Hybrid fuzzy-neural network-based composite contingency ranking employing fuzzy curves for feature selection

K.T. Chaturvedi a, Manjaree Pandit b,*, Laxmi Srivastava c, Jaydev Sharma c, R.P. Bhatel d

a Department of Electrical Engineering, IIT, Rajiv Gandhi Technical University, Bhopal, India
b Department of Electrical Engineering, M.I.T.S., Gwalior, Madhya Pradesh 474005, India
c IIT, Roorkee, India
d MPPTCL, Jabalpur, India

1. Introduction

Contingencies such as unexpected line outages, generator outages or other faults often lead to insecure operation leading to power system collapse. The task of maintaining power system security is one of the major concerns in competitive electricity markets driven by trade demands and regulations. If the system is found to be insecure, timely corrective measures need to be taken to prevent system collapse. The collapses in the power system can be prevented by monitoring suitable indices that can trigger the preventive or corrective control actions when predefined thresholds are reached to make the system insecure. Timely corrective actions can be taken only if an advance warning can be issued to the system operator at the central energy management center. Numerous indices based on Eigen value [12], singular value [6], sensitivity methods [11], worst-case margin [7], and reactive power [2] have been proposed. Ref. [3] proposed an approach for ranking islanding as well as non-islanding contingencies. Probabilistic assessment of voltage security margin was proposed in [5]. Fuzzy-set theory has been proposed for voltage contingency ranking [18] as it offers an efficient framework to model uncertainties existing in power system. Artificial neural networks have also been applied for on-line static [8–10,19,21,23] voltage contingency ranking due to their ability to provide accurate results instantaneously. The integration of fuzzy logic with artificial neural network has also attracted researchers as it combines the advantages of both these fields [24,20,16].

Conventionally voltage violations [2,19], line flow violations [8,23] and voltage stability margin [4,13,21] have been proposed as indicators of power system security and stable operation. Due to the increased use of compensating devices, which raise voltages to normal levels even when adequate reactive support is lacking, voltage violation alone becomes a poor indicator of security. Same is the case with line flow violation and voltage stability margin. Taken individually, voltage violation, line flow limit violations and system stability margin fail to capture the system state effectively. The modern practical power systems do not rely on these conventional methods as new and more efficient indices [20] are now required to assess the system condition for ensuring system security and its enhancement. The load angle also represents system stress and can be used to predict system security status. However in this paper a fuzzy composite performance index (FCPI), formulated by combining voltage violations, line flow violations and stability margin is being proposed for the composite ranking of contingencies.

This paper presents a simple multi-output fuzzy-neural network for composite contingency selection and ranking taking into account the uncertainty associated with loads. On-line ranking of
contingencies is done based on FCPI which indicates their severity level taking into consideration voltage violations, line flow violations and loading margin in a power system. A multi-output neural network is being used as a fuzzy inference engine. The membership values of loads to linguistic classes of low, medium, high, etc. constitute the input vector while the output vector presents the operator with the probability of a contingency belonging to different severity classes. Therefore, the proposed method can accept and analyze data in linguistic as well as in quantitative form. The fuzzy load modeling enables the handling of the uncertainty associated with power system loads and a whole set of scenarios is analyzed at one time.

The available literature [8,13,16,18,19,21] on contingency rankings models power system loads as deterministic quantities and employs conventional crisp ranking where a contingency is assigned to a particular class and all contingencies of a class are assigned equal severity/importance from security point of view. The conventional neural network approaches [8,19,21,23], are unsuitable for boundary cases as they provide a binary ranking and assign a pattern to the class producing highest activation. Hence, they often misclassify the boundary cases. In the proposed FNN-based method a flexible, realistic and more informative ranking is available because membership values to other classes are also available, which increase the information about the contingency. In the proposed hybrid approach the possibility of misranking is eliminated, because boundary contingencies can be represented by high memberships to more than one class. A contingency thus may belong to more than one class with a finite degree of membership. It is also possible to rank contingencies within a particular class based on their membership values. Once trained off-line using simulated data, the hybrid network is found to rank contingencies accurately for previously unknown system conditions very fast, on-line. To reduce the dimension and training time, a novel feature selection method, based on fuzzy curves is employed to select significant input features for the fuzzy-neural network. The performance of the proposed method has been tested on a large 69-bus practical Indian power system.

2. Proposed methodology

A fuzzy-neural network is employed for contingency selection and ranking. Pre-contingency loads at selected buses are employed to predict the ranking of short-listed critical contingencies. Load uncertainty is dealt with by representing loads as fuzzy variables in different linguistic categories. A fuzzy composite performance index (FCPI) is proposed to screen critical contingencies and rank the short listed contingencies on-line. This index is fuzzified in different severity classes to get a more informative ranking compared to conventional crisp approaches. The excellent non-linear mapping characteristics of an efficient high performance neural network are utilized to map inputs (fuzzy memberships of loads representing an operating state) with the expected outputs (memberships of PI which give the severity order). Fuzziness incorporated at the input as well as at the output level provides flexibility and insight into the ranking process and a whole set of load scenarios are analyzed at one time. The application of an efficient neural network as a fuzzy inference engine eliminates the complicated process of fuzzy if-then rule extraction. To reduce the burden on the ranking network an offline screening of contingencies is performed to short-list critical contingencies. Once the fuzzy-neural network is properly trained, contingencies are ranked on the basis of the class membership values of FCPI. It is assumed that the contingency belongs to the severity class having highest value of membership. Due to the fuzzy approach, its probability of belonging to other severity classes is also available in the form of membership to other classes. The block diagram of the proposed contingency screening and ranking approach is given in Fig. 1.

2.1. Fuzzy composite performance index (FCPI)

A new composite index is proposed in this paper for ranking contingencies occurring in power system. The index is based on (i) voltage violations, (ii) line flow violations and (iii) voltage stability...
margin. By including the effect of all three indicators it is ensured that the ranking achieved will be more realistic and accurate. The severity of a contingency has been traditionally evaluated for contingency ranking using the voltage performance index [2,19] given by

$$P_{Il} = \sum_{j=1}^{n}(w_j/M)(f_j)^{m}$$

(1)

Function $f_j = |V_i - V_j|$ where $V_i$ is the post-contingent voltage and $V_j$ is the upper/lower voltage limit at the $i$th bus, $w_j$ is the weighing factor and $M$ is the order of the exponent. Similarly an index-based on-line flow violations is defined below as Eq. (2) where the function is calculated as $f_j = |P_i - P_j|$, where $P_i$ is the post-contingent line flow and $P_j$ is the upper/lower line flow limit for the $i$th and $N$ is the order of the exponent:

$$P_{Il} = \sum_{j=1}^{n}(w_j/M)(f_j)^{N}$$

(2)

A contingency reduces the loadability margin of the power system. Hence the post-contingent maximum loadability margin has also been effectively used to assess the severity of a contingency [4,13,21]: larger is the reduction in margin, more severe is the contingency. Thus, the severity of a contingency can be evaluated by an index defined for the $i$th state and $j$th contingency as [21]

$$P_{IL}(i,j) = \frac{\lambda_{C}(i,j) - \lambda_{C}(i,j)}{\lambda_{C}(i,j)}$$

(3)

The loadability margin of the system for base case loading (with all lines and components intact) is $\lambda_{C}$ and the post-contingency loadability margin is $\lambda_{C}$. Line outage contingencies are traditionally ranked on the basis of $P_{IL}$, $P_{IL}$, and $P_{IL}$. To combine the effect of all three, a composite index is proposed here. The normalized values of $P_{IL}$, $P_{IL}$, and $P_{IL}$ for a contingency are fuzzified in different classes. Then the proposed index is computed as

$$FCPI = (\mu_{C} \times W_{C}) + (\mu_{L} \times W_{L}) + (\mu_{V} \times W_{V}) + (\mu_{M} \times W_{M})$$

(4)

where $\mu_{C}$, $\mu_{L}$, and $\mu_{M}$ are the memberships (highest value) of the class to which the contingency belongs on the basis of FCPI value, i.e. on the basis of the combined effect of voltage violations, line flow violations and reduction in loadability margin. The memberships of the adjoining severity class (next highest value) are $\mu_{C}$, $\mu_{L}$, $\mu_{M}$ and $W_{C}$, $W_{L}$, $W_{M}$, $W_{C}$, $W_{M}$, $W_{L}$ and $W_{L}$ are the weighing factors.

2.2. Fuzzy curves for feature selection

The training performance of a fuzzy-neural network depends on the input variables selected for its training. Variables like line flow, voltage, load angle, etc. can also be used as input parameters for contingency ranking in power system. In this paper, power system loads are used as inputs because the other variables like voltage, line flow, etc. ultimately depend on the loading condition. Also loads can be directly measured while other dependant variables need to be computed through load flow studies. All the loads are not used as input because it will increase the dimension and training time of the neural network, hence only significant loads are selected as inputs. To rank the inputs in order of their significance, fuzzy curves [24] are plotted for all input variables making use of the domain knowledge. For each input variable $x_k$, the $m$ data points in the $x_{k-}y$ space are available. For every point in the $x_{k-}y$ space, a fuzzy membership function $\phi_{jk}$ and fuzzy curve $c_{jk}$ can be found, defined by [24]

$$\phi_{jk}(x_k) = \exp\left(-\frac{(x_k - x_{\text{min}})^2}{b}\right), (k = 1, 2, \ldots, m)$$

(5)

$$c_{jk}(x_k) = \sum_{i=1}^{m} \phi_{ik}(x_k) y_k$$

(6)

Fuzzy curve for each input variable is plotted by taking $x_k$ on the $x$-axis and corresponding $c_{jk}$ on the $y$-axis. Importance of an input variable can be ranked according to the range covered by its corresponding fuzzy curve. If the fuzzy curve for a given input is flat, then this input has little influence on the output data and it is not a significant input. So the fuzzy correlation of the $i$th input to the output can be found using the difference of the maximum and minimum values of $c_{jk}$. Then a few optimum numbers of top ranking inputs are selected for contingency ranking. Fuzzy curves are plotted in Fig. 7 for a few significant as well as insignificant inputs and presented in the result section of the paper.

2.3. Fuzzy modeling of power system loads

Load uncertainty is modeled by representing it as a fuzzy variable in the range (0–1) with memberships in different linguistic categories, such as, very small (VS), small (S), medium (M), large (L) and very large (VL). The membership value of $i$th linguistic category (\(\mu\)) is calculated as [1]

$$\mu_i = \frac{1}{1 + \left(\frac{|x_i - a_i|}{b_i}\right)^2}$$

(7)

where $\mu_i$ is the membership value in $i$th linguistic category, $X$ is the crisp value to be fuzzified, $a_i$ and $b_i$ are parameters corresponding to linguistic category $X$ such as $a_i$ determines the center value of the corresponding category, where the membership value is equal to 1.0 and $b_i$ controls the width of the corresponding category. These parameters can be determined by carrying out simulations off-line under various operating conditions covering the possible range of variation. Past experience or operator judgment can also prove effective in setting these values. Non-linear membership functions are found to be most suitable to fuzzify power system variables (loads and FCPI) as they represent a more practical transition of loads from one category to the other compared to the common triangular or trapezoidal functions [1].

2.4. Data normalization

During training of a neural network, the higher valued input variables may tend to suppress the influence of smaller ones. Also the network does not produce outputs close to 1 or 0, as the neural network output governed by the activation or threshold function practically never realizes these values. To overcome this problem the input/output variables ($x$) are scaled in the range of 0.1–0.9. The normalized value $x_{\text{norm}}$ presented to the neural network as the input or target output is calculated using the equation:

$$x_{\text{norm}} = \frac{(x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})} 0.8 + 0.1$$

(8)

where $x$, $x_{\text{max}}$ and $x_{\text{min}}$ are the actual, maximum and minimum values of the variable which is to be normalized.
3. Hybrid fuzzy-neural network-based contingency ranking

The proposed hybrid fuzzy-neural network for contingency ranking is shown in Fig. 2. The steps followed for contingency ranking are:

- A large number of load patterns are generated randomly by perturbing the real and reactive loads at all the buses to cover the complete operating range of the power system under study.
- AC load flows are carried out for all the generated load patterns using PSAT tool [17], simulating all the single line outage contingencies. The corresponding value of \( P_L \) and \( P_M \) are computed for each case. The obtained values are normalized between 0.1 and 0.9 for each load pattern using expression (8) given in Section 2.4.
- Continuation power flow [17] is used to find post-contingent loadability margin-based index \( P_M \). The indices \( P_L \), \( P_L \), and \( P_M \) are computed for each load pattern for all the simulated contingencies. The obtained values are normalized pattern wise and then fuzzified for computing the fuzzy composite index (FCPI) using Eq. (6).
- In a power system all the line outages are not severe, i.e. most line outages do not disturb or affect the bus voltages, line flows or loadability margin significantly. For such lines the FCPI value is found to be low. These lines do not need operator attention. Therefore, only those line outages (contingencies) that cause high FCPI alone are short-listed for on-line ranking.
- Fuzzy curves are found for all the loads of the system and then significant loads are selected based on the fuzzy correlation, for training the network.
- The normalized loads at selected buses and normalized values of corresponding FCPI are fuzzified into different linguistic categories and along with line codes (bi-polar digits used to represent the contingency) are fed to the fuzzy-neural network as training inputs. The first contingency is represented as \( 01001 \) and so on. The membership values of FCPI for each of the selected critical contingencies form the desired output vector.
- A three-layered neural network is trained with Levenberg–Marquardt back-propagation algorithm for input–output map-learning. Once the network is properly trained, it is subjected to unseen patterns, for testing its performance.
- During testing, a contingency is assigned to the severity class for which it has highest value of membership.

4. Test results and discussion

The hybrid fuzzy-neural network was tested for contingency ranking of 69-bus practical Indian Power System. The indices \( M \) and \( N \) for calculating \( P_L \) and \( P_M \) are taken as 4 [2,23]. The weighing factors for computing FCPI in Eq. (4) were taken equal to 5, 4, 3, 2 and 1 for severity classes I, II, III, IV and V respectively, for \( P_L \), \( P_L \), and \( P_M \). The weights were selected in this manner to assign highest weight to the most severe class (i.e. class I) and least weight to the least severe class (class V). The study has been carried on a practical stressed power system taking random load variation of \( \pm 10\% \). The load flow for the system fails to converge beyond \( \pm 10\% \) load variation. Therefore, the generated 275 patterns with \( \pm 10\% \) random variation of loads at all the buses

![Fig. 2. Hybrid fuzzy-neural network for contingencies.](image)

![Fig. 3. Fuzzy representation of the voltage index \( P_V \).](image)
were found to cover almost the complete operating range for online application. The fuzzy-neural network was found to rank contingencies quite accurately for all the test cases. In this paper single line outage contingencies are ranked because they are normally the most frequent type of contingencies.

4.1. Description of the test system

The practical power system used for security assessment consists of 311 buses which has capacities of 132, 220 and 400 kV. There are 488 connecting lines. The 311 bus MP system was reduced to 69 bus system by removing 132 kV buses. The reduced system consists of 69 buses of capacity 220 and 400 kV. There are 25 buses of 400 kV and 44 buses of 220 kV. There are 9 generator buses, 136 lines (112 lines +24 transformers) and 20 compensators. There are real loads on 44 buses and reactive loads on 31 buses. The 69-bus practical power system is highly loaded. Some 25 loading scenarios were generated by randomly changing the load from 90–110% of the base case at all the buses of the system. Single line outages being most frequent, were considered in this work for on-line ranking. Out of 112 lines, there were 10 radial lines for which the system did not converge. The remaining 102 single line outages were simulated using continuation power flow and full AC load flow on PSAT [17] and corresponding FCPI values were computed for all load patterns, for each contingency case. Table 4 presents the computation of FCPI (for one loading scenario) from its constituent indices.

4.2. Training and testing set generation

Full AC load flow and continuation power flow [17] were run for all the load scenarios to obtain \( P_{IV}, P_{IL} \) and \( P_{IM} \) for single line outages of the 69 bus system. The normalized \( P_{IV}, P_{IL} \) and \( P_{IM} \) values were fuzzified using data given in Tables 1, 2 and 3, respectively. The graphical representation is given in Figs. 3, 4 and 5, respectively. The value of FCPI was computed using membership values of the indices \( P_{IV}, P_{IL} \) and \( P_{IM} \). During screening all line outage contingencies, 11 line outages out of 102 lines, were found to produce significant values of FCPI and therefore were considered severe from security point of view and short-listed for on-line ranking. The remaining lines

![Fig. 4. Fuzzy representation of the line flow index \( P_{IL} \).](image)

![Fig. 5. Fuzzy representation of \( P_{IM} \).](image)

<table>
<thead>
<tr>
<th>LO \textsuperscript{a} from-to</th>
<th>( P_{IV} ) values</th>
<th>( P_{IM} ) values</th>
<th>( P_{IL} ) values</th>
<th>FCPI (normalized)</th>
<th>Overall rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>23–29</td>
<td>0.9</td>
<td>1.01</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>24–25</td>
<td>0.495</td>
<td>0.18,0.18,0.18</td>
<td>0.656</td>
<td>0.915</td>
<td>0.915</td>
</tr>
<tr>
<td>53–52</td>
<td>0.399</td>
<td>0.54,0.54,0.54</td>
<td>0.656</td>
<td>0.915</td>
<td>0.915</td>
</tr>
<tr>
<td>18–51</td>
<td>0.413</td>
<td>0.44,0.44,0.44</td>
<td>0.646</td>
<td>0.915</td>
<td>0.915</td>
</tr>
<tr>
<td>16–35</td>
<td>0.211</td>
<td>0.21,0.21,0.21</td>
<td>0.293</td>
<td>0.915</td>
<td>0.915</td>
</tr>
<tr>
<td>25–37</td>
<td>0.547</td>
<td>0.21,0.21,0.21</td>
<td>0.103</td>
<td>0.891</td>
<td>0.891</td>
</tr>
<tr>
<td>16–25</td>
<td>0.116</td>
<td>0.06,0.06,0.06</td>
<td>0.95</td>
<td>0.891</td>
<td>0.891</td>
</tr>
<tr>
<td>18–50</td>
<td>0.114</td>
<td>0.03,0.03,0.03</td>
<td>0.95</td>
<td>0.891</td>
<td>0.891</td>
</tr>
<tr>
<td>34–52</td>
<td>0.100</td>
<td>0.02,0.02,0.02</td>
<td>0.297</td>
<td>0.891</td>
<td>0.891</td>
</tr>
<tr>
<td>59–58</td>
<td>0.534</td>
<td>0.04,0.04,0.04</td>
<td>0.94</td>
<td>0.891</td>
<td>0.891</td>
</tr>
<tr>
<td>23–22</td>
<td>0.550</td>
<td>0.06,0.06,0.06</td>
<td>0.95</td>
<td>0.891</td>
<td>0.891</td>
</tr>
</tbody>
</table>

\( \text{LO} \): Line outage from bus number-to bus number.
were not selected for on-line ranking because their outage did not cause voltage violations, line flow violations or margin reduction. Thus a total of 275 patterns (25 scenarios × 11 contingencies) were created for security assessment of the power system using fuzzy-neural network. Table 4 presents the computation of FCPI from its constituent indices for the selected 11 lines for one loading scenario. FCPI was computed using highest and next highest membership values of the indices \( P_{IV} \), \( P_{IL} \) and \( P_{IM} \) using Eq. (4).

(The overall rank (last column) is found using fuzzy values of computed FCPI which is later given in Table 7 for the same loading scenario.) Out of the 275 patterns generated 220 (20 \( \times \) 11) were used for training the neural network while remaining 55 (5 \( \times \) 11) unseen patterns were used to test its performance. Utility derived load compositions may also be employed to train the fuzzy-neural network instead of theoretically generated data.

The obtained value of FCPI is normalized in the range of 0.1–0.9. Pattern wise normalization of FCPI ensures accurate ranking under peak as well as off-peak times of the day, because the selected contingencies are ranked for the current load based on their relative severity. Table 5 data was used to fuzzify normalized FCPI values into five fuzzy classes. The graphical representation is given in Fig. 6. The flexibility in ranking due to the fuzzy representation can be clearly seen. The operators and planners can set the different parameters to suit their system (as low, medium, high, etc. would have different numerical significance for different systems/variables) and thus flexibility is incorporated in the model.

### 4.3. Feature selection

To reduce the dimension and training time of the fuzzy-neural network, available inputs were reduced to an optimum value by using fuzzy curves as mentioned earlier. Using (5) and (6) fuzzy curves were plotted for all inputs, i.e. loads of the system to find their correlation with the output, i.e. the FCPI. There are 31 loads in the systems which were ranked in order of their correlation with FCPI using fuzzy curves. Then loads at six most significant buses (bus numbers 27, 7, 17, 22, 5 and 13) were selected to serve as inputs. Due to space limitation fuzzy curves for bus no 27, 7, 17, 22 and 5 which are most significant inputs are plotted in Fig. 7.

![Fuzzy curves for bus nos. 15 and 16 which are insignificant are also plotted. It can be seen that the last two curves are quite flat showing less correlation with the output.](image)

The fuzzy correlation of the 31 buses is given in Fig. 8. Six buses were found to be optimum because increasing the input beyond six did not result in any further improvement in training accuracy. The loads at the selected six buses were fuzzified using data from Table 6. The values of parameters \( a_i \) and \( b_i \) for fuzzifying these loads in five linguistic categories were selected by observing the range of the generated loads. Extensive studies based on the generated load data resulted in the membership functions shown in Fig. 9.

![Fuzzy curves for bus nos. 15 and 16 which are insignificant are also plotted. It can be seen that the last two curves are quite flat showing less correlation with the output.](image)

![Fuzzy curves showing ranking of input loads.](image)

### Table 5

<table>
<thead>
<tr>
<th>Linguistic category for ( P_{IL} )</th>
<th>Class V</th>
<th>Class IV</th>
<th>Class III</th>
<th>Class II</th>
<th>Class I</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_i )</td>
<td>0.2</td>
<td>0.35</td>
<td>0.45</td>
<td>0.6</td>
<td>0.9</td>
</tr>
<tr>
<td>( b_i )</td>
<td>0.3</td>
<td>0.15</td>
<td>0.2</td>
<td>0.15</td>
<td>0.2</td>
</tr>
</tbody>
</table>

![Fuzzy representation of FCPI.](image)

![Fuzzy curves showing ranking of input loads.](image)
4.4. Architecture of the neural network

The membership values of loads at 6 selected buses were used as inputs to the fuzzy-neural network making the number of neurons in the input layer equal to 30 (6 buses × 5 classes). Two different structures were tried for training the network. First, a neural network with 30 input neurons and 55 (11 × 5) output neurons was used to predict the five class membership values for all the 11 selected contingencies in one pass. But the neural network did not train well and the error goal of $2 \times 10^{-4}$ was not achieved for any combination of hidden neurons ranging from 20 to 80. In the second case, the membership values of loads at 6 selected buses along with a four digit topology number representing 11 selected contingencies were used as inputs to the fuzzy-neural network making the number of neurons in the input layer equal to 34 (6 × 5 × 4). The first contingency is represented as $0001$ while the eleventh one as $1011$. There were five output layer neurons corresponding to the five membership classes of FCPI which reflect the security status of the contingency. Best training performance with mean squared training error goal of $2 \times 10^{-4}$ was obtained with 20 hidden layer neurons. With lesser neurons the error goal was not achieved and when neurons were increased beyond 20, more training time was required. Thus the fuzzy-neural network with $34 \times 20 \times 5$ structure was found to be most effective for contingency ranking of the system.

4.5. Training and testing details

The simulation was carried out using MATLAB 7.0.1 on a Pentium IV processor, 2.8 GHz with 512 MB RAM. The Levenberg–Marquardt algorithm [14,22] was used for training the neural network. It is a variation of Newton's method. The conventional multi-layer perceptron (MLP) networks are usually trained using gradient descent based on back-propagation (BP) algorithm, which is too slow for practical problems. Recently, several high performance algorithms have been developed to train MLP models that converge 10 to 100 times faster than the BP algorithm. These algorithms are based on numerical optimization techniques like conjugate gradient, quasi-Newton and Levenberg–Marquardt algorithms. Out of these, Levenberg–Marquardt (LM) algorithm is found to be the fastest method for training moderate size feed-forward neural networks [15]. It also has very efficient Matlab implementation. Simulations were carried out using MATLAB 7.0.1 on a Pentium IV processor, 2.8 GHz with 512 GB RAM.

The performance of the trained network was tested on 55 unseen patterns. Test results of one load scenario are presented in Table 7. Test results for all the 55 patterns are presented in Figs. 10–14 and it can be seen that fuzzy-neural network is capable of producing membership values of all the classes quite accurately. A contingency belongs to the class for which it has highest membership. The proposed fuzzy-neural network is very advantageous: (i) no rule formation required and (ii) misranking is eliminated.
Hybridization of fuzzy logic with neural network has eliminated the need for deriving complex if-then rules by directly computing the membership values of composite performance index in all five severity classes. The proposed FNN-based method has an edge over conventional methods [8,16,13,18,19,21] that rank a pattern to a particular class based on its severity index because here any possibility of misranking is avoided by giving increased information in the form of membership values to neighboring classes. For example, the contingencies 24–25, 53–52 and 18–51 all belong to class III with highest membership to class III but it can be clearly seen from Table 7 that 24–25 has a high value for class II as well while 53–52 has additional high membership to class IV. Thus, 24–25 is inclined towards class II and 53–52 is inclined towards class IV. A conventional crisp ranking would put all three in class III and assign them equal severity level. In the proposed approach it is possible to further rank the contingencies within their class based on memberships to neighboring classes.

The performance of the proposed FNN is compared with a conventional BP neural network in Table 8. It can be seen that the proposed FNN trained with LM algorithm is more than ten times faster.
4.6. Effectiveness of FCPI

The ranking of contingencies on the basis of $PI_V$, $PI_L$, $PI_M$ and FCPI is compared in Table 4 for one load scenario. The significance of using FCPI for contingency ranking becomes clear from Table 4 which lists the values of the constituent indices for one load scenario. It can be observed that for a few line outage contingencies (23–29, 16–35 for the given scenario), the ranking remains same for all three indices but in most of the other contingency cases the ranking based on indices $PI_V$, $PI_L$ and $PI_M$ is different. Contingencies (25–37, 59–58) are not severe from the point of view of margin reduction ($PI_M$) but are very critical on the basis of $PI_L$. The composite index FCPI is hence very useful for ranking the contingencies as it includes all the three indices. For many cases the rankings due to $PI_V$, $PI_L$ and, $PI_M$ are far apart because their severity level judged from margin point of view is different from voltage or line flow limit violation viewpoint. Weighing factors associated with $PI_V$ and, $PI_M$ may be adjusted based on past experience and system behavior to give reliable assessment for a given system. By using a composite index the effect of all three indices was effectively included for security assessment.

4.7. Ranking performance of hybrid network

The ranking performance of the proposed network for class I, class II and class III is shown in Figs. 15–17. Out of the 55 testing patterns, 5 belonged to severity class I, 8 patterns belonged to class II and 17 patterns belonged to class III. Remaining 25 patterns were less severe and belonged to classes IV and V, respectively. The boundary contingencies can also be clearly identified in Figs. 15 and 17 as they have high memberships to two classes. The proposed hybrid Fuzzy-neural network trained with LM algorithm is a model free estimator and its mapping accuracy is dependent on how closely the training patterns resemble the actual operating conditions. Being an intelligent system, it however has considerable fault tolerance and therefore can produce accurate results even for previously unseen operating conditions as long as they are within the same range. The computational time and complexity of conventional approaches increase when all AC limits and load compositions are incorporated in the model, but in case of the proposed approach there will be no such effect as once it is trained off-line using data obtained from conventional methods, the results will be produced instantaneously, during the on-line application (see Fig. 18).
5. Conclusion

A hybrid fuzzy-neural network is developed for on-line ranking of short listed critical contingency using pre fault load information at selected buses. The proposed composite performance index developed using the combined effect of stability margin, bus voltage and line flow limit violation is found to be very efficient for ranking contingencies compared to methods, which use conventional indices only. Loads are modeled as fuzzy variables in contrast to the conventional deterministic approaches. The complicated task of fuzzy rule framing is not required here because a trained neural network serves as an inference engine. It has been demonstrated that the proposed method is particularly suitable for ranking contingencies lying on class boundaries because the fuzzy environment increases amount of information available and provides ranking within a severity class.

The approach proposed in this paper is capable of producing results comparable in accuracy to full AC load flow almost instantaneously, whereas the conventional methods employed for security assessment are either computationally slow, or sacrifice their accuracy for producing fast results. The proposed method may be applied for on-line ranking in energy management systems as it is unaffected by the uncertainty and noise existing in available load data and is capable of producing fast and accurate results.

Acknowledgement

The authors sincerely acknowledge the financial support provided by Department of Science and Technology (DST), Government of India, New Delhi, India under research project entitled Integrated fuzzy-neural network approach for power system voltage security assessment of Madhya Pradesh State Electricity Board System vide letter no. SR/S3/ECE/2003-SERC dated 11/5/2004, and AICTE New Delhi for financial assistance. References dated 11/5/2004, and AICTE New Delhi for financial assistance.

5. Conclusion

A hybrid fuzzy-neural network is developed for on-line ranking of short listed critical contingency using pre fault load information at selected buses. The proposed composite performance index developed using the combined effect of stability margin, bus voltage and line flow limit violation is found to be very efficient for ranking contingencies compared to methods, which use conventional indices only. Loads are modeled as fuzzy variables in contrast to the conventional deterministic approaches. The complicated task of fuzzy rule framing is not required here because a trained neural network serves as an inference engine. It has been demonstrated that the proposed method is particularly suitable for ranking contingencies lying on class boundaries because the fuzzy environment increases amount of information available and provides ranking within a severity class.

The approach proposed in this paper is capable of producing results comparable in accuracy to full AC load flow almost instantaneously, whereas the conventional methods employed for security assessment are either computationally slow, or sacrifice their accuracy for producing fast results. The proposed method may be applied for on-line ranking in energy management systems as it is unaffected by the uncertainty and noise existing in available load data and is capable of producing fast and accurate results.

Acknowledgement

The authors sincerely acknowledge the financial support provided by Department of Science and Technology (DST), Government of India, New Delhi, India under research project entitled Integrated fuzzy-neural network approach for power system voltage security assessment of Madhya Pradesh State Electricity Board System vide letter no. SR/S3/ECE/2003-SERC dated 11/5/2004, and AICTE New Delhi for financial assistance under RPS project F No 8023/RID/BOR/RPS-45/2005-06 dated 10/03/2006. The authors also thank the Director, M.I.T.S. Gwalior for providing facilities for carrying out this work.

References


K.T. Chaturvedi obtained his M.E. degree in Electrical Engineering from Madhav Institute of Technology & Science Gwalior (India) in 2005. He is currently working as Senior Research Fellow in the department of Electrical Engineering, M.I.T.S, Gwalior (India). His areas of interest are Optimal Power Flow, Power System Security Analysis, and evolutionary computation applications to Power Systems.

M. Pandit obtained her M. Tech. degree in Electrical Engineering from Maulana Azad College of Technology, Bhopal, (India) in 1989 and Ph.D. degree from Jiwaji University Gwalior (India) in 2001. She is currently working as Professor in Department of Electrical Engineering, M.I.T.S, Gwalior (India). Her areas of interest are Optimal Power Flow, Power System Security Analysis, and evolutionary methods, ANN and Fuzzy neural applications to Power System.

L. Srivastava obtained her M. Tech. degree in Electrical Engineering from the Indian Institute of Technology, Kanpur, India in 1990 and her Ph.D. degree from University of Roorkee (Presently IIT Roorkee), Roorkee, India in 1998. She is working as a Professor in the Department of Electrical Engineering, M.I.T.S. Gwalior, India. She is currently involved in research in power system optimization and control, security analysis, operation and control of deregulated power systems, and ANN and fuzzy logic applications to power system.
J. Sharma obtained his M.E. and Ph.D. degrees in Electrical Engineering from University of Roorkee, Roorkee, (India), in 1971 and 1974, respectively. Presently he is Professor of Electrical Engineering, Indian Institute of Technology, Roorkee (India). He has published more than 200 technical papers in journals/conferences. He is actively involved in research; some of the areas being Power System planning and operation, security analysis and optimization, small hydro plant design and simulation, evolutionary computing and artificial intelligence applications to Power System.

R.P. Bhatele obtained his M.E. and Ph.D. degrees in Electrical Engineering from University of Roorkee (Presently IIT Roorkee), Roorkee, India in 1980 and 1985, respectively. He is currently working as Chief Engineer & Head, Power System Planning Unit, in Madhya Pradesh power Transmission Company limited (MPPTCL), Jabalpur, India. He has a long experience in the area of power system planning and designing. He is currently involved in research in Transmission Distribution Loss minimization.