Identifying high-impact operating states in power system reliability analysis

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***Abstract*— The reliability of a power system depends, among other things, on the operating states of the system. For reliability analysis for long-term planning purposes, it may be necessary to consider a large set of representative operating states, and clustering techniques can be applied to reduce this set to make the analysis computationally tractable. However, the values of reliability indices for the system may be dominated by the contributions from a relatively small number of *high-impact* operating states that are not easily captured in the analysis. The objective of this paper is to identify high-impact operating states in the context of power system reliability analysis based on clustering techniques. A secondary objective is to characterize features of these operating states to better understand how they could be recognized, prepared for, and if possible avoided. An approach and an algorithm are proposed, and they are illustrated using a reliability analysis case study for a region of the Norwegian transmission grid with realistic operating states for the Nordic power system.**

Keywords—system state, operational scenario, vulnerability, high-impact low-probability, HILP, critical operating states

I. Introduction

The reliability of a power system depends on a number of uncertain factors, not the least the *operating states* of the system. Also referred to as e.g. operational scenario or conditions, an operating state is the system state during a given period of time and includes the load and generation composition and import/export to neighbouring areas [1]. Power system reliability analysis requires such states as input data. For instance, for long-term planning purposes, such data may be provided by historic timeseries or power market models, whereas for day-ahead operational planning purposes they may be based on short-term forecasts of load and generation.

To accurately capture the variability and uncertainty associated with operational conditions, the number of operating states to consider in the reliability analysis may become very large (e.g. tens of thousands). A contingency analysis is needed to evaluate combinations of operating states and contingencies, and when the required computation time makes the reliability analysis computationally intractable, clustering techniques can be applied to reduce the number of operating states. However, a considerable contribution to the value of the reliability indices (e.g. expected interruption costs) may come from a small number of what will here be referred to as *high-impact* operating states. Although they may be associated with a low probability of occurring, their impact on the estimated reliability indices may be high due to the high consequences of contingencies when they occur in such operating states. However, as clustering methods in general do not adequately capture outliers [2], high-impact operating states are easily neglected in the analysis.

From the perspective of power system reliability, this may not necessarily be problematic if the long-run averages of all contributions give accurate estimates of the expected values of the reliability indices. In broad terms, reliability analysis is primarily concerned with high-probability events, whereas *vulnerability* analysis, on the other hand, puts particular emphasis on possible high-impact low-probability (HILP) events [3]. From the perspective of power system vulnerability, precisely these high-impact operating states may be among the key aspects one would like to capture in the analysis. If such operating states could be identified and characterized, one might be better able to recognize them, prepare for them, and if possible avoid them. This paper takes the perspective of both power system reliability and vulnerability, but takes as a starting point a reliability analysis based on clustering of operating states. Given this context, the primary and secondary objectives of this paper are to propose an approach to 1) identify and 2) characterize high-impact operating states.

The rest of the paper is structured as follows. Section II summarises relevant work previously done on clustering and identification of operating states in the context of reliability and vulnerability analysis. In Section III an approach is proposed for identification and characterization of high-impact operating states, including an algorithm based on clustering techniques. Section IV illustrates the application of the approach on a reliability assessment case study involving a large number of operating states generated by a power market model. The limitations of the approach are discussed in Section V, after which Section VI concludes the paper and points out some possible directions for future work.

II. Clustering and identification of operating states

Techniques to reduce or prune the state space to consider in a power system reliability analysis have been studied for several decades [4], [5], often with the objective of identifying loss-of-load states. Most previous work appear to focus on reducing the set of contingencies to consider (i.e. system states in term of grid topology and generator outages), but reduction of the set of system states in terms of load, generation and import/export have also been given attention. When referring to operating state in the following, only the latter aspects of the system state will be considered.

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Traditionally, analyses for long-term system planning purposes have considered only a few operating states, e.g. peak load [6]. In power systems dominated by power generation from variable and renewable energy sources, a multiplicity of operating states may be needed to characterize the full set of possible generation patterns [2] and to capture relevant worst-case conditions [6]. This strengthens the motivation for careful clustering of operating states, which in general is to reduce the computational efforts of the analysis by considering only a smaller selection of representative operating states.

A thorough investigation of clustering of operating states in the context of power system reliability analysis was relatively recently been reported in [2], which forms some of the basis for the present work. One of the main findings of [2] was the importance of selecting an appropriate set of *features* to use as input to the clustering method. A feature of an operating state is an attribute or characteristic that can be used to distinguish different states, such as e.g. load or generation at a given bus. It was also found that the actual clustering method (e.g. agglomerate clustering or K-means clustering) was not equally important to obtain accurate estimates for the reliability indices. More recently, several applications of clustering of operating states have been reported for transmission system planning [6]–[8]. Ref. [7] proposes a feature set based on the optimal power flow patterns in the system and argues how this “clustering based on effects” approach is superior to “clustering based on causes”, i.e. feature sets based on generation and load. However, there is a consensus that clustering methods generally are not well suited to handle outliers and extreme operating states [2], [8]. In a sense, clustering can be seen as counterproductive to the identification of outliers, given that the basic aim of clustering is *not* to search for specific operating states but rather to be able to discard as many operating states as possible.

In the context of power system vulnerability analysis, some previous works have considered the identification of so-called *critical* operating states, which when combined with critical contingencies can lead to HILP events [9], [10]. In [9], a small number of critical operating states were identified through a process involving expert elicitation and power flow analyses. References [6], [8], on the other hand, use the term critical operating state in a system development context as states for which investment might be required due to very high costs of generation re-dispatch or load shedding. Several clustering approaches for reducing the number of operating states to consider for the system development analysis were compared, and it was found that none of them succeeded to capture the most critical of the operating states. Ref. [8] also found that for the case considered there, the critical operating states were to a greater extent characterized by high wind power generation than by high (i.e. peak) system load.

III. Methodology

This section will first briefly present the necessary preliminaries and notation for the reliability analysis taken as a starting point for identifying high-impact operating states: The reliability analysis methodology is presented in Sec. III.A and the clustering of operating states is presented in Sec. III.B. On this basis, the proposed algorithm for identifying high-impact operating states and the approach for characterization are then presented in Sections III.C and III.D, respectively.

A. Reliability assessment

For simplicity, the reliability analysis methodology will be presented assuming a single year consisting of 8736 hours. The set of all operating states in the year will be denoted I, and the operating states will be indexed by $i \in I$. Furthermore, for simplicity, the expected annual interruption costs $\mathrm{IC_a}$ is the only reliability index that will be considered. Employing an analytical reliability assessment methodology based on contingency enumeration and minimal cut sets [1], [11], the expected annual interruption costs associated with an operating state are given by

$$\mathrm{IC}_i = \frac{\Delta t}{8736\ \mathrm{h}} \sum_d \sum_j \lambda_{i,j} r_{i,j} c_{i,d}\left(r_{i,j}\right) P_{i,d,j}^{\mathrm{interr}} \tag{1}$$

Here, $c(r)$ is the specific cost of energy not supplied (CENS) for an interruption of equivalent duration r, λ is the equivalent fault rate, and P_{interr} is the interrupted power as estimated by a contingency analysis. The sums go over all operating states i in the year, all delivery points d and all minimal cut sets (contingencies) j. It is assumed that all operating states have the same duration Δt. The methodology accounts for time dependencies of interruption cost data and reliability data by time-dependent correction factors, and λ, r and c are calculated for each operating state i by averaging over all hours of the year represented by this state [12], [11]. The annual expected interruption costs are calculated by summation of the contributions for all operating states:

$$\mathrm{IC_a} = \sum_{i \in I} \mathrm{IC}_i. \tag{2}$$

B. Clustering of operating states

Each operating state i can be defined by a vector feature vector $\boldsymbol{x}_i$ with $|F|$ elements (features). Using a Euclidean distance metric, the dissimilarity of two operating states i and i' are measured by [2]

$$D(\boldsymbol{x}_i, \boldsymbol{x}_{i'}) = \sum_{f \in F} \left(x_{i,f} - x_{i',f}\right)^2. \tag{3}$$

The set of operating states I can be clustered on the basis of the dissimilarity matrix $\left[D(\boldsymbol{x}_i, \boldsymbol{x}_{i'})_{i,i' \in I}\right]$ and a linkage criterion to form $|K|$ disjoint subsets of operating states [2], [6]. Let $K = \{1,2,\dots,|K|\}$ denote the set of clusters and let the set of operating states in cluster $k \in K$ be given by $J_k \subseteq I$ and the size of the cluster be given by $n_k = |J_k|$.

The operating state in each cluster that is the *centroid* state according to (3) is denoted by $i_k \in J_k$, and the set of all centroid operating states for the set of clusters is denoted by $L_k = \{i_k\}_{k \in K}$. When applying this clustering of operating states in conjunction with the reliability analysis method outlined in Sec. A, it will be assumed that each centroid state is representative for all operating states in its cluster. Therefore, only the centroid operating states $i_k \in L_k \subseteq I$ are evaluated by the contingency analysis rather than for the full set of operating states I. This approximation gives the following expression for the contribution to the expected interruption cost for each cluster k:

$$\mathrm{IC}_k = \frac{n_k \times \Delta t}{8736\ \mathrm{h}} \sum_d \sum_j \lambda_{k,j} r_{k,j} c_{k,d}\left(r_{k,j}\right) P_{i_k,d,j}^{\mathrm{interr}}. \qquad (4)$$

Here, the time-dependence of λ, r and c must be recalculated to account for all hours of the year corresponding to cluster k. Using (4), the annual expected interruption cost can be calculated as

$$\mathrm{IC_a} = \sum_{k\in K} \mathrm{IC}_k. \qquad (5)$$

and the expected interruption cost per hour represented by cluster k is given by $\mathrm{IC'}_k = \mathrm{IC}_k/(n_k \times \Delta t)$.

C. Reclustering operating states

Conceptually, the proposed algorithm for identifying high-impact operating states can be described as a process of iterative “reclustering” of the operating states included in the reliability analysis. Assuming that the other states in a cluster are in some sense similar to the centroid state, naively, one would search for high-impact operating states within those clusters already evaluated to have a high impact on the expected interruption cost IC_k. Thus, for each iteration, a cluster is split, a new set of clusters is formed, and new centroid states are evaluated.

The main idea is illustrated conceptually in Fig. 1, which shows a dendrogram that in this example forms the basis for the agglomerate (bottom-up) clustering of 20 operating states. Note that although agglomerative clustering methods conceptually lend themselves naturally to the idea of reclustering, the general principle of the algorithm applies to all clustering methods. The dissimilarity $\widetilde{D}_{k,k'}$ between pairs (k, k') of possible clusters of operating states is measured along the y axis [2]. Agglomerative clustering works by making a horizontal cut in the dendrogram; all leaves on the tree below an edge that is cut then belong to the same cluster. In the example in Fig. 1, the horizontal cut shown as a solid blue line forms two clusters of operating states.

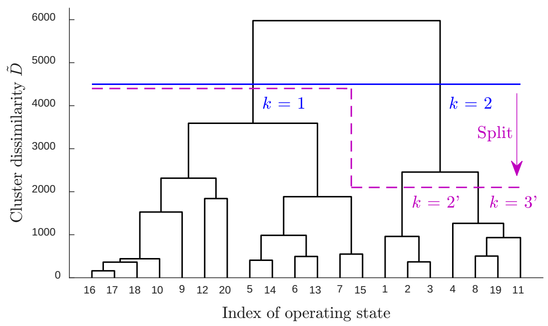

Fig. 1. Conceptual illustration of reclustering algorithm for identifying high-impact operating states based on splitting clusters of operating states.

Moving the horizontal cut downwards increases the number of clusters and generally increases the accuracy of the analysis. This algorithm proposes to increase the number of clusters in a more targeted manner by moving only a segment of the horizontal cut downwards, based on the estimate of IC_k associated with the segment. As illustrated by the dashed purple curve in Fig. 1, this effectively splits the corresponding cluster and reclusters the set of 20 operating states in three clusters.

The steps of the algorithm are outlined below and described in more detail in the following paragraphs.

Algorithm: Reclustering operating states

Input: Set K of clusters of operating state with reliability analysis results (expected interruption cost estimates) $\mathrm{IC}_k\ \forall\ k \in K$
Output: Set K' of clusters of operating states with $\mathrm{IC}_k\ \forall\ k \in K'$

1: **for** $m = 1$ to $m_{\max}$ **do**
2: **if** $\mathrm{mod}(m, \Delta m) \neq 0$
3: a) Select the cluster k_{split} with the highest IC_k
4: **elseif** $\mathrm{mod}(m, \Delta m) = 0$
6: b) Select the largest cluster $k_{\mathrm{split}} \in K$
7: **end do**
8: Recluster the operating states in cluster k_{split} to split it in a new set of l_{split} clusters
9: Form a new set K' with $|K'| = |K| + l_{\mathrm{split}} - 1$ clusters of operating states
10: Perform contingency analysis to evaluate P^{interr} for centroid operating states of K' not previously evaluated
11: Perform reliability analysis to estimate $\mathrm{IC}_k\ \forall\ k \in K'$
12: $K \leftarrow K'$
13: **end for**

The algorithm proposed is iterative with $m_{\max}$ being the number of iterations. For each iteration, a cluster k_{split} is selected to be split based on one of two criteria: a) For most iterations, the cluster to be split is the one with the highest contribution to expected interruption costs (step 3):

$$k_{\mathrm{split}} = \arg\max_{k\in K} \mathrm{IC}_k \qquad (6)$$

b) Every Δm^{th} iteration, one instead selects for splitting the cluster containing the largest number of operating states (step 5):

$$k_{\mathrm{split}} = \arg\max_{k\in K} n_k \qquad (7)$$

This step (b) is included to combine the search heuristic of criteria (a) with a more width-first search step. On the other hand, if an even more depth-first search approach is preferred, one can consider a criteria (c) instead of or combined with criteria (a): Select the cluster with the highest hourly expected interruption cost $\mathrm{IC'}_k$. For this heuristic, one can optionally consider only a subset $\underline{K} = \{k \in K | n_k \geq n_{\min}\} \subseteq K$ if one wants to avoid splitting clusters containing only a few states.

The set of operating states $J_{k_{\mathrm{split}}}$ is then (in step 8) split in l_{split} clusters with centroid states $L_{\mathrm{split}} \subseteq I$. (This clustering could be done using the same method as in the formation of the initial set of clusters.) The new, reclustered set of centroid states L', representing all operating states in I, is then formed:

$$L' = L \backslash i_{k_{\mathrm{split}}} \cup L_{\mathrm{split}} \qquad (8)$$

This corresponds to a new set of $|K| + l_{\mathrm{split}} - 1$ clusters that will be denoted K'. To truthfully capture the time-dependence of reliability and interruption cost input data for the new set of clusters of operating states, it is essential to keep track of which hours of the year each of the clusters in K' now corresponds to.

Given that only the centroid operating states in L have hitherto been evaluated by the contingency analysis, one now has to evaluate the new centroid states $i_k \in L_{\text{split}}$. The overall computation time of the analysis is approximately proportional to the total number of operating states evaluated. Note that although the previous centroid state $i_{k_{\text{split}}}$ can no longer be part of the new set of centroid states L', already existing contingency analysis results for previously evaluated states can if necessary the be retrieved for further analysis later. Finally (step 11), one must calculate the contributions IC_k to the annual expected interruption costs for all clusters k in the reclustered set K' according to (3). For the next iteration, the newly generated set of clusters K' will take the place of the previous set K.

D. *Characterization of high-impact operating states*

To investigate what characterizes high-impact operating states, a simple but objective and quantitative approach is to consider how the hourly expected interruption cost correlates with different features x of the operating states:

$$\rho = \frac{\sum_{k\in K'} n_k (x_{i_k} - \bar{x})(\text{IC}'_k - \overline{\text{IC}'})}{\sqrt{\sum_{k\in K'} n_k^2 \left(x_{i_k} - \bar{x}\right)^2 \sum_{k\in K'} \left(\text{IC}'_k - \overline{\text{IC}'}\right)^2}}. \quad (9)$$

This expression is a weighted variant of Pearson's correlation coefficient; the contribution for each cluster must be weighted with the number of operating states this cluster represents, and $\bar{x}$ and $\overline{\text{IC}'}$ are weighted mean values. For more sophisticated approaches able to also capture the nonlinearities of the correlations, one could consider replacing Pearson's correlation coefficients e.g. by Spearman's rank correlation coefficient or including only an appropriately chosen subset of the clusters with highest IC_k values.

IV. Case Study

In this section a reliability assessment case study for a region of the Norwegian transmission system is considered to illustrate the method for analysing high-impact operating state. This case was first considered in the context of an integrated power market analysis and reliability analysis for long-term planning purposes, and more information about the case is forthcoming in [13].

A. *Overview of case and reliability and market analysis*

The details of the power system models used and the specific region considered for this case cannot be published due to the confidentiality of the data, but this section gives an overview of the key points for the purpose of this paper. A hydro-thermal power market model [14], [15] was used to generate a large number of operating states for the hydropower-dominated Nordic power system (Norway, Sweden, Finland and Denmark). To capture climatic variability, the market data set includes 30 historical (climatic) years. Each week of the year is divided in 56 price segments of duration 3 hours each, which gives a total of $30 \times 52 \times 56 = 87360$ operating states from the market model. In the model, the power output of hydropower generators and thermal generators for each operating state is modelled endogenously, and in addition the market data set includes exogenous wind power generation time series.

A 1087-bus grid model representing the Nordic power system is used both in the market analysis and the integrated contingency and reliability analysis [11]. The market model integrates DC power flow calculations with the market clearing, assuming the same grid model for all operating states, meaning that planned outages are not considered in the market analysis. DC power flow is also used in the contingency analysis in combination with a system response model with relatively simple but conservative representations of cascading tripping due to thermal overloads, islanding and changes in generation due to contingencies. The case study focused on one particular 103-bus region within Norway connected with the rest of the Norwegian power grid through three interface transmission lines. According to the contingency analysis, the region was not N-1 secure for all operating states, and expected interruption costs were for this case dominated by N-1 contingencies within the region. For computational expedience and to be able to screen a larger number of operating states, higher-order contingencies were therefore neglected in the analysis.

In the reliability assessment for the case described above, a reduction of the number of operating states to consider was necessary to reduce the computation time of the contingency analysis. Hence, clustering was applied to consider 100 clusters of operating states per year. The method employed was agglomerate clustering with complete linkage, and the features of the operating states used for clustering were the net bus power injection on all buses as provided by the market model.

B. *Identification of high-impact operating states*

The results for the expected interruption costs for the case study described in the previous subsection are illustrated in Fig. 2. This figure is a duration curve showing how the contributions to the expected annual interruption costs are distributed over the operating states, and it is based on clustered operating states for all 30 climatic years. It illustrates how a relatively small number of operating states contributes to a relatively large part of the expected interruption costs. For the sake clarity, the case study will in the following illustrate the approach by considering the operating states from a single climatic year which apparently has small contributions from high-impact operating states.

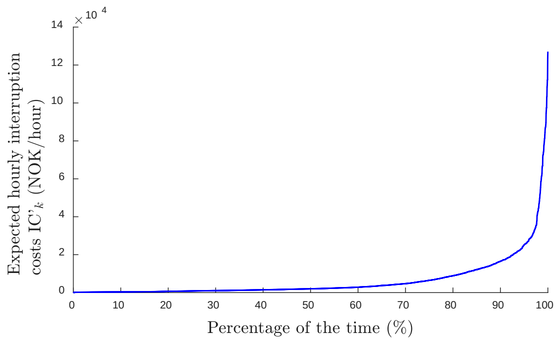

Fig. 2. Distribution of contributions to the estimated expected interruption costs for the case study, based on operating states from all climatic years.

The solid blue curve in Fig. 3 shows the duration curve for the expected interruption costs for a single climatic year based on 100 clusters of operating states. This is the starting point for the iterative reclustering algorithm described in Sec. III.C. For this case study, the parameters of the algorithm were determined by experimentation: Using $m_{\max} = 20$ iterations, each time splitting in $l_{\text{split}} = 2$ clusters with $\Delta m = 3$ appears to perform reasonably well for this case; determining the best search heuristic more generally is left for future work. The dashed/dotted curves in Fig. 3 are the duration curves for the hourly expected interruption costs estimated for different iterations. Throughout the process, clusters are iteratively split, and each curve corresponds to a different number of clusters included in the analysis. It can be seen how the algorithm after a few iterations has identified new high-impact clusters, having high hourly expected interruption costs, and the centroids of these clusters are thus high-impact operating states.

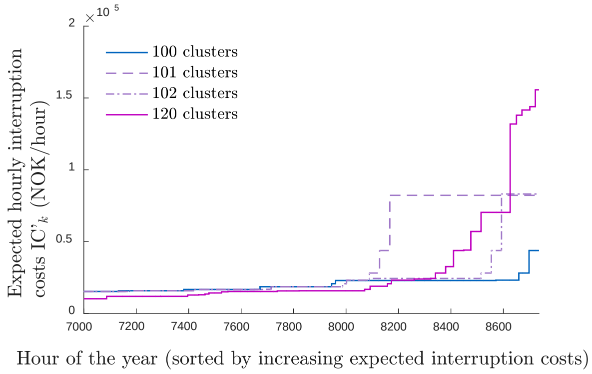

Fig. 3. Distribution of contributions to the estimated expected interruption costs resulting from the reclustering algorithm for identifying high-impact operating states.

C. Characterization of high-impact operating states

As the total load traditionally is used as the primary characteristic, this is the first feature that will be considered in the characterization of high-impact operating states. Fig. 4 is a bubble plot visualizing the correlation between the expected hourly interruption cost IC'_k and the total load in the region for the original (blue) and reclustered (purple) set of clusters from Fig. 3. The horizontal position of the center of each bubble is the total load for its centroid operating state, and the radius of the bubble is proportional to the number of states in the cluster. Comparing the results before and after reclustering, the newly identified high-impact operating states can be seen to predominantly be high-load operating states in this case.

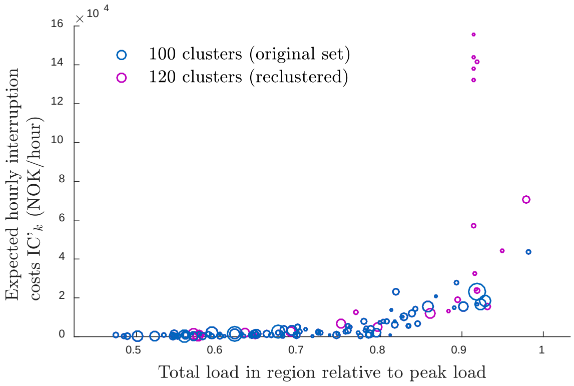

Fig. 4. Correlation between total load in the region and expected interruption costs for operating states, before and after applying reclustering algorithm for identifying high-impact operating states.

Applying (9), the correlation coefficient for the reclustered data in Fig. 4 was found to be $\rho = 0.539$. Similar figures and analyses were also made for other features, and IC'_k turned out to be marginally more strongly correlated with the total load than any individual bus load or branch power flow. Many of the latter features were furthermore found to be themselves very strongly correlated with the total load, and they therefore provide relatively little additional insight into the characteristics of high-impact operating states. Even though the region is a net importer of electric energy, the power flow on the three interface transmission lines of the region were found to be weakly correlated with IC'_k. On the other hand, generation at some of the buses in the region showed relatively strong correlation with IC'_k but only moderate correlation with the total load.

A simple example of the characterization of high-impact operating states is visualized in Fig. 5. Here, the total load is plotted together with the features total power imported to the region (correlation $\rho = 0.070$, bottom) and generation at one of the buses where the correlation is strongest ($\rho = 0.447$, top). The purple squares mark the centroid states of the eight clusters identified with highest hourly expected interruption cost (cf. Fig. 3 and Fig. 4). It can be seen that although total load may be the main characteristic of the operating states in this case, and thus a simple and useful feature, it does not by any means fully characterize the high-impact operating states.

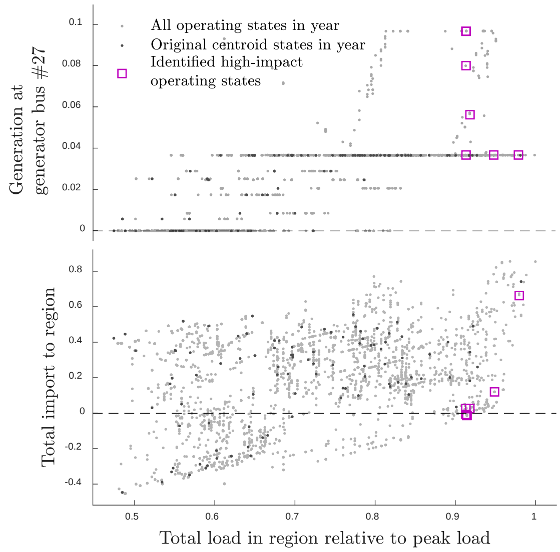

Fig. 5. Characteristics of identified high-impact operating states in terms of selected features: total load and total imported power (bottom), and total load and generated power at a specific bus (top), all relative to the peak load.

V. Discussion

An important assumption in the proposed algorithm is that the operating states in the original clusters in some sense are similar. Whether these operating states are similar in a sense relevant for the identification of high-impact operating states depends on the features of the operation states that were selected for the clustering. Thus, if the initial clustering allocated many high-impact operating states to low-impact clusters, this will negatively affect the algorithm's performance in identifying high-impact operating states. However, results from the characterization of high-impact operating states could form the basis for improved feature selection in the clustering. This is in line with the idea of clustering based on effects rather than based on causes [7]. For instance, one could regard the analysis presented in this paper as a first screening of operating states to identify features strongly correlated with reliability indices. Using this improved feature set, one could then cluster all operating states again and repeat the analysis. One should nevertheless keep in mind that spending too much computational efforts on finding a good feature set may defeat the purpose of applying clustering in the first place.

As mentioned in Sec. II, the term *critical* operating state is sometimes used in in the context of HILP events. What has been referred to as *high-impact* operating states in this paper does not by themselves constitute HILP events, and they are not necessarily inherently critical in the sense of being a precondition of certain HILP events [9]. Furthermore, HILP events historically result from combinations of external circumstances, initiating events, and vulnerabilities of the power system, and the identification of high-impact operating states presented in this paper only aims to capture a few of these aspects. It can also be argued that critical or extreme operating states should not realistically be generated by power market models meant to reflect a certain security criterion [2]. One should nevertheless keep in mind that unrealistic operating states, labeled as high-impact or critical by the analysis, could conceivably arise as artifacts from the power market models. At the same time, it is important to keep in mind that 1) neither market models nor historic data capture all high-impact or critical operating states that could plausibly occur, and 2) if such states are not present in the full set of operating states, they of course cannot be identified in any cluster of operating states [6].

VI. Conclusions and future work

This paper has proposed a simple algorithm for identifying operating states associated with high expected interruption costs in a power system reliability analysis based on clustering of operating states. It is illustrated how this both allows for capturing the large impact they have on estimates of reliability indices and allows for a better understanding of what characterizes specifically these operating states. Although most characteristics of such high-impact operating states are likely to be case-specific and depend on modelling assumptions made in the contingency and reliability analysis, it should be emphasized that the algorithm and approach proposed in this paper are general and can be applied irrespective of which methods are employed for the contingency and reliability analysis.

The context of the case study was reliability assessment for long-term planning purposes; in this case, operating states were provided by a power market model and clustering had to be applied to reduce the number of states to consider. However, the approach to identifying high-impact operating states is also applicable e.g. when faced with a large set of historic operating states or where operating states are provided by short-term ensemble forecasts accounting for stochasticity and correlations in e.g. wind or solar power generation.

There is also potential for improving the identification of high-impact operating states by using insights from the characterization of already identified operating states. For instance, the characteristics could inform the selection of features to use for the clustering. Also for analyses where operating states have not been clustered in the first place, the proposed characterization approach could inform the development of methods for searching the space of possible operating states for high-impact states and visualizing results. Extending these methods to identifying operating states that are critical in the context of high-impact low-probability events also remains as an interesting direction for future research.

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