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A composite metric for assessing flexibility available in conventional generators of power systems

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HIGHLIGHTS

- Novel framework to assess flexibility available from generators in power systems.
- Composite metric with appropriate weighting, normalization and aggregation methods.
- Sensitivity analysis demonstrates robustness of metric to methodological changes.
- Adaptive metric automatically adjusts to other generating units in power system.

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ABSTRACT

With increasing levels of integration of intermittent renewable energy in the power grid, it has become essential for power system planners to quantify future requirements of power systems in terms of *flexibility*. It is also equally important to evaluate whether the flexibility available in a given power system is adequate to meet more frequent and larger variations in the net load. In this paper, we present a novel framework to develop a composite metric that provides an accurate assessment of flexibility within conventional generators of a power system. This assessment is performed using eight technical characteristics of generating units as indicators. An Analytic Hierarchy Process is applied to assign weights to these indicators in order to reflect their relative importance in the supply of flexibility. Following normalization with min–max method, the indicators are linearly aggregated to give the composite flexibility index for each generator. The proposed methodology is tested on an adapted IEEE RTS-96 system. Our results demonstrate the consistency of the composite flexibility metric. It is further observed that the proposed metric is adaptive since it automatically adjusts to the addition and/or removal of generating units. To evaluate the robustness of the proposed framework, we also performed sensitivity and uncertainty analysis in the presence of alternative methodological choices in the composite metric construction process.

1. Introduction

In recent years, the growing integration of intermittent renewable energy sources (RES) in the power grid has emphasized the importance of flexibility in the reliable operation of power systems [1–3]. Flexibility refers to the ability of a power system to deploy its resources in response to changes in net load [4]. Net load is defined as the residual demand that must be supplied by conventional generation resources after all variable renewable energy generated has been used. Traditionally, power systems have been required to adjust their generation output in order to balance fluctuations on the demand side. However, load variations are predictable as their correlations with time and weather patterns are well understood. Consequently, they are reliably dealt with as long as the peak load is adequately met by the available generation capacity. As increasing shares of variable RES are integrated in a power system, the flexibility requirements become more severe [5]. Intermittent RES output not only varies considerably over short time spans but is also very difficult to predict accurately. These features increase the uncertainty and variability associated with the net load. While demand-side management, interconnection to neighboring power systems and energy storage facilities have the potential to contribute significantly to the overall flexibility of a power system, their impact in the medium term is expected to be limited [6]. In the foreseeable future, existing conventional generation resources will play a key role in effectively compensating more frequent net load fluctuations of higher amplitudes [6–8]. A power system composed mostly of insufficiently flexible generation resources will be typified by forced load shedding and

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curtailment of intermittent generation output [6,9,10]. As a result, it is critical for current power planning methodologies to account for generator operational characteristics that affect system flexibility [11–13]. Thus, power system planners must ensure that sufficiently flexible resources are available in the generation fleet to enable reliable operation of the power system under increased RES penetration. This emerging interest in power system flexibility has driven the development of metrics that provide an indication to operators about the inherent amount of flexibility they can call upon to balance generation and net load at all times. In particular, as will be shown, measures of the level of flexibility offered by individual generating units of a power system are found to be of greatest importance.

Assessing the flexibility available in power systems is a difficult exercise and has been the focus of active research recently [14]. A few metrics have been proposed to evaluate the availability of flexible resources in power systems. They vary in complexity, ranging from metrics that are derived from physical characteristics of the power system elements to those that require detailed simulations based on substantial historical time-series data. One of the most commonly used metric in the latter category is the insufficient ramping resource expectation (IRRE) [4]. It refers to the expected number of times over specific time horizons that a power system fails to cope with changes in the net load. For each time horizon, time-series data of the ramping requirements for the net load is computed from past time-series data of output from all generating units along with synchronized demand data. The upward and downward ramping capabilities available from the fleet of generators are also calculated from their operational characteristics for each time period. Ramp availability data is subsequently matched up to corresponding ramp requirement data to determine the flexibility deficits encountered on the system over the various time horizons. The Electric Power Research Institute proposed a more comprehensive flexibility assessment tool, InFLEXion, which integrates four flexibility adequacy metrics [15]. In addition to IRRE, InFLEXion uses period of flexibility deficit (PFD) and expected unserved ramping (EUR) to measure the number of periods when the power system is likely to experience flexibility shortfalls in a given direction during a particular time horizon and the total magnitude of these deficits respectively. The fourth metric, flexibility well-being, extracts information from EUR and PFD to categorize the power system in a user-defined safe, warning, or dangerous state [15]. Other tools, such as REFLEX [11] and FAST version 2 [16], involve an assessment of potential flexibility capabilities of the generation resource fleet as part of the detailed simulation of power system operation.

Simpler and less data-intensive flexibility metrics consider primarily the physical characteristics of the power system resources without delving into operational details. Yasuda [17] proposed a flexibility chart that provides a glimpse of the potential flexibility resources in a power system. The percentages of installed capacity, pumped hydro, hydro, combined cycle gas turbine, combined heat and power, and interconnection relative to peak demand are graphically illustrated. However, information conveyed by the chart is limited as capacity alone is not a suitable indicator of flexibility. Kirby and Milligan [18] observed the operating range together with the up and down ramping rates of each generator to determine the aggregate ramping capability available in a power system on an hourly basis. It was then compared with hourly load data to assess whether the available system flexibility is able to meet the required flexibility needs. Brouwer et al. [19] identified minimum generation level, ramp rate, start-up time and its associated cost as key flexibility parameters of a thermal power plant. These parameters were subsequently applied as constraints in power system models in order to assess the technical and economic operation of power plants in distinctly diverse future power system scenarios. FAST version 1 [20] quantifies the available flexibility from generating units for four different time horizons ranging from 15 min to 12 h, in terms of up and down ramping rates. Assumptions are made to cater for flexibility provision through storage, interconnection and demand response. The maximum load variability on the power system which can be met by its combined flexibility resources is then estimated. Ma et al. [21] devised a promising offline flexibility index that estimates the contribution of individual generators to the overall system flexibility based on their technical parameters. In order to determine the flexibility of each generator, the authors considered two important technical characteristics. Firstly, the capability to respond quickly to changes in load, given by the average of ramp-up and ramp-down rates, and secondly, the adjustable capacity, calculated as the difference between the maximum and minimum stable generation capacity levels. The index is then normalized with respect to the maximum capacity of the generator. The appeal of this index lies in its simplicity and its intuitive ability to compare the flexibility of individual generators in a power system.

Both categories of flexibility metrics identified in the foregoing literature review have their limitations when they are applied to power system planning. The use of approaches that are heavily reliant on past chronological data is restricted by several factors. Firstly, they require a considerable amount of data together with detailed simulations of balancing load and generation at small temporal resolutions over long time horizons. Unfortunately, not all power systems have historical databases of load synchronized with output power from all conventional and intermittent renewable energy generators. Another caveat of these tools relates to their exploitation of historical data to evaluate the degree of uncertainty and variability that can be envisaged in future power systems. In particular, the past generation output from RES determines the anticipated variability in net load. But renewable regimes are intrinsically dynamic and depend on the complex interplay of many climate factors. Their inconsistency has been exacerbated by climate change [22–24]. Studies have pointed to the unreliability of counting on present and past RES studies to adequately characterize future output [25–27]. Given the wide uncertainty range, estimates of ramps in variable renewable energy production from past output changes can be misleading, predominantly in long-term energy planning studies. Finally, traditional long-term power system planning is a highly constrained, large-scale, mixed-integer nonlinear programming problem [28,29]. Integrating computationally intensive flexibility calculations in an already convoluted problem will significantly increase its complexity.

These limitations do not apply to the category of simpler metrics, making them ideal for the flexibility assessment of potential generation mixes in long-term power planning. Nevertheless, some inadequacies have been identified in the formulation of the metrics. Most of them consider only ramp rates and operating range when determining the flexibility supplied by generators. Yet, there are several other technical characteristics of a generator that influence its flexibility level. Features such as start-up, shutdown, minimum up and down times have not been taken into account in the existing metrics. Moreover, the current operational state of a generator is key in establishing the extent of flexibility it can supply [16]. For example, if a generator has recently been shut down, it will be able to come online only after the minimum down and start-up times have elapsed, highlighting the significance of these factors. Another important issue relates to the relative importance assigned to the technical characteristics of a generator when computing its overall flexibility. For example, Ma et al. [21] assumed that average ramp rate and operating range have equal importance in determining the flexibility of a generator. Accordingly, equal weightage was assigned to the two characteristics when aggregating them in the flexibility index. However, several studies have shown that some characteristics of generators are more important than others in establishing their capability to handle unexpected changes in their output [30–32]. Therefore, the relative importance of the various technical parameters must be taken into consideration in formulating the flexibility metric to enhance its accuracy. Finally, the mathematical treatment of simpler metrics is such that the flexibility index of a particular generating unit remains constant irrespective of the power system of which it forms part. But the contribution of a unit to the overall power system flexibility depends on the characteristics of other constituent units. Basically, a moderately flexible generator will contribute less towards overall system flexibility in a highly flexible generation mix than in a relatively inflexible one. Ideally, the flexibility index must be able to adjust automatically in order to reflect the relative contribution of a generator to the power system flexibility.

This paper contributes to the growing field of flexibility metrics by providing a more realistic assessment of the flexibility availability from generating units, when considered individually as well as when aggregated within a power system. In this context, we propose a systematic formulation of a new composite flexibility metric (CFM). Composite or aggregated metrics have been extensively used to provide comparisons of countries with regards to complex issues in diverse fields such as economic, environmental and technological performance and development [33]. They have recently been extended to energy-related areas, mostly for the analysis of energy supply security [34–37]. The most important contribution of this paper is that it addresses the major shortcomings identified in the simple flexibility metrics reviewed in this section. Thus, the proposed metric takes into account a comprehensive set of technical flexibility parameters of a generating unit. It further assigns weights to these parameters based on their relative importance in determining the flexibility available in the generator. Besides evaluating the flexibility availability in individual generators of a power system, the CFM can also be used to compare the flexibility availability in different power systems. Another interesting feature of the CFM is that it automatically adapts to the flexibility characteristics of other units in the power system. In other words, the same generating unit will have a lower flexibility index in a power system with a highly flexible generation portfolio than in one composed of less flexible units. All these features contribute to make the CFM a valuable tool for power system planners in countries where comprehensive power system data required for intricate simulations is not available. It can also be used as an effective communication tool for policy makers to provide quick and insightful information about power system flexibility.

The remainder of the paper is organized as follows: Section 2 elaborates on the technical characteristics of power plants that contribute to flexibility. In Section 3, we describe a framework that aggregates the defining characteristics identified previously into a meaningful CFM. In Section 4, we describe the application of the proposed methodology on a test system, analyze the results and discuss the limitations of the proposed approach. Finally, we provide a summary of the contributions in Section 5.

2. Generator flexibility attributes

As power system planners shift their focus to having adequate flexibility resources, flexibility available in conventional generators assumes greater importance since these units are responsible for meeting the net load. The flexibility potential of a conventional generator depends on its present operational state and on the following technical constraints imposed by the technology on which it is based.

2.1. Operational range

A generator is designed to produce electricity reliably within a certain operating range (*OR*) under normal operating conditions, bounded by its maximum capacity, $P_{\max}$ and the minimum stable generation level, $P_{\min}$. *OR* and its two limits are commonly given in terms of MW but $P_{\min}$ is expressed as a percentage of $P_{\max}$ in this study to give a measure of both characteristics in a single value. Operating a unit at $P_{\min}$ is often not cost-effective but has the benefit of keeping the unit online so that it can be called upon to meet increases in net load.

2.2. Ramping capabilities

With growing RES integration in the power system, conventional generating units need to adjust their output levels more rapidly to meet more frequent and larger fluctuations in net load. The ramp rate is basically the average speed at which a generator can increase (ramp up rate – *RUR*) or decrease (ramp down rate – *RDR*) its output level between the limits of its *OR* and is usually expressed in MW/h. Ramp rate is constrained by the operating condition of the generating unit.

2.3. Start-up and shut-down times

Start up time (*SUT*) refers to the time taken, measured in hours, from turn-on to the generator breaker closure, at which point the generating set is synchronized with the grid and its power output is equal to $P_{\min}$. Shut-down time (*SDT*), also specified in hours, is the time interval from the instant the power output of the generating unit drops below $P_{\min}$ to that when the unit reaches a complete stop. *SUT* is highly dependent on whether the generator is started in a cold, hot or warm state, based on the time elapsed since its last shutdown [16]. Offline generating units with short *SUT* are able to provide extra power on short notice.

2.4. Minimum up and down times

For mostly economic reasons, a conventional generator must remain online and generate electricity for a minimum up time (*MUT*) following start-up. *MUT* ensures that the operating and maintenance costs associated with start-up and subsequent electricity generation are recovered. On the other hand, to prevent thermal stress that will reduce its lifetime, a generator must be maintained offline during a minimum down time (*MDT*) once it has cycled off. Both constraints are generally expressed in hours. Hence, extended *MUT* and *MDT* restrict the generator flexibility.

Power systems consist of conventional generating units that have varying technical constraints. Traditionally, these constraints have, to a large extent, influenced the role of generators in the supply of electricity. Thus, base load units are characterized by long *SUT*, *SDT*, *MUT* and *MDT* as well as slow ramp rates and relatively high $P_{\min}$, making them suitable to run at constant output almost continuously. On the other hand, peaking units typically have opposite technical characteristics so that they can follow rapid changes in demand. With increased penetration of variable RES, the outputs of conventional generators must be skillfully adjusted to follow net load ramps at all times. Thus, periods marked by sudden fall in RES output will need running generating units with steep *RUR* and large *OR* together with offline units with fast *SUT* and *MDT*. Conversely, a sharp rise in RES production will call for operating units with fast *RDR*, low $P_{\min}$ as well as small *MUT* and *SDT*.

3. Material and methods

Construction of an aggregated indicator is complex and involves a sequence of steps, each of which needs careful examination [38]. Weighting, aggregation and normalization of individual indicators, in particular, are critical in determining the quality and reliability of the composite metric [39]. The proposed framework ensures that suitable methodological decisions are employed during the important stages of metric construction. The motivation behind these methodological choices is made explicit and transparent. Sensitivity analysis is further performed to demonstrate the robustness of the composite indicator to the uncertainties associated with the selection of weighting and normalization methods during the modeling process. Fig. 1 summarizes the different steps involved in the construction of the CFM.

3.1. Normalization

The individual flexibility indicators of generators are expressed in different measurement units and disproportionate scales. They must therefore be normalized for ease of comparison and aggregation. Another purpose of normalization is to cater for the correlation direction of individual indicators with the phenomenon to be evaluated. In this case, *SUT*, *SDT*, *MDT*, *MUT* and $P_{\min}$ are negatively correlated with flexibility whereas *RUR*, *RDR* and *OR* are positively correlated with it. The normalization procedure then ensures that an increase in these normalized indicators invariably results in an increase in the flexibility index. Min–max normalization method is selected in the present study as it converts all indicators to an identical range between 0 and 1 using Eq. (1) [33].

$$I_{ji} = \frac{x_{ji} - \min_i(x_j)}{\max_i(x_j) - \min_i(x_j)} \tag{1}$$

where x_{ji} is the value of indicator j for generator i, I_{ji} is the normalized value of x_{ji} while $\min_i(x_j)$ and $\max_i(x_j)$ are the minimum and maximum values of indicator j across all generators i.

3.2. Weighting

Formulating a meaningful methodology to combine the eight flexibility indicators of conventional generators constitutes the most decisive and challenging issue in the construction of the metric. In this context, an explicit weighting model must be selected to assign weights to the indicators in order to reflect their relative importance in the supply of flexibility. Weighting schemes can be broadly categorized as statistical or participatory, depending on whether they are data-driven or based on expert opinion respectively. In the absence of a reliable database that could lead to underlying statistical relationships among the technical characteristics of generators, a participatory approach is adopted in this study. As opposed to other participatory methods like Budget Allocation, Conjoint Analysis and Public Opinion, the Analytic Hierarchy Process (AHP) is deemed to be most appropriate for this application. AHP has the advantage of being simple as it processes qualitative information compared to quantitative data needed by other techniques. So, it does not require a complex system with expert knowledge embedded in it. Furthermore, it has an in-built consistency index which provides a measure of the consistency in the expert opinions used to elicit weights for individual indicators. Besides, AHP provides the mathematical approach to process the inevitably subjective expert judgements characteristic of real-world applications [40]. The fact that AHP does not presume that experts are error-free in eliciting preference scores makes it even more appealing for the CFM as the intensity of importance of individual flexibility indicators with respect to each other is not unequivocal.

AHP is widely applied in multi-criteria decision-making and relies on pairwise comparisons of criteria (or indicators) with respect to the objective in order to systematically extract weights [41]. In each pair-wise comparison, a preference score on a scale of 1–9 as per Table 1 is used to express the intensity of importance of one criterion with respect to the other. For a problem with N criteria, all combinations of pairwise comparisons are summarized in an $N \times N$ pair-wise comparison matrix (PCM), from which the weight of each criterion is computed by solving the normalized principal eigenvector. Sometimes, experts can become inconsistent in their judgements as the number of comparisons increases rapidly with the number of criteria. A consistency ratio (CR) is then calculated using Eq. (2) along with the weights to preserve the integrity of the judgements. A CR of 0.10 or less is generally accepted, otherwise the comparisons should be carefully revised [40].

$$\mathrm{CR} = \frac{\lambda_{\max} - 1}{n - 1} \tag{2}$$

where $\lambda_{\max}$ is the principal eigenvalue and $n = N(N-1)/2$ is total number of pair-wise comparisons.

3.3. Correlation analysis

When assigning weights to indicators, caution must be exercised if two indicators have a high degree of correlation as it may induce an element of double counting in the composite index [33]. To deal with this issue, the statistical correlation among each pair of individual indicators x and y is first determined using their Pearson correlation coefficient given by Eq. (3).

$$r_{xy} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{(n-1)\sigma_x \sigma_y} \tag{3}$$

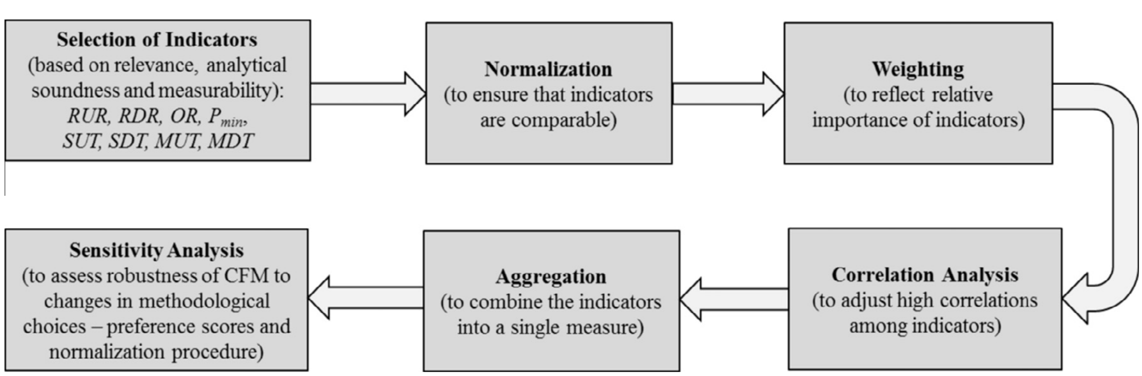

Fig. 1. Methodology for constructing the composite flexibility metric.

Table 1
Scale for pair-wise comparisons of two criteria [42].

Intensity of importance	Definition	Explanation
1	Equal importance	The two criteria contribute equally to the objective
3	Moderate importance	Slightly favors one criterion over the other
5	Strong importance	Strongly favors one criterion over the other
7	Very strong importance	Very strongly favors one criterion over the other. Its dominance is demonstrated in practice
9	Extreme importance	Evidence favoring one criterion over the other is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate importance between two adjacent values	

where there are n 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. As a rule of thumb, if the correlation coefficient is higher than a predefined threshold, the aggregate weight allocated to the pair is revised downward so that the common component in these indicators is not over-represented in the composite metric [33]. In the case of the CFM, if the value of r_{xy} exceeds 0.9, the preference scores of the two highly correlated criteria are adjusted during their pairwise comparisons by reducing the intensity of importance of each indicator by one level as per Table 1.

3.4. Aggregation

The last step in the construction of the CFM is the aggregation of normalized indicator scores with the relative weights. A linear summation is used here so as to allow generators with high values in some flexibility indicators to compensate for lower values of other indicators. The flexibility index of each generator is given by Eq. (4).

$$\mathrm{Flex}_i = \sum_{j=1}^{k} (I_{ji} \times w_j) \tag{4}$$

Subject to $\sum_j w_j = 1$ and $0 \leqslant w_j \leqslant 1$, where I_{ji} is the normalized value of indicator j ($j = 1, \ldots, k$) for generator i and w_j is the weight for indicator j determined through AHP.

3.5. Robustness analysis

Several subjective choices are made at various stages of CFM construction. The final aggregated value may largely hinge on the approach selected at each stage. As such, it is important to conduct sensitivity analysis to study the impact of any modification to the methodological choices on the results of the CFM. Sensitivity analysis helps to evaluate all possible sources of uncertainty in the metric construction process, explores the robustness of the process to these sources and enhances transparency and confidence in the model [39]. The adopted methodology applied z-scores to normalize the individual indicators and AHP to derive their relative weights. Although the consistency of the pairwise comparison judgements can be gauged by the CI and the AHP has the inherent ability to deal formally with judgement errors, modifications in the preference scores will alter the elements of the PCM, thereby causing changes in the criteria weights. The sensitivity analysis therefore investigated different criteria weights to demonstrate the robustness of the metric to variations in preference scores. Clearly, trying all possible combinations of preference scores for the eight indicators would not only be computationally intensive but also irrational. For example, it would be unreasonable to assume that *MDT* is extremely important with respect to *SUT* or ramp rates. Thus, only a judiciously selected subset of preference score variations is investigated. It consists of the following changes with respect to the baseline PCM, one at a time (the code referring to each scenario is given within brackets):

(i) *SDT* is equally important as ramp rates, *MUT* and *MDT* (**SDT3**)
(ii) *RUR* is equally important as *OR*, $P_{\min}$ and *SUT* (**RUR1**)
(iii) *MUT* is equally important as *OR*, $P_{\min}$ and *SUT* (**MUT1**)
(iv) *MDT* is equally important as *OR*, $P_{\min}$ and *SUT* (**MDT1**)
(v) *OR* is equally important as ramp rates, *MUT* and *MDT* (**OR3**)
(vi) $P_{\min}$ is equally important as ramp rates, *MUT* and *MDT* (**P3**)
(vii) *SUT* is equally important as ramp rates, *MUT* and *MDT* (**SUT3**)
(viii) Equal weights are applied to all indicators (**EW**)

It can be observed that in each scenario except **EW**, the intensity of importance of a single indicator is modified by one step. In cases where the intensity of importance can either decrease or increase, the more credible alternative is selected. For instance, scenario **MUT1** is preferred to **MUT5** as it is very unlikely that *OR*, $P_{\min}$ and *SUT* are strongly more important than *MUT* in determining power plant flexibility. On the other hand, the inclusion of the **EW** scenario is crucial for two reasons. Firstly, it is widely applied in composite metric applications where it is difficult to assess the relative importance of indicators [33]. Secondly, **EW** alters the preference scores of all indicators rather than a single one. Consequently, it implements a drastic change in the criteria weights with respect to the baseline case and can be considered as the "acid test" for the robustness of the proposed metric to variations in preference scores.

The effect of applying a different normalization technique was also explored. As opposed to the min–max scheme which reduces all indicators to the same range [0, 1], z-scores normalization method converts all indicators to a common scale with an average of 0 and standard deviation of 1 using Eq. (5) [33].

$$I_{ji} = \frac{x_{ji} - \bar{x}_j}{\sigma_j} \tag{5}$$

where I_{ji} is the normalized value of x_{ji}, $\bar{x}_j$ is the mean value and σ_j is the standard deviation of indicator j across all generators of the power system. In a nutshell, the z-score indicates how different a particular generator is from the average of all generators for a particular flexibility characteristic. A z-score of 0 implies that the generator has a value similar to the average for that particular flexibility characteristic, a positive z-score is above the average, and a negative z-score is below average. This characteristic of the z-score normalization method justifies why it is not used in the CFM framework. Since the average of all normalized values for each flexibility indicator is 0, the cumulative CFM score of all generators in a power system will also be equal to 0. Hence, unlike the min–max scheme, z-score normalization does not allow comparison of flexibility availability across different power systems.

18 different scenarios, including the baseline, were obtained when the normalized values of indicators through min–max and z-scores were aggregated with the weights resulting from the substitute PCMs. The first step in sensitivity analysis is to rank the CFM score of each generator under each scenario in increasing order of importance. A number of statistical measures such as the median, mean, standard deviation and percentiles of the generator ranking under all scenarios is used to depict the uncertainties induced by changes brought to the CFM construction framework. Another key statistic that supplements sensitivity analysis is the average shift in flexibility rankings of generators under different scenarios

with respect to the baseline case. The average shift in ranking under each scenario, R_s, is calculated as the average of the sum of absolute differences in the CFM ranks of all I generators in the power system with respect to the baseline case and is given by Eq. (6) [33].

$$R_s = \frac{1}{I}\sum_{i=1}^{I}\left|\text{Rank}_{ref}(CI_i) - \text{Rank}(CI_i)\right| \tag{6}$$

where $\text{Rank}_{ref}(CI_i)$ and $\text{Rank}(CI_i)$ are the CFM ranking assigned to generator i in baseline and examined scenario respectively.

3.6. Test system

The proposed flexibility index is tested on a generating system based on the single-area version of IEEE Reliability Test System (RTS-96) [43]. Notwithstanding hydro generating units, the test system consists of 26 generating units of 8 different types with a total generating capacity of 3105 MW. The IEEE RTS-96 is used because it is well documented and all the flexibility characteristics of its units have been defined in literature. They are summarized in Table 2 [44,45].

4. Results and discussion

4.1. Weighting scheme

All the eight flexibility characteristics of generators identified in Section 2 and depicted in Table 2 are compared in pairs in terms of their relative importance in contributing to the flexibility of a power system. For this purpose, expert judgement was based on the results of previous research work on the ability of generators to respond to net load variability [31,32,46,47]. Fast ramping rates, low $P_{\min}$, short *SUT* and wide *OR* are most commonly cited as highly important requirements for flexible operation of generators followed by rapid *MUT* and *MDT* and finally, quick *SDT*. However, the correlation analysis revealed a very strong positive correlation between *RUR* and *RDR* with a Pearson correlation coefficient of 0.97. Accordingly, their preference scores were adjusted to the next lower level of intensity of importance and the resulting PCM is shown in Table 3, in which element a_{ij} specifies the intensity of importance of indicator i relative to indicator j in providing flexibility. An element 1 implies that two indicators have the same importance. Clearly, $a_{ii} = 1$ and $a_{ji} = 1/a_{ij}$.

The PCM data was synthesized to obtain the relative weights of the individual indicators in the CFM using the right eigenvector method [40]. The weights are calculated and are shown in the last column of Table 3. It should be noted that the relative weights are scaled such that their sum is equal to 1. The computed consistency ratio for the PCM was found to be 0.007, indicating a very high level of consistency in the judgements.

Table 3
Pair-wise comparison matrix of individual indicators and their calculated weights.

	$P_{\min}$	*OR*	*SUT*	*RUR*	*RDR*	*MUT*	*MDT*	*SDT*	Weights
$P_{\min}$	1	1	1	3	3	3	3	5	0.218
OR	1	1	1	3	3	3	3	5	0.218
SUT	1	1	1	3	3	3	3	5	0.218
RUR	1/3	1/3	1/3	1	1	1	1	3	0.078
RDR	1/3	1/3	1/3	1	1	1	1	3	0.078
MUT	1/3	1/3	1/3	1	1	1	1	3	0.078
MDT	1/3	1/3	1/3	1	1	1	1	3	0.078
SDT	1/5	1/5	1/5	1/3	1/3	1/3	1/3	1	0.033

4.2. Composite flexibility indices of generators

The CFM indices for the eight types of generators in the IEEE RTS-96 are given in Table 4 along with the ranking of the generators based on their flexibility index. The ranking obtained by Ma et al. [21] for the same generators is also provided.

It can be inferred from Table 4 that all four generating units of capacities less or equal to 100 MW have the highest CFM indices. The ranking of the CFM indices corroborates with the findings of the robust dispatch model implemented by Thatte and Xie on the IEEE RTS-96 [48]. The dispatch model established that the bigger coal and nuclear units supply the base load, Oil/Steam units provide load following and Oil/CT units are used as peaking units. The CFM ranks these units as the least flexible, moderately flexible and most flexible respectively showing a correlation between the proposed composite metric and the dispatch priority.

It is interesting to note that the Oil/CT unit was ranked as least flexible by Ma et al. [21] whereas with the proposed methodology, it is the most flexible unit of the generation mix. This absolute disparity is not surprising as the Oil/CT unit had the worst normalized scores in both flexibility indicators accounted by Ma et al.'s model [21], namely average ramp rate and *OR*. As a result, the Oil/CT unit had the smallest flexibility index among all generating units of the power system. In contrast, the Oil/CT unit presents the best values for the additional operational parameters considered in the CFM, namely $P_{\min}$, *SUT*, *SDT*, *MUT* and *MDT*. The low values of the Oil/CT unit in respect of average ramp rate and *OR* are dwarfed by its excellent ratings in the five other indicators considered in the CFM framework. The high CFM index computed for the Oil/CT unit is in agreement with its suitability to provide flexible power as reported in literature [49,50]. To some extent, CT units are implemented with flexibility in mind so as to follow variations in load that occur on shorter time scales. The conflicting results from these two approaches also highlights the importance of considering a wider range of technical characteristics of generating units in evaluating their flexibility.

Table 4 also reveals that both methods rank the flexibility indices of the three largest generating units among the poorest. Although these generators have best *OR* and ramp rates, their $P_{\min}$, *SUT*, *SDT*, *MDT* and *MUT* are among the worst. The 155 MW Coal/Steam unit has the last but one CFM score in the generation

Table 2
Details of generating units in IEEE RTS-96.

No. of units	Unit size (MW)	Unit type	$P_{\min}$ (%)	*OR* (MW)	*RUR* (MW/h)	*RDR* (MW/h)	*SUT* (h)	*SDT* (h)	*MUT* (h)	*MDT* (h)
5	12	Oil/Steam	0.2	9.6	9.6	9.6	4	0	0	0
4	20	Oil/combustion turbine (CT)	0.2	16	16	16	0	0	0	0
4	76	Coal/Steam	0.2	60.8	38.5	60.8	12	1	3	2
3	100	Oil/Steam	0.25	75	51	74	7	2	4	4
4	155	Coal/Steam	0.35	100.76	55	78	11	2	5	3
3	197	Oil/Steam	0.35	128.05	55	99	7	2	5	6
1	350	Coal/3 Steam	0.4	210	70	120	12	3	8	5
2	400	Nuclear	0.25	300	50.5	100	24	4	8	5

Table 4
CFM indices and ranking for individual generators in the IEEE RTS-96.

Unit type (code – capacity in MW)	CFM index	CFM ranking	Ranking by Ma et al. [21]
Oil/Steam (O/S-12)	0.589	2	1
Oil/CT (O/CT-20)	0.643	1	8
Coal/Steam (C/S-76)	0.559	3	2
Oil/Steam (O/S-100)	0.537	4	3
Coal/Steam (C/S-155)	0.425	7	4
Oil/Steam (O/S-197)	0.481	6	5
Coal/3 Steam (C/S-350)	0.424	8	7
Nuclear (N-400)	0.498	5	6

portfolio while it ranked fourth with the previous technique. In the proposed methodology, all the individual normalized flexibility indicator values for this generator, except ramp rates, are among the poorest leading to an inferior aggregate value. The fact that ramp rate had a 50% weightage in Ma et al.'s formulation [21] reflected positively on the flexibility index of the 155 MW Coal/Steam generator.

4.3. Robustness analysis

The statistics of the rank distribution under all scenarios for each generator forms the basis of uncertainty and sensitivity analysis. They are synthesized in the box plot shown in Fig. 2. The interquartile range, represented by the shaded rectangle, indicates the range in which the bulk of ranks under the 17 scenarios for each generator lies. In all cases, the interquartile range extends only one rank beyond the median while in the case of three generators, it corresponds to the median. The small interquartile range for all generators indicates that the proposed framework is stable in the presence of uncertainties in preference scores and normalization method. Moreover, it is observed that the median rank matches with the rank in the baseline scenario for all generators except for a minor rank shift from 7 to 8 in the case of the 155 MW Coal/Steam unit. The compactness of the rank distribution of each generator around its baseline value is further verified by its mean being very close to its median. Such a statistical feature implies that there are very few ranks which deviate significantly from the baseline value, thereby confirming the robustness of the metric to changes in methodological choices.

The upper and lower whiskers of the box plot represent the worst and best ranks of the generators. In Fig. 2, they indicate that there are some outliers for a few generators, the most prominent being the 12 MW Oil/Steam unit ranked 7 and the 400 MW Nuclear unit ranked 1. A more detailed analysis of the results shows that these two outliers arise in the scenarios **RUR1** and **SUT3** respectively. In the first case, considering *RUR* to be among the most important flexibility characteristics of the generator will considerably inflate the importance of ramp rates in the formulation. As mentioned in Section 4.1, *RUR* and *RDR* are strongly correlated. Upgrading their importance will therefore lead to double counting and favor big generators which generally have high values in *OR* and ramp rates but achieve low scores in time-related indices. Hence, improving the significance of ramp rates penalizes small generators like the 12 MW Oil/Steam unit. The same explanation is valid in the second case where reducing the importance of *SUT* results in only *OR* and P_{min} being most influential while simultaneously raising the weight assigned to ramp rates to a small extent. Consequently, the biggest unit is favored at the expense of the smaller ones. It is interesting to note that the **SUT3** with *z*-scores scenario also corresponds to the only one where the 20 MW Oil/CT unit is not ranked first but second. These observations further justify the judgements made during the CFM development given that it would be unconceivable for the nuclear unit to be the most flexible and the 12 MW Oil/Steam unit among the least flexible in the generation portfolio.

Fig. 3 presents the average shift in rank, R_s, of CFM scores for all generators under each of the 17 different scenarios considered with respect to the baseline. It is observed the maximum value of R_s is 1.5 and R_s exceeds 1 only in four scenarios. The small sensitivity of flexibility ranking to changes in preference scores assignment and normalization method suggests a high degree of robustness of the proposed framework. Interestingly, R_s is greater or equal to 1 in scenarios **SUT3**, **P3** and **RUR1** irrespective of the normalization method. In fact, even these scenarios tend to substantiate the selection of preference scores in the baseline. Just like in the cases of outlier ranks observed in the box plot, scenarios **SUT3**, **P3** and **RUR1** correspond to preference score assignments which allocate excessive importance to flexibility characteristics *OR* and ramp rates at the expense of time-related flexibility features. For example, scenarios **P3** and **SUT3** assign weights of 0.255 to *OR* as compared to 0.091 to *MUT* and *MDT*. So, these 6 scenarios promote bigger generators to the detriment of smaller ones, leading to more changes in flexibility rankings relative to the baseline. On the other hand, all other scenarios produced values of R_s not exceeding 0.75, showing very few changes in ranking of generators. Most importantly, scenario **EW** which implements the most substantial changes in the weights of the CFM indicators with respect to the baseline, resulted in an R_s value of only 0.75 for both normalization methods. This confirms the robustness of the CFM framework to variations in preference scores and normalization procedures.

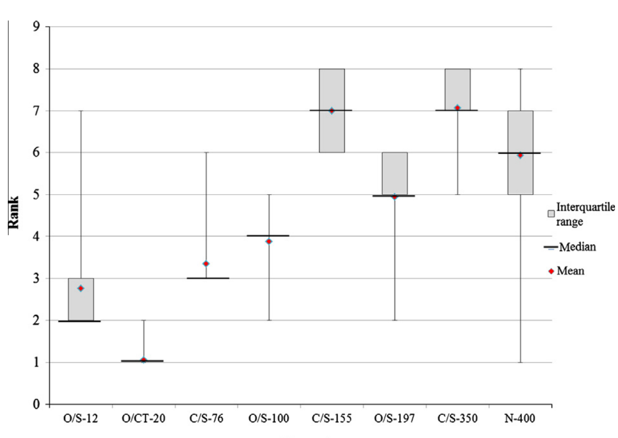

Fig. 2. Box plot showing the rank distribution for each generator under all scenarios.

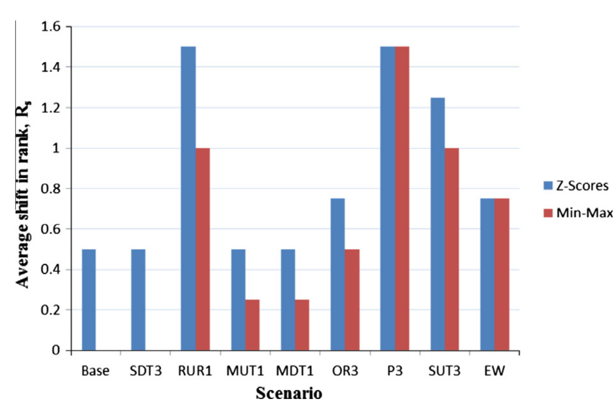

Fig. 3. Average shift in rank of flexibility indices with respect to the baseline.

4.4. Impact of new generators on composite flexibility indices

The impact of adding a new generator on the CFM indices of existing generators is also investigated. For this purpose, a generator known for its flexible operation is introduced into the IEEE RTS-96 generation mix. The 56 MW open cycle gas turbine (OCGT) unit is taken from the Irish Single Electricity Market modeling study [51] which provides comprehensive technical data about its generators. It is fueled by distillate oil and is commonly employed as a flexible peaking unit. The generator has a $P_{\min}$ of 5 MW, representing only 9% of its maximum capacity as well as *MUT* and *MDT* of about 1 h. It can also start up, shut down and reach full power output within minutes, underlining its fast-acting nature. The new CFM indices of the generators following the addition of the OCGT unit to the portfolio are given in Table 5. As expected, the CFM index of the OCGT outclasses those of the other generators, showing that it is much more flexible than the other units. A comparison of the CFM scores of existing generating units in Table 4 and Table 5 shows that they have decreased following the addition of the OCGT unit. For example, CFM index of the 20 MW Oil/CT unit has decreased from 0.643 to 0.565. These results highlight the adaptive nature of the CFM as it automatically adjusts the flexibility index of a generator to the technical characteristics of all generators in the power system.

4.5. Comparing composite flexibility indices of different power systems

An additional aspect of the CFM is that it can be used to contrast the flexibility available in different power systems. For this purpose, the CFM indices of all generators forming part of the power systems under consideration are computed collectively as if they belonged to a single power system. The CFM score of each power system is subsequently determined by adding the CFM indices of all its constituent generating units. This principle is illustrated by using the results of Table 5 to compare the flexibility available in the IEEE RTS-96 with that of a similar power system in which the four 76 MW Coal/Steam units have been replaced by five 56 MW OCGT units so as to maintain the total generation capacity of the power system approximately constant. The number of generation units of each type in the IEEE RTS-96 is given in Table 2. The CFM score of the power system with the OCGT units, calculated as 14.157, is logically higher than the value of 12.477 found for the IEEE RTS-96.

4.6. Limitations and future work

The simplicity of the CFM, nevertheless, comes at the expense of some limitations. Understanding these limitations not only ensures that the metric is used judiciously but also helps to identify interesting opportunities for further research. First of all, the proposed approach does not consider the actual operational state of generators. In real operations, a generating unit with a higher CFM score might not always be able to provide more flexibility than one with a lower score. For example, a generator with high CFM score but running near its $P_{\max}$ or $P_{\min}$ rating will not be able to contribute much towards meeting upward and downward net load ramping events respectively. It would be interesting to incorporate the CFM into a unit commitment algorithm in an attempt to study the impact of technical flexibility constraints of generators on the short-term operational decisions. Besides generator operational state, other time-specific characteristics of flexibility such as net load profile and generator outages are not considered by the CFM. Secondly, there are other important sources of flexibility in a power system in addition to the technical characteristics of generators considered here. They include demand-side management techniques, geographical spread of the power system and storage facilities, among others. These flexibility sources could be integrated sensibly in the proposed framework to provide a more holistic evaluation of flexibility availability. Thirdly, the CFM does not relate the cost-effectiveness of the generating units to their flexibility availability. This is indeed a very important consideration in power system planning. In this context, it is also worth noting that the CFM methodology assumes that all generators can be subjected to regular cycling. But frequent cycling of conventional power plants increases equipment wear and tear resulting in reduced lifetime and cost-effectiveness. Economic analysis of the flexibility availability in generators could be performed by integrating long-term viability of the generating units as well as operations and maintenance costs.

Table 5
CFM indices for individual generators in the extended IEEE RTS-96.

Unit type (capacity – MW)	CFM index	Ranking
Oil/Steam (12)	0.511	3
Oil/CT (20)	0.565	2
OCGT (56)	0.722	1
Coal/Steam (76)	0.482	4
Oil/Steam (100)	0.479	5
Coal/Steam (155)	0.406	9
Oil/Steam (197)	0.462	6
Coal/3 Steam (350)	0.424	8
Nuclear (400)	0.440	7

5. Conclusions

Composite metrics are extremely useful and widely used tools in decision-making in diverse fields such as economic, environmental and technological performance and development. Until recently, their application to the energy sector has been limited to the assessment of energy security. In this work, we have made what is probably a first attempt at applying composite indicators to the study of power system planning. A CFM framework was developed to evaluate the availability of flexibility from individual generating units in a power system based on their operational constraints. The proposed approach is also useful in comparing the flexibility available in different power systems. When tested on the IEEE RTS-96 system, the CFM scores of the generating units were found to be consistent with the flexibility levels usually associated with them in existing literature. Furthermore, sensitivity and uncertainty analyses showed that the CFM is robust to methodological choices that underpin its construction. The proposed CFM is useful in many ways. It not only uses a simple approach to provide an insight into a key area that needs substantial efforts from power system planners but also aggregates multiple and incommensurate information into a single measure. Another appealing feature of the technique is its ability to adapt the CFM score of a unit to those of the other units in a power system. This enables power system planners to intuitively visualize how the flexibility available in a new generating unit will compare with that in existing units.

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