEP-CF. The smaller number of more expensive SPC units justifies the much lower total costs of GEP-CF plans as opposed to GEP-CE plans noted in Table 4. The scarcity of SPC units in the GEP-CF solutions is offset by higher numbers of cheaper and more flexible CCGT and OCGT units compared to GEP-CE, leading to improved CFM indices. There is an average of nine units of both CCGT and OCGT for GEP-CF as opposed to 4.1 and 6.3 respectively for GEP-CE.

GEP-CE plans have higher variability in the number of each type of candidate unit in comparison with those of GEP-CFE. In contrast, GEP-CF generation mixes are characterized by the smallest spread in number of units, justifying its limited range of objective values observed in Table 4. The limited spread is explained by the fact that since the CFM of the two VRE technologies is 0, the diversity of GEP-CF solutions that maximize flexibility at least cost with the remaining three candidate technologies is restricted.

To better understand the effects of ignoring flexibility in GEP, the CFM of GEP-CE Pareto-optimal expansion plans are computed post-optimization. It is found that the flexibility indices of the GEP-CE solutions lie in the range of 18.68 to 24.06. Thus, the expansion mixes of GEP-CE and GEP-CF are mutually exclusive since the least flexible GEP-CF solution has a CFM index of 25.29, as indicated in Table 4. It follows that none of the expansion portfolios output by the GEP-CE would be considered optimal if the environmental objective was replaced by the flexibility objective.

5. Validation of GEP-flexibility framework

The proposed GEP-Flexibility framework relies heavily on the CFM to provide a meaningful indication of the ability of the generation portfolio to respond to net demand variability. However, there is no evidence so far that a generation portfolio with a CFM index of 27, for example, is actually more robust to net load variations than one with a CFM value of 24. In addition, it has not yet been demonstrated that more severe net load uncertainty will call for generation fleets with

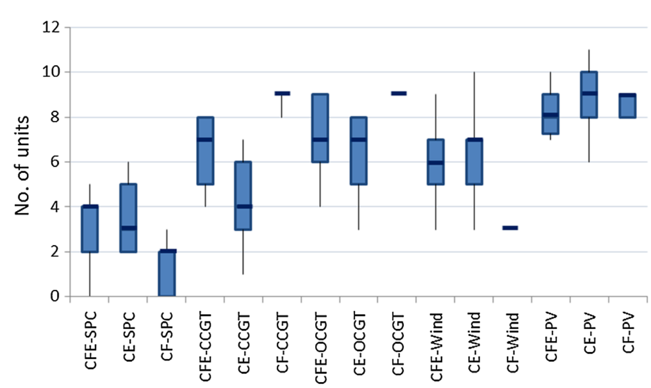

Fig. 6. Distribution of candidate units in Pareto-optimal generation mixes for the three formulations.

higher CFM indices to ensure feasible operations. In order to validate the proposed MOO GEP-Flexibility framework and demonstrate the effectiveness of the CFM in this process, the operational feasibility of optimal expansion plans is tested by applying a UC formulation that captures the full range of generator technical constraints.

5.1. Unit commitment model

The UC model minimizes the total operational costs, comprising of variable costs, start-up costs, shut-down costs and no-load costs, while accounting for all eight operational constraints of conventional generators. This model is applied to the IEEE RTS-96 system for a scheduling period of 24 h, where each hour is divided into four 15-minute sub-periods to capture realistic sub-hourly operational dynamics. It is assumed that changes in the commitment status of units as well as initiation of start-up and shut-down procedures occur only at the start of sub-periods. Moreover, the power generation level of an online unit is assumed to be constant during a sub-period. The 15-min demand data is obtained from the power system used in a UC study by Pozo et al. [48] and scaled according to the projected IEEE RTS-96 system demand in the final year of the planning horizon. VRE generation data is also taken from the same study [48] and adjusted so that the renewable integration rate lies in the 15–25% range assumed for the final phase of the planning horizon. Three scenarios are considered to test the resilience of generation portfolios to different net load variability conditions: (a) "normal" net load where mean value of VRE generation data is considered, (b) "high" variability net load where renewable output and demand are changing simultaneously in opposite directions, and (c) "moderate" variability net load whose variability is intermediate between the first two scenarios. Fig. 7 shows the total system demand as well as the net loads for the three scenarios. VRE curtailment is not modeled to sustain the UC process, as the aim of the validation exercise is to verify the ability of generation portfolios to maintain operations throughout the scheduling horizon.

5.2. Unit commitment results

The sub-hourly UC model is applied to selected optimal investment plans output by each of the three formulations. Generation portfolios subjected to UC are chosen such that their CFM values (for CEP-CF and GEP-CFE) and total cost values (for GEP-CE) are evenly spaced over their whole range of values given in Table 4. In this way, the selected plans provide a consistent representation of the entire solution space. Table 6 presents the outcome when GEP-CE, GEP-CF and GEP-CFE portfolios are tested with the three net load profiles. The feasibility of the UC exercise is indicated either by "Yes" if successful or by the time at which the generation mix first fails to follow the net load. In the former case, the operational cost for the 24-h UC exercise is also provided. For example, consider the first two GEP-CF generation mixes in Table 6 when they are subjected to the moderate-variability net load profile (cells shaded in grey). It is observed that the plan with CFM index of 25.29 is unable to complete the UC exercise as it encounters a flexibility deficit at 22.15 h. On the other hand, the investment plan with CFM index of 26.02 can be successfully scheduled to match the net load. The total operational cost for this plan to meet the moderate-variability net load is 4,574,000$ for the 24-h period under consideration.

The most prominent result is that when flexibility is ignored in the GEP process, the resulting optimal generation portfolios are unable to meet net load with moderate or high variability. Many GEP-CE investment plans even fail to match the normal-variability net load profile. The deficit of flexibility in the generation mixes is encountered between 20.00 and 22.30 h for the normal- and moderate-variability net loads. As illustrated in Fig. 7, a steep ramp-up is experienced at a net load level higher than 5000 MW during this time interval. The UC details reveal that the most flexible units in the generation portfolios are already committed to meet the previous steep ramp-up which occurred between 07.00 and 10.00 h, leaving the system vulnerable to subsequent upward ramps. Moreover, when GEP-CE generations portfolios are subjected to the high-variability net load profile, it is observed that the UC process is aborted much earlier, between 07.30 and 09.30 h. This time interval corresponds to a sustained extreme ramp-up event present in this net load scenario. It can therefore be concluded that while the GEP-CE investment plans have adequate capacity, they lack sufficiently flexible units to manage the increased net load variability. This predisposition to flexibility deficiency was correctly indicated by the low CFM indices of the GEP-CE investment plans. As expected, the only two feasible GEP-CE plans that successfully completed the UC exercise under the normal-variability net load scenario have CFM indices of 24.06 and 23.12, that is, close to the upper limit of the flexibility range.

In contrast, all selected GEP-CF optimal generation mixes can be successfully scheduled to match the normal-variability net load profile. This performance was anticipated as they all have CFM indices higher than the upper flexibility limit for GEP-CE solutions. All of them can also follow the moderate-variability net load with the exception of the least flexible expansion plan. It is also noted that all selected GEP-CF investment plans successfully pursue the UC exercise beyond the extreme ramp-up event encountered initially in the high-variability net load profile between 06.00 and 10.00 h. However, those with CFM indices less than 27 are unable to go through the acute ramp-down event occurring around 22.00 h. The nearly vertically decreasing net load requires several already committed units with fast *RDR* to ramp down simultaneously. Such a condition is satisfied only in generation portfolios with very high CFM indices. Again, the CFM provides a good indication of the ability of the generation fleet to respond to net load fluctuations. Finally, the same trend in performance is observed for GEP-CFE generation plans with respect to their CFM indices.

An analysis of the UC results for all three models enables the general inference that generation portfolios with CFM indices higher than 23, 26 and 27 can match the net load profiles with normal-, moderate- and high-variability respectively for this particular power system. Naturally, more flexibility is required from the generation fleet to maintain security of supply as the variability of net load becomes more severe. These results substantiate the outcomes of previous studies which concluded that neglecting flexibility in GEP with large shares of VRE will result in expansion plans that are infeasible in operations [4,15].

It is also obvious from Table 6 that operational costs generally tend to decrease as the flexibility of the expansion plan increases. For example, if the two GEP-CF expansion plans found at the extremities of the flexibility range are considered under normal-variability net load, a drop of 34% in operational costs is noted for a CFM index increase of about 2.5. In the case of the two boundary GEP-CFE solutions under the same net load variability scenario, operational costs decrease by about 33% as the CFM index rises by 4. This negative correlation occurs

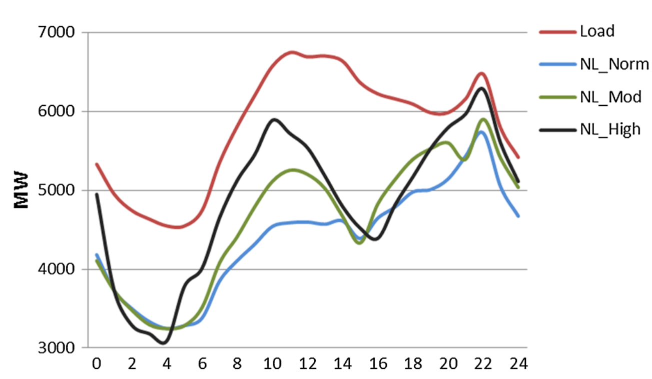

Fig. 7. System demand and net load for the three variability scenarios.

Table 6
Feasibility of operations for GEP-CE, GEP-CF and GEP-CFE generation portfolios.

Model		CFM index	Feasibility					
			NL_Normal		NL_Moderate		NL_High	
	Tot Cost (10^9\$)		Feas. (Yes/Time)	Op. Cost (10^3\$)	Feas. (Yes/Time)	Op. Cost (10^3\$)	Feas. (Yes/Time)	Op. Cost (10^3\$)
GEP-CE	10.40	24.06	Yes	3568	22.30		09.30	
	10.79	23.17	Yes	3822	22.15		09.30	
	11.43	22.57	21.15		21.45		09.15	
	12.03	20.03	21.00		21.00		09.00	
	12.53	21.35	20.45		20.30		08.30	
	13.25	21.64	20.45		20.00		08.00	
	13.96	20.74	20.30		20.15		07.30	
	14.47	18.68	20.00		20.00 h		07.30	
GEP-CF		25.29	Yes	3939	22.15		22.15	
		26.02	Yes	3751	Yes	4574	22.30	
		26.61	Yes	3248	Yes	4030	22.30	
		27.19	Yes	2878	Yes	3537	Yes	4183
		27.77	Yes	2601	Yes	3118	Yes	3701
GEP-CFE		20.16	21.00		20.00		09.15	
		21.64	21.15		20.30		09.15	
		22.76	21.15		20.30		09.30	
		23.59	Yes	3568	22.00		09.30	
		24.08	Yes	3378	22.15		09.45	
		25.28	Yes	3422	22.30		22.15	
		26.25	Yes	2945	Yes	3697	22.30	
		27.60	Yes	2408	Yes	2872	Yes	3409

because fewer flexible generation mixes force more units than required to stay on in order to ensure that there is enough ramping capability available to cater for the enhanced net load variability. The standby online status of less flexible units affects the operational costs considerably due to the high start-up and no-load costs normally associated with them. In addition, other improved technical constraints also contribute towards lower operational costs. Thus, reduced minimum stable generation allows additional output at lower costs by already committed generating units, thereby supplanting costlier generation from other units. Similarly, shorter *MUT/MDT* times enable savings on fuel costs. The above results are entirely consistent with the conclusions of earlier research on this topic [49–51].

Finally, it is also observed that operational costs rise quickly for the same expansion plan as the degree of net load variability increases. For instance, the operational costs of the UC process for the same GEP-CFE solution with CFM index of 27.60 increases by 19.3% and 41.6% if the net load variability scenario changes from normal to moderate and high respectively. Greater net load fluctuations imply more frequent generator cycling with recurrent start-ups and shut-downs, faster up and down ramps and frequent operations at minimum generation levels. It follows that the start-up, shut-down and production costs are inflated.

It must also be pointed out that in actual operations, "flexibility-aware" GEP-CFE generation mixes are better prepared to cope with a number of issues that may arise in flexibility-deficient GEP-CE solutions, including VRE output curtailment and load shedding. In the long term, avoiding these issues is expected to result in additional savings. Besides, higher flexibility in the generation fleet facilitates the displacement of conventional generation by VRE production, resulting in less cycling and operation of thermal generating units. Therefore, planning for additional system flexibility at an early stage enables cost-effective integration of large VRE shares in the future. Finally, the decision to incorporate flexibility as a separate objective in the framework is validated by the UC results of the traditional GEP-CE formulation. They clearly illustrate that omission of flexibility has resulted in generation portfolios that are operationally infeasible as VRE integration in the grid increases.

6. Conclusions

This paper presents a novel multi-objective framework for long-term GEP with high shares of VRE that incorporates flexibility screening of candidate investment plans. The framework relies on a composite metric to assess the flexibility available in generation portfolios, thus enabling flexibility to be considered as a fully-fledged objective. The application of the model on an illustrative planning case study has clearly demonstrated how including flexibility as an objective radically changes the composition of investment plans and their objective function values. More importantly, results show that omission of flexibility from the planning exercise gives rise to flexibility-deficient energy mixes that are unable to match the more frequent and steeper variations in net load. Analysis of the set of Pareto-optimal solutions generated by the framework for the different formulations showed some pertinent relationships between the objectives for this specific case study.

It is important to remember that the framework carries out a high-level evaluation of the overall flexibility available from generation portfolios. The main strength of the framework lies in the low modeling effort it requires to shed light on a key aspect of power system planning. Evaluating a multi-dimensional concept like power system flexibility within a highly complex planning problem represents a significant challenge. It necessitates large historical databases of load, generation and weather data at small temporal resolution, together with accurate power system information and considerable computational power. These requirements soar as the assessment period becomes longer. This CFM-based framework is best suited to power systems for which these data are not available. It provides quick and intuitive information about the generation mixes that will most likely abide by existing economic, reliability and environmental restrictions. DMs can subsequently decide which objectives they will favor when selecting the most appropriate generation mix. Hence, the proposed framework can contribute to cleaner generation, security of supply and cost-effective electricity for the overall benefit of society.

Nevertheless, the simplicity of the proposed framework has been made possible at the expense some limitations. Understanding these limitations not only ensures that meaningful insights are obtained into the outcomes of the proposed framework but also helps in identifying opportunities for future research. In particular, the contribution to system flexibility from sources other than the generation fleet have been ignored since the main motivation is to optimize the flexibility available from the non-dominated generation plans. For example, energy storage, interconnections to neighboring power grids and flexible demand technologies such as demand-side management techniques and electric vehicle batteries, can relieve the burden of flexibility provision from the generation resources. They could be integrated in the proposed mathematical formulation either in the form of additional parameters or by adding their contribution in the flexibility objective. Furthermore, the proposed framework assumes an optimized transmission system as it omits transmission constraints. Including the latter in the framework can provide useful insights into the possible impacts that an imperfect transmission system can have on future investment plans and on the flexibility requirements of the power system. Finally, this work has studied the GEP problem from the perspective of a vertically integrated power system and the proposed framework also holds for a perfectly competitive market. In a market-based environment, different bidding strategies will affect the market operation unevenly and change the economic value associated with flexible generation. Further research could investigate different approaches to the formulation of bids for both flexible and inflexible generation and their outcomes on the market. Eventually, such work could explore the conditions under which the market provides adequate incentives for rewarding the supply of flexible generation.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.113589.

References

[1] Richter M, Oeljeklaus G, Görner K. Improving the load flexibility of coal-fired power plants by the integration of a thermal energy storage. Appl Energy 2019;236:607–21.
[2] Ye LC, Lin HX, Tukker A. Future scenarios of variable renewable energies and flexibility requirements for thermal power plants in China. Energy 2019;167:708–14.
[3] Koltsaklis NE, Dagoumas AS. State-of-the-art generation expansion planning: a review. Appl Energy 2018;230:563–89.
[4] Palmintier BS, Webster MD. Impact of operational flexibility on electricity generation planning with renewable and carbon targets. IEEE Trans Sustain Energy 2016;7(2):672–84.
[5] Pereira AJC, Saraiva JT. Generation expansion planning (GEP)–A long-term approach using system dynamics and genetic algorithms (GAs). Energy 2011;36(8):5180–99.
[6] Pereira S, Ferreira P, Vaz AIF. Generation expansion planning with high share of renewables of variable output. Appl Energy 2017;190:1275–88.
[7] Poncelet K, Delarue E, Six D, Duerinck J, D'haeseleer W. Impact of the level of temporal and operational detail in energy-system planning models. Appl. Energy 2016;162:631–43.
[8] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. Renew Sustain Energy Rev 2014;33:74–86.
[9] Zhang Q, Mclellan BC, Tezuka T, Ishihara KN. An integrated model for long-term power generation planning toward future smart electricity systems. Appl Energy 2013;112:1424–37.
[10] Pina A, Silva CA, Ferrão P. High-resolution modeling framework for planning electricity systems with high penetration of renewables. Appl Energy 2013;112:215–23.
[11] Welsch M, Deane P, Howells M, Gallachóir B, Rogan F, Bazilian M, et al. Incorporating flexibility requirements into long-term energy system models – a case study on high levels of renewable electricity penetration in Ireland. Appl Energy 2014;135:600–15.
[12] Batlle C, Rodilla P. An enhanced screening curves method for considering thermal cycling operation costs in generation expansion planning. IEEE Trans Power Syst 2013;28(4):3683–91.
[13] De Jonghe C, Delarue E, Belmans R, D'haeseleer W. Determining optimal electricity technology mix with high level of wind power penetration. Appl Energy 2011;88(8):2231–8.
[14] Zhang T. Generation planning using screening curve method Doctoral dissertation University of Texas; 2016.
[15] Ma J, Silva V, Belhomme R, Kirschen DS, Ochoa LF. Evaluating and planning flexibility in sustainable power systems. IEEE Trans Sustain Energy 2013;4(1):200–9.
[16] Koltsaklis NE, Georgiadis MC. A multi-period, multi-regional generation expansion planning model incorporating unit commitment constraints. Appl Energy 2015;158:310–31.
[17] Merrick JH. On representation of temporal variability in electricity capacity planning models. Energy Econ 2016;59:261–74.
[18] Abdin IF, Zio E. An integrated framework for operational flexibility assessment in multi-period power system planning with renewable energy production. Appl Energy 2018;222:898–914.
[19] Palmintier B, Webster MD. Heterogeneous unit clustering for efficient operational flexibility modeling. IEEE Trans Power Syst 2014;29(3):1089–98.
[20] Flores-Quiroz A, Palma-Behnke R, Zakeri G, Moreno R. A column generation approach for solving generation expansion planning problems with high renewable energy penetration. Electr Power Syst Res 2016;136:232–41.
[21] Meus J, Poncelet K, Delarue E. Applicability of a clustered unit commitment model in power system modeling. IEEE Trans Power Syst 2018;33(2):2195–204.
[22] Deb K. Multi-objective optimization using evolutionary algorithms. John Wiley and Sons; 2001.
[23] Aghaei J, Akbari MA, Roosta A, Baharvandi A. Multiobjective generation expansion planning considering power system adequacy. Electr Power Syst Res 2013;102:8–19.
[24] Kannan S, Baskar S, McCalley JD, Murugan P. Application of NSGA-II algorithm to generation expansion planning. IEEE Trans Power Syst. 2009;24(1):454–61.
[25] Antunes CH, Martins AG, Brito IS. A multiple objective mixed integer linear programming model for power generation expansion planning. Energy 2004;29(4):613–27.
[26] Ren H, Zhou W, Nakagami KI, Gao W, Wu Q. Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects. Appl Energy 2010;87(12):3642–51.
[27] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 2002;6(2):182–97.
[28] Zitzler E. Evolutionary algorithms for multiobjective optimization: methods and applications; 1999.
[29] Fonseca CM, Fleming PJ. An overview of evolutionary algorithms in multiobjective optimization. Evol Comput 1995;3(1):1–16.
[30] Ben Yahia W, Ayadi O, Masmoudi F. A sensitivity analysis of multi-objective cooperative planning optimization using NSGA-II. Multiphysics modelling and simulation for systems design and monitoring. Springer; 2015. p. 327–37.
[31] Purshouse RC, Fleming PJ. On the evolutionary optimization of many conflicting objectives. IEEE Trans Evol Comput 2007;11:770–84.
[32] European Commission. Identification of appropriate generation and system adequacy standards for the internal electricity market. Brussels; 2014.
[33] IEA. Variability of wind power and other renewables: management options and strategies; 2005.
[34] Fraunhofer. The European power system in 2030: flexibility challenges and integration benefits; 2015.
[35] IEA. Status of power system transformation – advanced power plant flexibility. Execut Summ 2018.
[36] IEA. Flexible resources for flexible transmission system operation; 2017.
[37] Hargreaves J, Hart EK, Jones R, Olson A. REFLEX: an adapted production simulation methodology for flexible capacity planning. IEEE Trans Power Syst 2014;30(3):1306–15.
[38] Electric Power Research Institute. Metrics for quantifying flexibility in power system planning; 2014.
[39] Lannoye E, Flynn D, O'Malley M. Evaluation of power system flexibility. IEEE Trans Power Syst 2012;27(2):922–31.
[40] Nosair H, Bouffard F. Flexibility envelopes for power system operational planning. IEEE Trans Sustain Energy 2015;6(3):800–9.
[41] Oree V, Sayed Hassen SZ. A composite metric for assessing flexibility available in conventional generators of power systems. Appl Energy 2016;77:683–91.
[42] Grigg C, Wong P, Albrecht P, Allan R, Bhavaraju M, Billinton R, et al. The IEEE reliability test system 1996: a report prepared by the reliability test system task force of the application of probability methods subcommittee. IEEE Trans Power Syst 1999;14(3):1010–20.
[43] Go RS, Munoz FD, Watson JP. Assessing the economic value of co-optimized grid-scale energy storage investments in supporting high renewable portfolio standards. Appl Energy 2016;183:902–13.
[44] Frontier Economics. Input assumptions for modelling wholesale electricity costs;

2013.
[45] Acil Allen Consulting. Fuel and technology cost review. Brisbane (Australia); 2014.
[46] Deb K. Evolutionary multi-objective optimization without additional parameters. Parameter setting in evolutionary algorithms. Heidelberg (Berlin): Springer; 2007. p. 241–57.
[47] Inselberg A. Multidimensional detective. Proceedings of the IEEE symposium on information visualization. 1997. p. 100–7.
[48] Pozo D, Contreras J, Sauma E. Unit commitment with ideal and generic energy storage units. IEEE Trans Power Syst 2016;29(6).
[49] Lew D, Brinkman G, Kumar N, Lefton S, Jordan G, Venkataraman S. Finding flexibility: cycling the conventional fleet. IEEE Power Energy Mag 2013;11(6):20–32.
[50] Palchak D, Denholm P. Impact of generator flexibility on electric system costs and integration of renewable energy NREL/TP-6A20-62275 National Renewable Energy Laboratory; 2014.
[51] Hirth L, Ueckerdt F, Edenhofer O. Integration costs revisited - an economic framework for wind and solar variability. Renew Energy 2015;74:925–39.