Decision Fusion of Voltage Stability Indicators for Small Sized Power Systems

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Abstract: In this paper we consider a probabilistic approach to at the issue of voltage stability of a small power system. We do this via data fusion technique using the Bayesian rule, which is well suited for such applications. We use three proximity indicators in this study. On their own each of these indicators have some amount of probability of error when used in deciding whether the system is stable or not. A data fusion center is used here to minimize the probability of error in deciding whether the system is stable or not. Here we employ a data fusion center that fuses the decision made by each individual proximity indicator (rule) in an optimal way using the Bayesian technique. . Monte Carlo runs are employed to generate 10,000 different realizations of load levels from which we find the conditional probability density functions for each of the three proximity indicators (rules). The study is conducted on a 5-bus system.

Keywords: voltage stability, probability, decision fusion.

INTRODUCTION

The factors that affect power systems are probabilistic in nature, for example load changes, generator status, the weather, etc are all probabilistic and hence it is necessary to look at power system phenomenon in this manner. We consider here only the effect of probabilistic nature of the load on a system and we model the load as a constant PQ load with zero mean Gaussian noise. The three proximity indicators we use here are based on voltage, available transfer capability and the condition of the load flow Jacobian

In power systems there are a wealth of existing indicators all laying claim to characterizing voltage stability the best, even though it is known that each of these indicators are all system dependent and heavily dependent on the approximations and assumptions they are based on. In this light it is difficult to find a single indicator that works well on all systems and has a very low probability of error. One way of getting an optimal rule for this purpose is to combine the good attributes of a number of indicators. In so doing the probability of error of the combined rule is low compared to any of the others individually. In the field of data handling techniques, the growth of methods in the area of data fusion have proven to be very beneficial to applications such as this. We seek to achieve the above by combining the three indicators through a data fusion center [1,2,3].

A lot of work has been done in the area of indices for system voltage stability. Most methods have sought to represent how far a system was from voltage collapse by employing some approximate system models to capture the phenomenon. These have included dc load flow, eigenvalue sensitivity methods, energy margins [4,5,6] etc. In all these methods a number of assumptions and approximations are made that are system specific, for example, negligible line losses, operating level, radial network structure and the type of load. As a result of this no particular approximate model can be used across board for all types of systems. Work by Kam et al. [2] also used the approach used here in this paper. The most significant difference here is the fact that the definition of their hypothesis was based on load flow feasibility and also their choice of local proximity indicators. The differences can be seen in the different sections of the paper.

As stated before, the focus of this paper is to use a number of approximate models that are able to capture the onset of voltage collapse phenomenon through a data fusion center to reduce the risk of making a wrong decision.

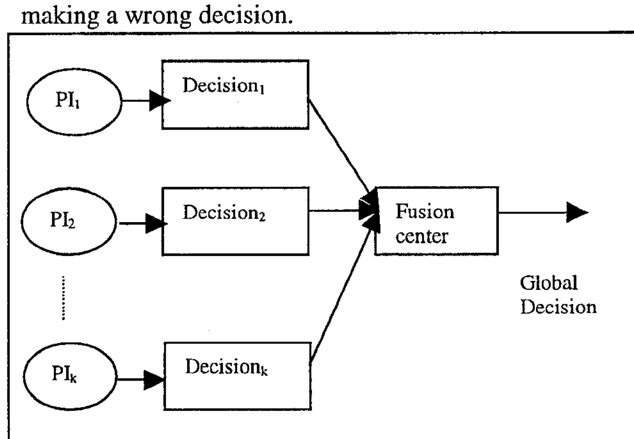

Figure 1: A pictorial representation of the data fusion process.

As shown in the above diagram, a bank of approximate local decision rules (labeled PI_k, k represents the index number for a specific local decision rule.) is employed here. Each makes a decision based on hypothesis testing that is done locally. A decision d_k is made by each one and is then fed as an input to the center along with the statistics of the local decision rule. An optimal decision is made by the center using the quality of each individual rule as weighing factors.

In this study the local decision rules definitions will be given along with the quality of their performance in terms of their probability of miss and false alarm. We will also show their operating characteristic curves. Finally we will show the performance of the optimal rule. The next sections will be in the following order: Problem formulation, Methodology, Examples and Conclusions.

PROBLEM FORMULATION

In the study of power system security and survivability a means of detecting various stability phenomena are needed. In our study we are interested in detecting the phenomenon of static voltage collapse, the point were we exceed the maximum loading level for the system. To do this we need the mathematical model of each of our three local rules and their statistical performance in capturing the phenomenon of voltage collapse.

We define static voltage stability in terms of the maximum load limits of the particular system that we are dealing with. Hence if continuation method produces no solution to the load flow equations of the system then the phenomenon of voltage collapse has occurred. The voltage stability toolbox [7] applies continuation method to solve the load flow equations close to the point of collapse. This toolbox is used here.

As has been defined, the issue of capturing static voltage collapse can be defined in term of a null and an alternate hypothesis.

$$H_0 : [P_i, Q_i] \in \{ \text{solution exists for the system by continuation method} \}$$

$$H_1 : [P_i, Q_i] \notin \{ \text{solution exists for the system by continuation method} \}$$

Where $[P_i, Q_i]$ represent the load realizations used to capture the statistical properties of each of the local decision rules. Since the load realizations represent the statistical uncertainties associated with load they are defined in the form shown below and are obtained by adding zero mean Gaussian noise to the mean load level since generally such uncertainties are normally distributed.

$$\begin{bmatrix} P_i \\ Q_i \end{bmatrix} = \begin{bmatrix} P_m \\ Q_m \end{bmatrix} + \begin{bmatrix} \Delta P_i \\ \Delta Q_i \end{bmatrix}$$

P_m, Q_m represent the mean (nominal) load level and ΔP_i, ΔQ_i represent the disturbance which is zero mean Gaussian noise of a specified variance.

Each local decision rule will make a decision based on the hypothesis stated above.

PI<=Thresh hold value → Hypothesis H_0

PI > Thresh hold → Hypothesis H_1

Hence the decision from the local decision makers will be binary.

PI<=Thresh hold value → decision, d=0 (system is stable).

PI > Thresh hold → decision, d=1 (system is unstable).

For the three local rules there will be a set of decisions such that $D = \{d_1, d_2, d_3\}$ with $d_i \in (0,1)$. The statistical performance of the local decision tools are evaluated their probabilities of false alarm and miss (P_{FA}, P_M).

P_{FA}=P {PI>Thresh hold|H_0}

P_M= P {PI<=thresh hold| H_1}=1-P_D where P_D is the probability of a detection.

To calculate the probabilities of miss and false alarm, the conditional probability densities of the decision rules for the system being analyzed are needed. This method requires the use of the Monte Carlo technique to calculate the probabilities needed. This is because of the nonlinear nature of the system provides no explicit equations for the various probability densities and conditional probability densities. Also the a priori probabilities of the hypothesis H_0 and H_1 are obtained this way. The different load realizations are obtained using a random number generator that is seeded randomly to generate a normal distribution with zero mean.

Fusion rule

There are a number of available methods [3] to determine the rule for fusing the local decisions optimally. These methods include the maximum risk Bayesian criterion that we apply here, the Neyman-Pearson rule and the maximum likelihood decision strategy. An important assumption in this work is that we consider the decisions made by each individual rule as independent from each other.

In the Bayesian approach, given the set of local decisions, D= $\{d_1, d_2, d_3\}$ we find the optimal decision $d_G=g$ (D) that minimizes the average Bayesian cost [2,3]:

$$C = C_{00}P\{d_G = 0 \mid H_0\}P\{H_0\} + C_{10}P_M^G P\{H_1\}$$
$$+ C_{01}P_{FA}^G P\{H_0\} + C_{11}P\{d_G = 1\}P\{H_1\}$$

Where the global probability of false alarm is defined as $P_{FA} = P\{d_G = 1 \mid H_0 \text{ is true}\}$ and the global probability of a miss is defined as $P_M = P\{d_G = 0 \mid H_1 \text{ is true}\}$. The costs associated with making a decision are the values C_{00}, C_{01}, C_{10}, C_{11}.

Here since we are interested in minimizing the probability of making a wrong decision we consider the cost of making a correct decision to have a small cost, that is $C_{00}=C_{11}=0$. The cost of making a wrong decision is made very high, that is $C_{10}=C_{01}=1$. This is done to make the overall cost very sensitive to wrong decisions.

With the above values of costs the equation for the average Bayesian costs reduces to $C = P_M^G * P\{H_1\} + P_{FA}^G * P\{H_0\}$.

To determine the probabilities of false alarm and miss by the fused rule or indicator its conditional probability densities have to be determined. The fused indicator is calculated as follows [1,2].

$$PI_G = \sum_{i=1}^{M} a_i d_i$$

$$where \ a_i = \log \frac{(1 - P_{M,i})(P_{FA,i})}{P_{FA,i} P_{M,i}}$$

M is the number of local decision rules.

$$TH_G = \log\left(\frac{P\{H_0\}}{P\{H_1\}}\right) - \sum_{i=1}^{M} \log\left(\frac{P_{M,i}}{P_{FA,i}}\right)$$

It can be deduced from the fusion rule that the fused indicator makes a better decision in terms of the probability of error attached to the decision than any of the individual rules. In the worst-case scenario the probability of error associated with the decision made will be that of the best individual rule.

Local decision rules

The three decision rules here are defined as follows;

1. $$PI_v = \sum_{i \in \{loadbuses\}} \frac{V_i - V_{critical,i}}{V_{u,i} - V_{critical,i}}$$

Where V_i is the voltage a t the load bus i for a particular lead level.

$V_{critical,i}$ is the critical voltage at the load bus i when the load at bus i is increased to the maximum limit.

$V_{u,i}$ is the upper limit on the voltage at bus i. It is set to the maximum limit.

2. The second rule we use here is based on the load flow equations.

$$f_P(V,\delta,u,y) \equiv P_i(V,u,\delta,y) - P_i = 0$$
$$f_Q(V,\delta,u,y) \equiv Q_i(V,u,\delta,y) - Q_i = 0$$

Where y represents the set of independent variables such as the generator voltage and u represents the operating level.

In the NR algorithm the following equation is solved iteratively for the vales of the angles and voltages.

$$J^v \Delta x^v = -f(x^v)$$

where J^v represents the Jacobian of the load flow equations.

At points close to the loading limit of the system the inversion of the Jacobian matrix becomes a problem because it tend to become singular. An approximation of how far a system is close to that point can be obtained from the condition number (cond) of the Jacobian matrix.

$$PI_c = cond(J^v)$$

where J^v is the jacobian at iteration v.

3. The third rule is evaluated as follows:

Where P_r and Q_r are the receiving end active and reactive powers on the line. V_s and Z_s represent the sending end receiving voltage and line impedance.

The third rule is evaluated as $PI_v=max\ \{Pi\}$.

METHODOLOGY

First the apriori probabilities of existence or non-existence of a solution to the system at the various load levels (that is load realizations from Monte Carlo simulations) are computed. This is done using the VST toolbox. The simulation of the different realizations of load is done using a random number generator to produce a normal distribution of mean zero and variance of 0.5. To achieve the randomness needed the generator is seeded with a different integer to get each realization. It is important that the random number generator generates at least pseudo randomness because the premise of load disturbances

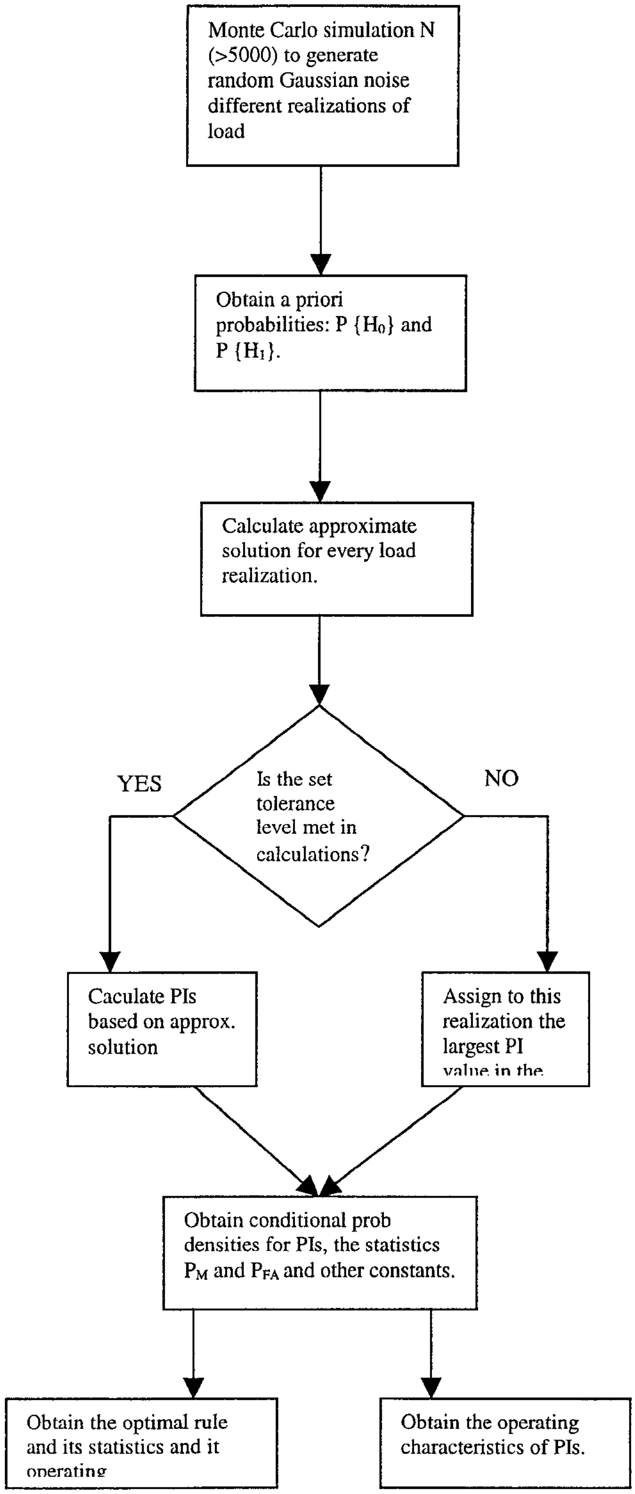

Fig. 2 Flow chart showing the algorithm

is known to approximate to a random variable of zero mean.

To evaluate the PIs used here an approximate solution of the system at each load realization is needed. This can be seen from the fact that the variables in each PI include some of the variables load flow solution at the load level. In our approach we make use of only an approximate solution that we get using a few iterations from the Newton-Raphson algorithm with a preset tolerance. This is done to facilitate the speed of processing. Because of the set tolerance there are occasions where there is no solution for a particular realization of load. In this vain there are two possibilities in the evaluation of the PIs associated with any case. The first is a case where we can evaluate the PIs because we have approximate solution with satisfies the tolerance limits of the NR iterations and the second is a case where the approximated solution does not meet the tolerance limits of the NR iterations. We employ a simple heuristic in such a case. We assign to such a case the largest values of the PIs in the set of all PIs evaluated from the first set that met the tolerance criteria of the NR.

The set of PIs are then used to obtain the conditional probability densities associated with each one. This is achieved by separating the each set of PIs into two groups by comparing with the apriori knowledge of which load realizations were of the group that did not exceed the maximum load limits of the system.

In our next step we evaluate the various probabilities of false alarm and misses based on our thresholds for each PI. Also we obtain the operating characteristics curve for each PI. We can then evaluated all the parameters needed to calculate the over all probability of miss and false alarm associated with any new contingency of a load change. Shown below is a flow chart of the process.

RESULTS

The test system is a five-bus system [3]. The load variations are modeled as zero mean Gaussian with a variance of 0.5. We consider two cases; the first shows the performance of the fusion rule when the system is operating at base case. The second example shows the performance of the fusion rule under load increase. Load at each bus is increased by 5% (real and reactive powers).

CASE 1:

The apriori probabilities of the system for the base case are P{H0}=0.6781 and P{H1}=0.3219.

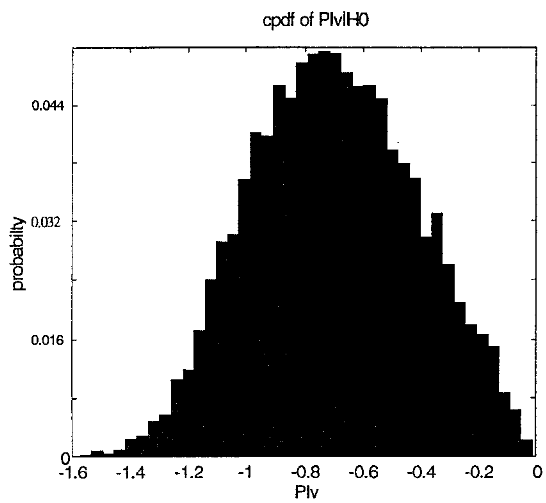

Fig4. The cpdf of PI_v given H0 for 5-bus system

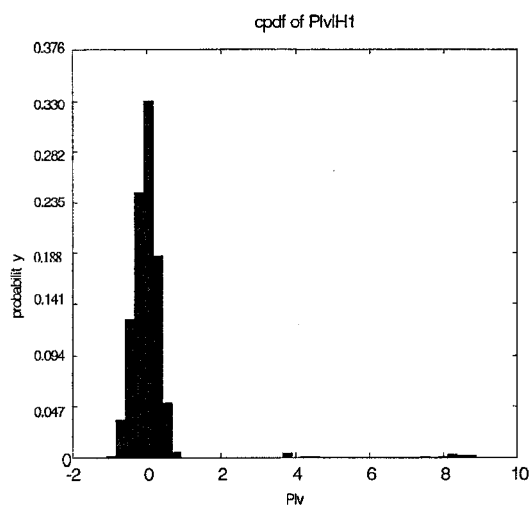

Fig3.cpdf of PI_v given H1 of for 5-bus system.

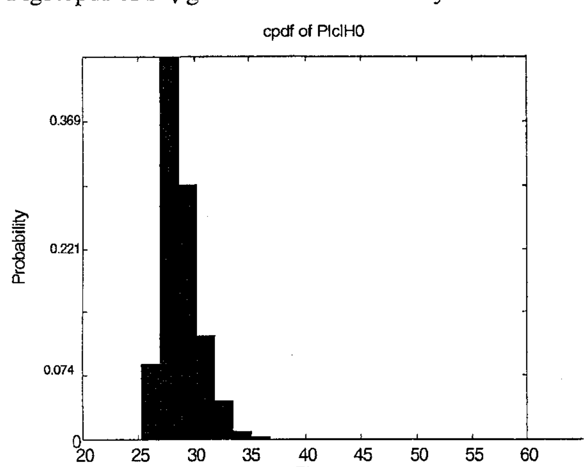

Fig 5. The cpdf of PI_c given H0 for 5-bus system

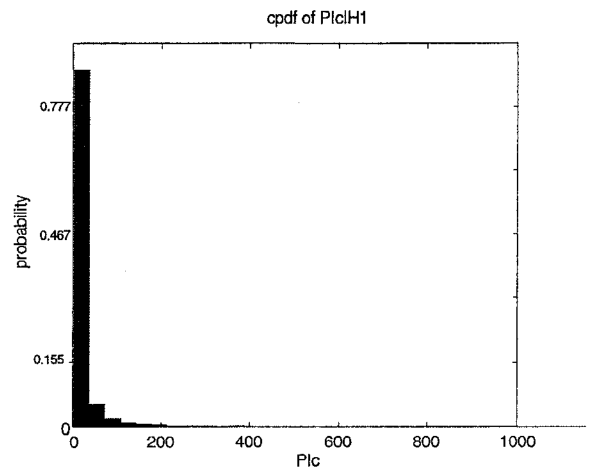

Fig 6. The cpdf of PIc given H1 for 5-bus system

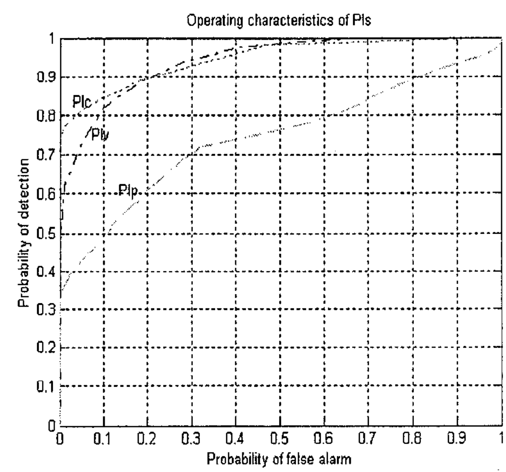

Fig. 7 Operating Characteristics for the individual rules.

Indicator	P_{FA}	P_M	P_E
PI_v	0.0905	0.1982	0.1252
PI_c	0.0985	0.1431	0.1129
PI_p	0.1068	0.5033	0.1620
PI_{global}	0.0618	0.1386	0.0865

Table 1: Summary of performance of the individual rules and the global decision rule.

PI_v	TH=-0.30
PI_c	TH=31.00
PI_p	TH=0.78
PI_{global}	TH=1.9800, a1=1.6100, a2=1.7388, a3=1.6720

Table 2: Summary of parameters.

CASE 2:

The apriori probabilities of the system for the base case are P{H0}=0.3421 and P{H1}=0.6579.

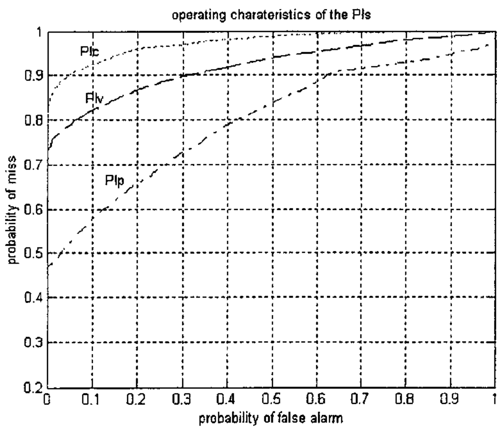

Fig. 8 Operating Characteristics for the individual rules.

Indicator	P_{FA}	P_M	P_E
PI_v	0.2488	0.1155	0.1611
PI_c	0.2017	0.0407	0.0957
PI_p	0.1068	0.5033	0.2333
PI_{global}	0.2017	0.0293	0.0883

Table 3: Summary of performance of the individual rules and the global decision rule.

PI_v	TH=-0.40
PI_c	TH=40.00
PI_p	TH=0.70
PI_{global}	TH=2.4858, a1=1.3640, a2=1.9698, a3=0.9580

Table 4: Summary of parameters.

From the results shown above in the two examples one can infer that for the system used for our test the indicator PI_c performs better in both cases. This may not be always the case since these individual indicators have noted to be system dependent. We see however that, a fused decision performs better than the individual rules. Also we note that the performance of the rules change when the operating conditions change. In our examples the performance of all three individual rules improved from the case 1 to case 2.

CONCLUSIONS

In this paper we have shown the importance of using a number of voltage collapse indicators in studies such as this. It is clear that using a fusion rule reduces the probability of a wrong decision being made. We say in conclusion that the probability of error introduced by various assumptions and approximations associated with individual indicators for a system is reduced if a number of these indicators are fused to make an assessment of the security of the system. Also since the approach relies on approximate calculations for evaluating the indicators it can be employed in cases when speed of computation is an issue.

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