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VOLTAGE SECURITY MARGIN IN POWER SYSTEMS USING FUZZY INFERENCE SYSTEM AND QV SENSITIVITY ANALYSIS

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ABSTRACT
This paper presents a methodology to predict a security index of power systems for forecasted operating points based on a voltage security diagnostic and a modal analysis of QV sensitivity matrix in regard to the voltage stability modeling with fuzzy inference systems, like ANFIS. Local variables like active and reactive lines power flows are used as input variables and reduced by the technique known as principal component analysis (PCA). Two methods are used in order to find a security index for the inference process. The first method uses the loading parameter of the continuation power flow and the second uses a QV modal analysis criteria. These methodologies allow the calculation of the distance from the current operation point to the collapse point taking into account different possible conditions in a day ahead operating planning. These methodologies are tested and validated with the RTS-96 single area and the computer times of each method are compared.

KEY WORDS
Continuation Power Flow, Fuzzy Inference Systems, Neuro-fuzzy networks, Voltage stability, QV analysis.

1. Introduction

Modern power systems have evolved to a point in which the voltage stability has became the main limiting phenomenon for different operating conditions, such as the growth in the demand, the increase of limitations imposed by environmental restrictions to the grid expansion, delays imposed by the energy market transition, and the hourly change of the network topology caused by the introduction of energy markets. The importance of the voltage collapse has increased in the power systems security assessment as a consequence of major events related to this phenomenon, like blackouts in large cities as London, Tokyo and New York, making evident the necessity to have diagnostic models for real time applications. This phenomenon is characterized by loss of control over voltage levels in a power system, but all mechanisms related to this phenomenon are not yet identified. However, it is known that voltage instability occurs when the power system works on overstressed conditions [1]. This paper presents two methods as a tool for diagnosis and prediction, which measures the distance between forecasted operating point and voltage collapse point for different network topologies that are probably achieved in a current day.

The analysis of different uncertainties during the operation of the power system is included through the most critic contingencies analysis, the stochastic characteristic of loading and the day ahead economic dispatch. The proposed model is constructed using neuro-fuzzy networks, which is a tool that gives the adaptive characteristics of the model. Even though, there are other tools that use fuzzy logic theory. Most of them have taken as input variables global system indicators, such as reactive power margin, maximum eigenvalue of the inverse Jacobian matrix and/or minimum voltage of the system [2]-[5]. The work made in [6] develops a tool with fuzzy logic using local parameters such as voltage and voltage angle in all buses. This paper is focused taking into account that some of the voltage collapse events that have been registered, relates to the development of local problems and high demand conditions. So, it proposes a tool that uses as explaining variables the active and reactive power flow on transmission lines and as security index the loading distance from the current operating point to the voltage collapse boundary, found by using the continuation power flow (CPF) [7], on the first place. On the second place, the other methodology consisted in finding the contingencies ranking using participation factor analysis through a QV analysis.

2. Methodology

A fuzzy inference process is proposed in order to predict voltage security margins based on the current conditions of an operating point of the power system and previous observed or generated conditions. Two different methods are evaluated in order to rank the voltage security contingencies. The method 1 uses the CPF and the method 2 uses a QV analysis. The following are the main steps of the procedure for both methods, where the difference between them is step 2:

1. Initial Database construction by generation of random load conditions due the demand
2. Computation of contingency ranking and loading parameters (security margin) for each load conditions in the Database through one of the methods.
3. Selection of variables for the Fuzzy Inference using the Principal Component Analysis.
4. Training a neuro-fuzzy network.
5. Validation of the trained fuzzy-network.

Both proposed methodologies are tested and validated on the RTS-96 single area system [8], which has 24 buses. Firstly, an offline database with the 76 active and reactive lines flow is built [9]. In addition, the database includes the maximum loading parameter obtained from the CPF for each considered topology. Then, variables for the inference process are selected using three procedures: first, variables with minimum variance are eliminated; second, variables with high correlation are eliminated; third, the database without collinearly problems is simplified using the principal component analysis technique (PCA) [10]. The new database is used to check the training of the neuro-fuzzy network. The advantage of this methodology over traditional techniques is that it requires less real time computing effort, which makes it useful for online applications of monitoring and analysis of the power system state in real time and for predicting the operating performance on a "Day Ahead" planning framework. Also, the system is modeled based on observations of its own behavior, making easy the inclusion of new information of its behavior, as a consequence of the learning capability of neuro-fuzzy networks. Besides that, the modal analysis permits to lessen even more the time computing effort.

2.1 Database Construction

At first a database is built with different random load conditions for each hour. Generation of random load conditions is made taking into account correlations between loads in different nodes. The assumption used to model the correlation between loads is that loads that are nearly localized between each others are highly correlated and loads that are far localized between each others are low correlated. Loads were modeled like normal random variables, where mean value is given by the mean load in its corresponding node, considering an ordinary day for the corresponding hour. The correlation matrix can vary from one hour to other. The probabilistic model allows the definition of correlated loads' zones, stated intra-group region of buses, based on high positive correlations. By contrast, the model allows the definition of inter-region correlations to represent non-correlated zones of buses, normally with low correlation absolute values. The number of different load conditions is determined by the reliability coefficient α, the expected relative error, the mean and variance as it is shown in (1). Where $\kappa \approx 1.96$ if $\alpha = 95\%$. The respective confidence interval for the relative error would be (2). If that interval contains the zero, it means that the error is not skewed with that mean, variance and α.

$$n = \left(\frac{\kappa}{e_r}\right)^2 \frac{\sigma}{\mu} \tag{1}$$

$$I_{CError} : \left[\mu - 2*\sigma, \mu + 2*\sigma\right] \tag{2}$$

Another uncertainty in the power system operation is the topology due to changes provoked by contingencies. Therefore, as the power system changes from one topology to another, a contingency analysis is required. The first method uses as ranking criteria the loading parameter of the CPF [6]. The second method uses as ranking criteria the relative importance of each branch in the QV sensitivity behavior, explained below in Section 2.2 (IBPF). The contingency ranking is computed for the entire load conditions in the database, as a consequence of the variableness of contingencies ranking from one operation point to another one. The objective is to observe how different the ranking is from one operation point to another and also, to compare both ranking methods. With these results, the decision to be taken would be either to fix the contingencies ranking for each hour, or not.

The measurement of the severity is assumed to be the distance from the actual operating point to the collapse point given the different network topologies, determined by each contingency. The severity is ranked from the smaller maximum loading parameter to the highest loading parameter, in the case of the CPF method. In the case of the QV analysis, it is ranked from the greatest IBPF to the smallest. Then, a matrix is constructed, in which each row represents a different contingency in order of criticality where, the first row has the most critical contingency; the second one has the next critical contingency, and so on. In general, the results show that the ranking does not have significant variations between different load conditions and between each one of the methods. The most critical contingencies are 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. The database with all the information about load and contingencies is built with the active and reactive lines flows. The database 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.

2.2 Contingency Ranking through IBPF

There have been made some techniques based on the analysis of operating 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 [11]. The QV sensitivity is obtained by the operating 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 (3). Making $\Delta P=0$, it could be established a close relationship between ΔQ and ΔV through the reduced Jacobian matrix J_R, shown in (4).

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{P\theta} & J_{PV} \\ J_{Q\theta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta \theta \\ \Delta V \end{bmatrix} \quad (3)$$

$$\Delta Q = \left[-J_{Q\theta} J_{P\theta}^{-1} J_{PV} + J_{QV} \right] \Delta V = J_R \Delta V \quad (4)$$

The reduced Jacobian matrix can be diagonalized as it is shown in (5), 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 (6). As $\xi=\eta^{-1}$, it can be obtained a relationship between the modal variations of voltage and reactive power as shown in (7), and the relative weight of each k node in modal sensitivity i, through the nodal participation factor p_{ki} shown in (8).

$$J_R = \xi \Lambda \eta \qquad and \qquad J_R^{-1} = \xi \Lambda^{-1} \eta \quad (5)$$

$$\eta \Delta V = \Lambda^{-1} \eta \Delta Q \qquad v = \Lambda^{-1} q \quad (6)$$

$$v_i = \frac{q_i}{\lambda_i} \quad (7)$$

$$p_{ki} = \xi_{ki} \eta_{ik} \quad (8)$$

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 [12] and [13] is defined an index of the participation of each bus for each λ_i, called the Participation Factor (PF). 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. A redefinition of the PF of each branch can be proposed, 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 (9). W_{ij} is chosen according to the sum of the respective participation factors. If that sum is greater than 0.15 (an established value which gives good results), W_{ij} is 1; otherwise, W_{ij} is zero. This factor can be weight again to the largest value of the IPF through branches, obtaining the variable given in (10).

$$IPF_{bj} = W_{ij} \cdot \frac{\Delta Q_{loss-bi}}{\lambda_i} \quad (9)$$

$$AdQ_{loss\_bj} = \frac{IPF_{bj}}{\max_b \left[IPF_{bj} \right]} \quad (10)$$

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 (11).

$$IBPF_{bj} = \frac{AdQ_{loss\_bj}}{\sum_{b=i}^{n} AdQ_{loss\_bj}} \quad (11)$$

In order to make the contingency ranking and the selection of contingencies N-1, the procedure made to use this index is as follows:

1. Run a power flow
2. Find the Jacobian matrix with (4)
3. Find the eigenvalues and the participation factors with (8) and find the IBPF for each branch using (11).
4. Establish a reference value which serves to identify the critical contingencies to the non-critical ones.
5. Group the critical contingencies, using the previous step.

2.3 Variable Selection

This database has a lot of variables and the model should not be constructed with so many variables because of complexity, computing time, and loss of generalization capability. So there are chosen two initial filtering methodologies: variables with minimum variance and variables that are highly correlated. This method permits to create a new database which is passed through the principal component analysis (PCA), reducing its dimensionality [10]. PCA makes a linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate, the second greatest variance on the second coordinate, and so on. The disadvantage that PCA technique represents is that it makes a linear transformation from the original space state to a new space state with dimensionality reduction, causing that each variable of the new database does not correspond to a specific physical variable.

2.4 Fuzzy Inference Process

An adaptative neuro-fuzzy-network (ANFIS) is the hybrid between two mapping techniques, neural network and fuzzy logic [14]. The fuzzy model used in this methodology is the Sugeno inference system and the calculations used in the inference process are made by a neural network. Certain percentage of the database is used as training data and the rest as checking data.

3. Test Results

The methodology is tested with the test system RTS-96 single area [8], 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 operating areas). The contingency ranking is made using all the random load conditions previously generated. The CPF method is chosen using as stopping criteria the last point in which the power flow converges. The measurement of the severity is defined as the loading parameter taken in the limit in which power flow stops converging. The QV analysis method takes into account that this system has only one area.

Fig. 1 shows the criticality of contingencies for all load conditions. Y label represents all contingencies and X label represents all load conditions. The gray scale bar shows the range of the maximum loading parameter, where the smallest number represents the most insecure conditions and the greatest represents secure conditions. Conditions are constituted by two elements, the contingency and the load condition. Thus, a constant gray scale color through a row denotes that the corresponding contingency is critical in almost all load conditions. Likewise, a constant gray scale color through a column denotes that the corresponding load condition is critical for nearly all contingencies. Table 1 and Table 2 show the different contingency ranking with each method. The relevant differences between both of them are due to some lines that are radial and they should not be taken into report. For instance, the contingency 11 is the most critical for the CPF method, because it splits up the system into two different subsystems. This means that the generator at the bus 7 has to supply all the demand for that load. On the other hand, this contingency is not so critical in the QV analysis, because it refers to the mode and its affection to the entire system.

Fig. 1 shows that contingencies 7, 10, 11, 16 and 27 are the most critical, because they have in front a row of a black tonality. These results can also be seen in Table 1, which shows the contingency ranking for all single contingency using the CPF. The most critical contingencies are related with lines in the 138 kV area of the RTS-96 single area and their absence causes load isolation. On the other hand, the QV sensitivity shows another type of ranking, shown in Table 2.

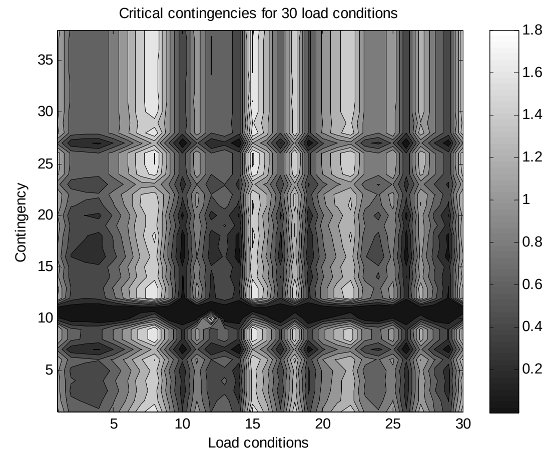

Fig. 1 Severity of contingencies for 30 load conditions.

Table 1. Contingency Ranking using CPF

Ranking	No	From	To	Ranking	No	From	To
1	11	7	8	20	12	9	4
2	10	10	6	21	22	10	5
3	7	15	24	22	6	9	3
4	27	24	3	23	13	13	23
5	16	11	10	24	29	19	16
6	17	12	10	25	24	16	15
7	18	16	14	26	34	17	16
8	20	13	12	27	35	1	2
9	14	13	11	28	28	18	17
10	23	11	9	29	36	23	20
11	5	2	6	30	37	23	20
12	15	1	5	31	1	19	20
13	4	10	8	32	30	19	20
14	3	2	4	33	32	22	17
15	19	14	11	34	33	18	21
16	2	9	8	35	31	18	21
17	21	1	3	36	38	21	22
18	8	23	12	37	25	21	15
19	9	10	8	38	26	21	15

Table 2. Contingency Ranking using QV analysis

Ranking	No	From	To	Ranking	No	From	To
1	23	16	14	20	19	14	11
2	21	23	12	21	30	18	17
3	7	24	3	22	1	1	2
4	17	12	10	23	5	2	6
5	27	15	24	24	36	23	20
6	16	11	10	25	37	23	20
7	22	13	23	26	8	9	4
8	28	17	16	27	13	10	8
9	18	13	11	28	29	19	16
10	25	21	15	29	2	1	3
11	26	21	15	30	3	1	5
12	15	12	9	31	4	2	4
13	31	22	17	32	34	19	20
14	38	21	22	33	35	19	20
15	14	11	9	34	24	16	15
16	10	10	6	35	6	9	3
17	20	13	12	36	9	10	5
18	11	7	8	37	32	18	21
19	12	9	8	38	33	18	21

The database is built with the power flows through lines and not with load at nodes. These variables permit to include in the database the most severe contingencies without including a dummy variable to indicate the contingency in fact. The number of contingencies is selected depending on the severity of the mean value of the maximum loading parameter. But in general sense, it is an arbitrary criterion because the criticality of a considered loading parameter depends on the level of security that the operator wants to give to the system. Also a great number of variables can cause loss of generality of the model. The technique used to reduce dimensions of the database is the PCA. So the physical space of 11 variables is reduced to a space in which the first five variables explained the 98% of variations in the database. Table 3 shows the percentage explained by each principal component.

Table 3. Principal Component Explained Percentage

Component No.	*% Explained*	*Component No.*	*% Explained*
1	45.5931	5	3.4812
2	30.0451	6	1.1322
3	13.0208	7	0.0272
4	6.6906	8	0.0097

The transformed database was divided in two parts, ¾ parts are put in training database and ¼ is put into a checking database. Fig. 2 and Fig. 3 show the matching between the Anfis output and original data in training database and checking database, using both methods. Anfis output follow the original data in the majority of cases. The biggest errors are presented in data near the lower and upper level of space, as a consequence of the absence of a lot of information in this area. Anfis output for checking data shows a good performance of the network learning process. These results show that the network can predict the measure security for data that are not in the training database.

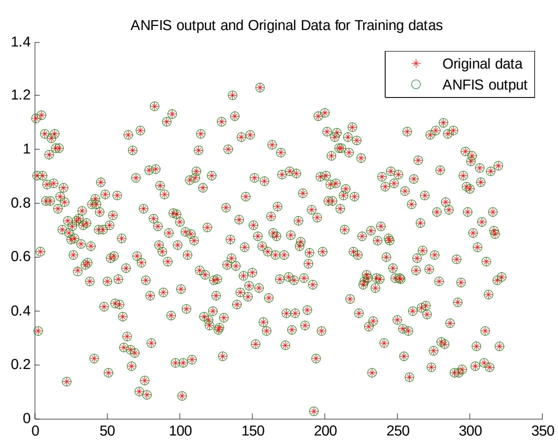

Fig. 2 Anfis Output and Original Training Data for CPF data

Training and Checking errors distributed N~(0,0.002) and N~(0,0.003) for the CPF analysis and N~(0,0.05) and N~(0.0015,0.03), respectively. The fact that their mean is near to zero shows that there are not systematic errors and the variance reduction show that in all cases error will not be great for both cases. This is shown in Fig. 4 and Fig. 5. This is a way to validate the great reduction done to the size of the database, in order to achieve the speed of analysis, without scarifying quality of the results.

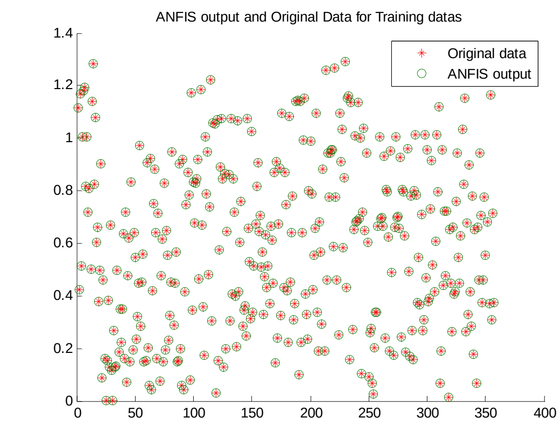

Fig. 3 Anfis Output and Original Checking Data for QV data

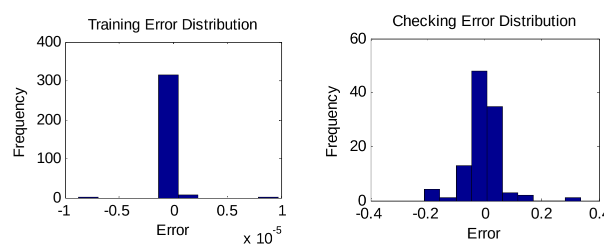

Fig. 4 Training and Checking Error Distribution.for CPF data

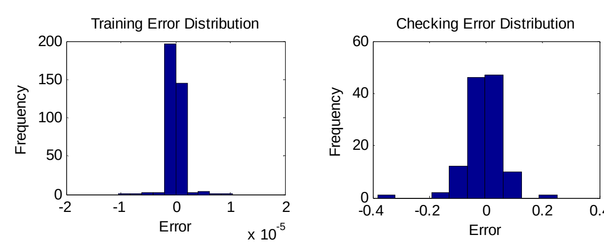

Fig. 5 Training and Checking Error Distribution.for QV data

The tests were made in PSAT from MATLAB® in a PC Intel® Core™2 Duo CPU 6750 2,66GHz, and a RAM of 3.23GB. Table 4 shows the difference between each one of the methods depending on its process. The elapsed time for making the new database through PCA analysis is so fast that it is considered to be zero. Finally, the prediction capacity of the network is tested with load conditions that are not either in training and checking data. Table 5 shows Anfis output for different network conditions (topology and loading) depending on its ranking, and its corresponding loading parameter obtained by the CPF. Each of the contingencies with its respective branches can be seen in Table 1 and Table 2.

Table 4. Difference in computing time effort between methods

Type of event in CPF	Time elapsed in CPF (CPUs)	Time elapsed in QV (CPUs)
Database calculation	0.3750	0.3750
Contingencies Ranking	142.9844	0.7344
New filtered Database	102.3750	79.3281
New filtered Database (PCA)	0	0
Network training	4	1.6563
Loading parameter calculation	0.0156	0.0313
Total time	249.75	82.1250

Table 5. Results for Model Validation

Contingency	LCCPF	CPFD	QVAD	Relative Error CPF	Relative Error QV
23	2.0841	2.2660	2.3842	8.7280	14.3995
21	2.3263	2.3537	2.4319	1.1778	4.5394
7	2.2550	2.2764	2.3921	0.9490	6.0798
17	2.1074	2.2752	2.3786	7.9624	12.8689
27	2.2913	2.2778	2.3832	-0.5892	4.0108
16	2.1192	2.2706	2.3725	7.1442	11.9526
22	2.3892	2.3274	2.3572	-2.5866	-1.3394
28	2.9726	2.2790	2.4007	-23.3331	-19.2390
18	2.6265	2.2749	2.5030	-13.3866	-4.7021
			Mean	-1.5482	3.1745

LCCPF: λ's calculated through CPF
CPFD: λ's from Anfis Database through CPF
QVAD: λ's from Anfis Database through QV analysis Data

4. Conclusion

Current operation conditions of power systems near to the voltage security boundary make necessary the development of computing tools that can be used in real time to predict the security condition of the system. This paper has proposed a model to develop a tool for predict the loading from the operation point to the voltage collapse point modeling through ANFIS, using two methods to rank the contingencies.

The use of local parameters (flow through lines) as input variables to find the security condition of a system make more efficient and precise the forecasting of a possible non desirable event and also includes all the network topology. In addition, the fact that the input variables are flows through lines implies that they are directly related to the demand, and generation in different load buses, resulting more suitable for the forecasting.

Fuzzy logic has shown a good identification tool based on the system behavior data. This gives the possibility of having a feedback with more data for the ANFIS system. On the other hand, this identification tool avoids the complex analytic modeling with higher computing requirements and mathematical problems such as matrix singularities for each operating condition of the system.
The security index allows the comparison between current operation, and other operating conditions, due to its normalized index. As one of the great limitations is the computing time taken by the contingency ranking selection using CPF, it is proposed another methodology called IBPF, which uses the QV sensitivity matrix. It is very noticeable that it took so much less time to present similar results, for which it is safe to say that the second method is better in those aspects. To sum up, future work must include the use of parallel computing technicality to reduce significantly the time it takes to consolidate the database.

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