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PREDICTION OF SECURITY MARGIN UNDER CONTINGENCIES: A FUZZY INFERENCE SYSTEM

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ABSTRACT
This document presents a methodology which shows the operative state of an analyzed power system to know its closeness to the voltage collapse. This analysis uses the Mamdani type Fuzzy Inference System (FIS), considering two cases where the input is an index that shows the voltage stability contingency ranking. One of the indexes is the Reactive Support Index (RSI) which establishes the extra amount of reactive generation from all existing dynamic VAr devices, required to get from the normal case nose to the contingency nose when calculating the Power Flow (PF). The second index is the Improved Branch Participation Factor (IBPF), which represents normalized incremental changes in response to the voltages of a system to incremental changes of the demand. The output of this FIS is the operative state of the system. This methodology is tested in MATLAB, using the RTS-96 single area and the IEEE 118 bus system.

KEY WORDS
Fuzzy Inference Systems, Voltage Security Index, Voltage Stability

1. Introduction

Voltage stability has become the main limiting phenomenon for different operative conditions, such as the nowadays growth in demand, the increase of limitations imposed by environmental restrictions to the grid expansion, delays imposed by the energy market transition, hourly change of the network topology caused by the introduction of energy markets, and the implementation of new technologies.

This phenomenon is characterized by loss of control over voltage levels in a power system working on overstressed conditions. The actual problem is that operators do not perceive when there are big chances for a system to collapse totally, because the voltage drop is quite slow. So, there is the necessity for creating tools which help operators to know what are the operative conditions of a system when it is under contingencies. Even more, there are several uncertainties during the operation of the power system, which involves a more profound analysis, such as the characteristics of load, day ahead economic dispatch, different topologies, etc. So, to characterize the impact that a contingency may have overall, there have been some approaches to classifications of the operative states on a power system according to [1], called normal, alert, emergency, extreme emergency, and restorative states. The important states to be analyzed are the alert, emergency and extreme emergency, because the interest is to know what the operator should do when the system is under contingencies. The normal state is not necessary to analyze, because its results does not take into account the stressed conditions. The restorative state is not taken into account either, because it is a transition state.

For each operative condition, there have been also some approaches to rank adequately the impact of possible contingencies. Nevertheless, the operator cannot act if some normalized number obtained from these analyses is not expressed as a kind of suggestion on what to do. For example, the first ranked contingency in a system could lead to a collapse; but in another system, it could only be an alert state. So, the importance of having these states is for the operator to know what the operative condition of the system really is and act according to each state in a reliable and fast way. Then, the operator should know the respective state rather than a number.

That is the main reason why the proposed model uses these indexes as part of the main numerical solution, and converts all these numbers into expressed grammatical solutions. That means that any index used to rank the possible contingencies are expressed at the end as states that the operators can observe and act depending on their severity. This is possible with the Fuzzy Inference System (FIS), which uses fuzzy modeling and makes this conversion.

The methodology uses two proposed indexes for the contingency ranking, tested on the RTS-96 single area system [2], and in the IEEE 118 bus system, and then uses these results to make the Mamdani type FIS for the linguistic state of the system.

2. Basic Concepts and Fundamentals

There have been made some techniques based on the analysis of operative conditions called snapshots, representing incremental changes in response to the voltages of a system to incremental changes of the demand. That is, a QV sensitivity analysis [3].

The QV sensitivity is obtained by the operative condition analyzed in function of the Jacobian matrix of the corresponding power flow. So, the equation that relates the behavior of incremental changes between injected power and voltages in each bus is expressed as (1). Making $\Delta P=0$, it could be established a close relationship between ΔQ and ΔV through the reduced Jacobian matrix J_R as in (2). The reduced Jacobian matrix can be diagonalized as it is shown in (3), where ξ_i is the ith column of ξ, η_i the ith row of η, and λ_i is the ith row and column of Λ. In other words, ξ and η are the respective eigenvectors of each eigenvalue λ, as shown in (4). As $\xi=\eta^{-1}$, it can be obtained a relationship between the modal variations of voltage and reactive power as shown in (5), and the relative weight of each k node in modal sensitivity i, through the nodal participation factor p_{ki} shown in (6).

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix}=\begin{bmatrix}J_{P\theta} & J_{PV}\\ J_{Q\theta} & J_{QV}\end{bmatrix}\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \tag{1}$$

$$\Delta Q=\left[-J_{Q\theta}J_{P\theta}^{-1}J_{PV}+J_{QV}\right]\Delta V=J_R\Delta V \tag{2}$$

$$J_R=\xi\,\Lambda\,\eta \quad and \quad J_R^{-1}=\xi\,\Lambda^{-1}\,\eta \tag{3}$$

$$\eta\,\Delta V=\Lambda^{-1}\,\eta\,\Delta Q \qquad v=\Lambda^{-1}q \tag{4}$$

$$v_i=\frac{q_i}{\lambda_i} \tag{5}$$

$$p_{ki}=\xi_{ki}\eta_{ik} \tag{6}$$

The system is stable in voltage if λ_i is positive, because it warrantees that an incremental change in the magnitude of the reactive power injected to each bus increases the incremental voltage in that bus. These λ_i are critical when they approach zero. In [4] and [5] is defined an index of the participation of each bus for each λ_i, called the Participation Factor (PF). So, for each branch lj associated to the ith mode is (7). This means that for each mode i, it is possible to know which branches consume a larger amount of reactive power given a modal incremental reactive power. So, the branches which have the largest PF are assumed as the ones which could lead to the most critical contingencies.

$$P_{lj-i}=\frac{\Delta Q_{lj-i}}{\Delta Q_{l-\max(i)}} \tag{7}$$

In [6] it is proposed a redefinition of the PF of each branch, applying weighting values to each eigenvalue in the system and to the incremental losses of the reactive power flows in each branch, $\Delta Q_{loss-bi}$. In this way, there can be selected the values that correspond to the most significant modes, obtaining a new index, called "Improved Participation Factor" (IPF) shown in (8). This factor can be weight again to the largest value of the IPF through branches, obtaining the variable given in (9). Finally, this expression is normalized in relation to the sum of all the branches, obtaining the proposed index, called "Improved Branch Participation Factor" (IBPF), given in (10).

$$IPF_{bj}=W_{ij}\cdot\frac{\Delta Q_{loss-bi}}{\lambda_i} \tag{8}$$

$$AdQ_{loss\_bj}=\frac{IPF_{bj}}{\max_b\left[IPF_{bj}\right]} \tag{9}$$

$$IBPF_{bj}=\frac{AdQ_{loss\_bj}}{\sum_{b=i}^{n}AdQ_{loss\_bj}} \tag{10}$$

The second index that is used is the Reactive Support Index (RSI) [7], which is based in the definition of a criticality for a contingency. That is, the additional amount of reactive power generation needed to carry the nose of the curve QV of the base case (without contingencies) to the nose of that curve with the respective contingency [8]. To know the reactive power requirements, the Q generation limits of the dynamic available sources are removed. The RSI for the ith contingency is calculated as (10), where Q_j^{cr}, is the reactive injection at jth bus at pre-contingency critical point with open reactive limits, Q_{ji}^{cr} for jth contingency, m_j a weighting factor (which can be the reciprocal of reactive generation at jth bus), and N_g the number of reactive resources for controlling voltage.

$$RSI_i=\sum_{j=1}^{N_g}\left[m_j\left(Q_j^{cr}-Q_{ji}^{cr}\right)\right] \tag{11}$$

A fuzzy inference system (FIS) is a structure in which it is formulated an output from a given input using fuzzy logic. The fuzzy model used in this methodology is the Mamdani inference system and the calculations used in the inference process are made by if-then rules. The final objective is to find parameters of the membership functions and the respective rules that can establish the linguistic approach of the index to an operative condition. The Mamdani System has, in general terms, the following structure [9]:

IF x_1 *is* $A1^j$ *and* x_2 *is* $A2^j$ *and… and* x_n *is* An^j
THEN y is B_j*, j=1, 2, …, M*
where
x_i *are linguistic input variables for i=1, 2, …, n;*
Ai^j *are input fuzzy sets for i=1, 2, …, n;*
y= is the linguistic output variable;
B_j *is the output fuzzy set;*
M is the number of fuzzy rules.

The Mamdani type FIS has a fuzzifier, which transforms the indexes into previously designed fuzzy membership functions; a reasoning module, which applies the designed rules; and a defuzzifier, which converts the fuzzy signals into an appropriate level which shows the operative state. The methodology proposed is divided into two main procedures. The first one involves the construction of an initial database of different operative conditions or "snapshots" of the system and the ranking of contingencies. The second one deals with the application of the FIS. Thus, the problem consists of two general blocks in cascade, where the output of the first block (the contingency ranking) is the input of the second block. The final output is the operative condition, which is different between systems and when conditions such as demand, topology, etc. are changed.

3. Prediction Methodology

The database is constructed by generation of random load conditions, depending on the hourly demand and on the correlation between loads. The assumption made for this correlation is the proximity between loads, so that loads that are far away from others are low correlated and vice versa. Based on these results, the contingency ranking computation is done, depending on the chosen index. That is, either if this ranking is done with the IBPF index or with the RSI index. The severity of each contingency can be understood in a more intuitive way, taking the regular PF as an example. So, this ranking would depend on the distance from the current operative point to the collapse point given the different topologies of the network. As the point gets closer to the collapse point, the contingency at that point is more critical.

In the case of the IBPF, where it is a QV analysis, the ranking goes from the greatest to the least number. So in a normalized case, 1 would be the value for the most critical contingency and 0 the least critical. In the case of the RSI, which is also a QV analysis, the ranking goes from the least to the greatest number. The difference of each method is the computing time, because the IBPF is faster than the RSI. The application of either method depends on the type of system to be analyzed. For system with multiple areas, the IBPF should be applied, because it is an index that establishes the criticality of each area. It could be applied also to systems with one area, but there, the RSI method could be more direct.

The database with all the information about load and contingencies is built with the active and reactive line flows. The database also includes this information for each load condition and for the most critical contingencies. The output variable is the maximum loading parameter for each case of the above. In addition, those branches which are radial are not taken into account, because any contingency there would not affect the entire system. In general, the results show that the contingencies ranking does not have significant variations between different load conditions and between each one of the methods. The most critical contingencies were chosen in general for any load condition. The criteria is to take a mean value for the maximum loading parameter obtained for each load condition for each contingency, and then order them from minimum to maximum.

In order to make the contingency ranking using the IBPF and the selection of contingencies N-1 the procedure is as follows:

1. Run a power flow and find the Jacobian matrix with (2).
2. Find the eigenvalues and the participation factors with (6) and find the IBPF for each branch using (10).
3. Normalize and order from greatest to least.

In order to make the contingency ranking using the RSI the procedure is as follows:

1. Run a power flow and apply (11) for every contingency. If the power flow does not converge, the index is assigned as zero.
2. Normalize and order from least to greatest.

The normalization between zero and one for both schemes can be done as (12), where $\bar{I}n_i$ is the i^th^ normalized index, In_i is the i^th^ index, and *ind* is a vector that contains all the indexes:

$$\bar{I}n_i = \frac{1}{\max(ind) - \min(ind)}\left[In_i - \min(ind)\right] \tag{12}$$

For both indexes, it is necessary to establish critical reference values, where the FIS can identify when the power system is at the limit of both extreme emergency and emergency state, or at both emergency and alert state. The RSI ranking and its critical points are shown in Fig. 1. Intuitively, it can be established a normalized index of 0.8 as a limit between alert and emergency state due to that behavior. The figure is divided from zero to that point and the following critical point is found by quantiles in such way that the probability of finding the relevance of the values that are considered to be in extreme emergency and in emergency is ½.

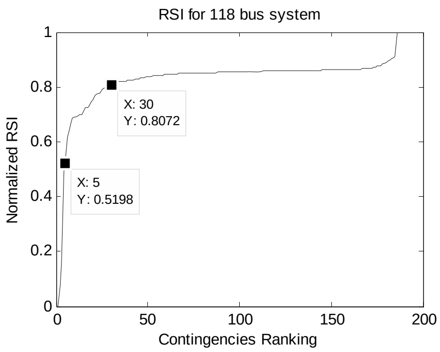

Fig. 1. RSI ranking for 118 bus system

The IBPF ranking is shown in Fig. 2. For this index, things are a little bit different if the FIS is implemented in the same way the RSI is. This is convenient, because in that way the methodology for both indexes does not need to be changed at all. The reasons why this method is different are because firstly, the greatest index does not represent alert state, but extreme emergency and vice versa; and secondly, because the scheme for the IBPF represents the manipulation of different areas. For making the methodology for IBPF similar to the RSI, it would be necessary to make the inverse of this ranking, as shown in Fig. 2 and also normalize the contingencies ranking in order to sense the criticality. Then, the intuitive approximation of the first critical point as 0.8 is still valid, and so the quantile-based analysis.

The tuning of the membership functions depends on the type of index to be used, the type of membership function, and the type of system. For any system, the membership functions of the outputs are rectangular functions cut into three equal parts, as shown in Fig. 3. This would be the case for a tuned RSI, and for the IBPF would be on the contrary, i.e. alert, emergency and extreme emergency.

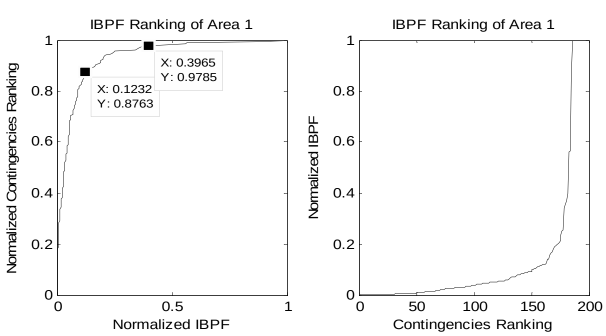

Fig. 2. Inverse of IBPF ranking and IBPF ranking for 118 bus system of Area 1

For the inputs the procedure is different, and here it is only shown the one for the RSI, since the IBPF is similar. The type of membership functions used is a generalized bell-shaped [10], chosen for being the smoothest one. This type of membership functions is defined as (13), where a, and b are parameters that modify the shape of the function, and the parameter c modifies the mean value.

$$y = \left[1 + \left| \frac{x - c}{a} \right|^{2b} \right]^{-1} \tag{13}$$

The tuning of these inputs depends on the parameters and on the critical numbers found previously, in such way that there can be established intervals for each operative state. For this tuning, there can be complex methods or just some approximations. In the case of the RSI, the parameter c is 0 for the first interval (from zero to the found quantile), the found quantile for the second interval (from the found quantile to 0.8), and one for the third interval (from 0.8 to 1). For all the cases, the parameter b can be a relatively big number such as 15 or 20, in order to have better approaches and a similar shape between membership functions. The parameter a is calculated depending on the equations presented below and based on (13), and it does not depend on how the other parameters are taken, as they are fixed. This can be also understood following those equations with Fig. 4.

Fig. 3. Membership functions of the outputs

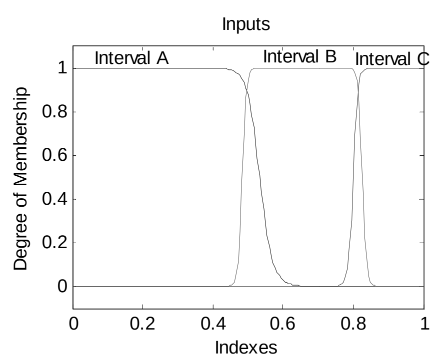

Fig. 4. Membership functions of inputs using the RSI for 24 bus system

For the parameter a of the interval C, the function y is taken to be 0.5 for making a simpler calculation and analysis, as shown in (14). The equations (15)-(18) are derived easily from this result and from Fig. 4, where a_3, a_2, and a_1 are the parameters a for the intervals C, B, and

A, respectively in (13). x_1 and x_2 are the x in y when y_c=y_b and y_b=y_a, respectively. The parameter x_c is the critical established number of 0.8, and Q is the found quantile.

$$a_3 = |c_3 - x_c| = 1 - x_c \quad (14)$$

$$x_1 = 3^{-1/b} * (x_c - 1) + 1 \quad (15)$$

$$a_2 = 3^{1/b} * (x_1 - Q) \quad (16)$$

$$x_2 = Q - 3^{-1/b} * a_2 \quad (17)$$

$$a_1 = 3^{1/b} * x_2 \quad (18)$$

These numbers can be changed, but are the most suitable numbers found for this problem. Finally, the rules to be established are one-to-one, for simplicity. That is:

IF (Index is in IntervalA) THEN (OperativeState is XtrEmerg)
IF (Index is in IntervalB) THEN (OperativeState is Emerg)
IF (Index is in IntervalC) THEN (OperativeState is Alert)

Nevertheless, for the IBPF analysis, the rules to be taken have to analyze the behavior of the criticality between areas, if the system has more than one area. This would lead to another block of membership functions depending on the index and on the areas. The outputs are the same all the time.

4. Tests Results

The methodology is tested with the test system RTS-96 single area, which has 24 buses and the IEEE 118 bus system, assuming high correlation (around 0.8) in loads that are close together (same area), and low correlation (approximately 0.2) between loads that are distant (different operative areas). The contingency ranking is made using all the random load conditions previously generated. The IBPF method takes into account that this first system has only one area and the second system has three areas. The analyses were made in the PSAT [11] and the FIS Toolbox [10] from MATLAB®.

The normalized RSI ranking for the 24 bus system is shown in Fig. 5. The critical x_c shown in (14) can be calculated by eye on this figure, and be approximated also as 0.8. The inputs are calculated with (13)-(18) and are shown in Fig. 4. It is expected to have a similar result for the IBPF, since this system has only one area. Fig. 6 shows the Inverse Normalized Contingency Ranking using IBPF for this system, taking into account the same criteria to choose x_c. This critical point is found to be around 0.3. As it is like the RSI, but with the inverse, the analysis must be made in that way. If it were a RSI analysis, this critical point should be around 0.7.

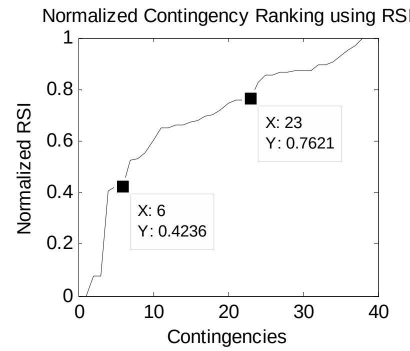

Fig. 5. Normalized Contingency Ranking using RSI for 24 bus system

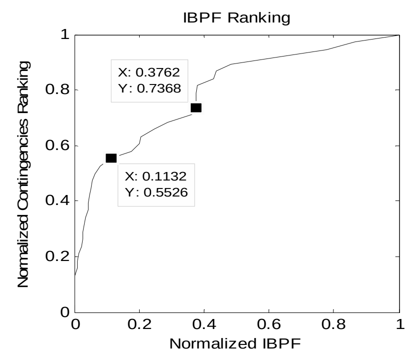

Fig. 6. Inverse IBPF Ranking for 24 bus system

The membership functions of the inputs are done using similar equations for RSI, but are not presented in this paper. Fig. 7 shows the inputs using IBPF for this system. It is clear that it is very different from inputs calculated with the RSI. Nonetheless, this does not affect the final results. Recalling what is the important issue, the operator sees the operative state, and both methods show the state in a similar way. For having better results, the x_c should be tuned accurately for each method. Nevertheless, the comparison between indexes cannot be actually seen in tables, because the indexes measure different parameters and this is consistent with Fig. 5 and Fig. 6.

In Fig. 1 in the previous section, it is shown the Normalized Contingency Ranking using RSI for the 118 bus system. The inputs for this analysis do not require the analysis of areas as the RSI does not depend on it. This is shown in Fig. 8. This figure probes that systems are different and each one depends on its topology. As it can be seen between this figure and Fig. 5, is that the main difference is the critical point of the interval A and the interval B. This implies that this index determines that the 118 bus system can be more stable to contingencies than the 24 bus system.

In the previous section it is also shown the IBPF for area 1, in Fig. 2. The membership functions of the inputs for each area are very similar to those shown in Fig. 7. This does not imply that the results will be the same, for two reasons. The first one is because are different systems, and the second one, because these tuned inputs have to be compared with another index (for instance, the loading point should be one) in order to know what is the real ranking of the contingency. This is not shown in this paper.

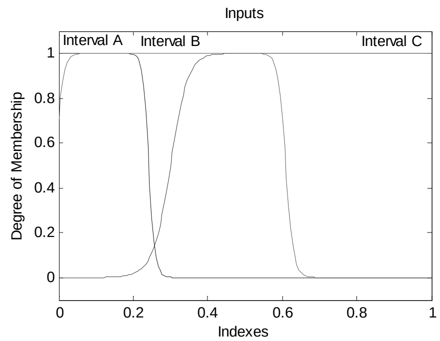

Fig. 7. Membership functions of inputs using the IBPF for 24 bus system

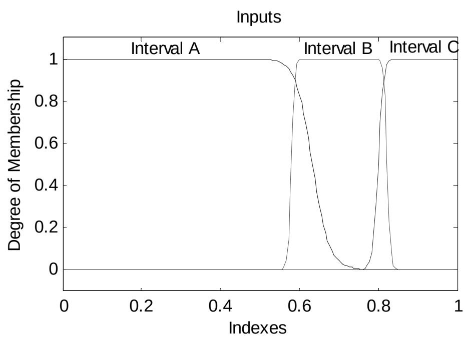

Fig. 8. Normalized Contingency Ranking using RSI for 118 bus system

Another interesting parameter is the computing time. The simulations were made in PSAT from MATLAB® in a PC Intel® Core™2 Duo CPU 6750 2,66GHz, and a RAM of 3.23GB. Table 1 shows the difference between each one of the methods depending on its process.

Table 1. CPU Times for both Methods

	24 Bus (CPUs)	118 Bus (CPUs)
RSI	5,1094	33,2500
IBPF	0,7188	0,9063

5. Conclusion

It is presented a methodology using fuzzy inference to know the operative condition of a system, depending on the load, the demand, and primarily, on two different indexes that show the criticality of the system due to contingencies. This is another example of how fuzzy logic can be applied to solve power system problems.

When comparing computing times, the interesting thing is that there are not big differences between times when systems are relatively small or relatively big, like in this case. Also, marked dissimilarities between the interpretations of each index about the operative states are so small that the application of any of them as the inputs of the FIS is indifferent. If it is necessary to compare again with an index such as the loading point for the case of the IBPF for more than one area, the computing times would be greater, and RSI should be preferred. Thus, it can also be said that the indexes depend on the type of system. The RSI should be applied to small systems with a single area, without loss of accuracy. The IBPF can also be applied to small systems with more accuracy, but with more calculations. The methodology made for both systems is very similar and easily applicable, so the final tuning is actually almost the same. This also shows that this methodology can be used in any system, considering the generation, load, lines, etc.

For future work based on an IBPF analysis, it should be included a methodology that can establish the operative condition of systems with more than one area. Here it can be seen that the RSI is applicable to any system. The main difference is that for systems with many areas, the IBPF could be more appropriate, but the RSI more practical. Also, there shall be also refinements of the operative states, like intermediate states. For instance, knowing when the system is almost preceding the alert, but not being in emergency. Future analyses should include more complex problems, such as contingencies in cascade. That is, n-x contingencies, for x>1, due to the fact that systems are becoming more and more complex, and these analyses are only a first step.

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