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Neural network approach to contingency screening and ranking in power systems

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Abstract

An artificial neural network (ANN) approach to power system contingency analysis is proposed. Using fast voltage and line-flow contingency screening. Full AC load flow is performed for each contingency case. The off-line results of full AC load flow calculations are used to construct two kinds of performance indices, namely the real power performance index (PI_{MW}) and voltage performance index (PI_{V}), which reflect the degree of severity of contingencies. The results from off-line load flow calculations are used to train the "*screening module*", which is a multi-layered perceptron (MLP) network, for estimating the performance indices (PI_{MW}, PI_{V} PI_{V}). The MLP is trained to classify the contingencies either as critical or non-critical cases using back-propagation (BP) algorithm. The screened critical contingencies are passed on to the "*ranking module*" for ranking of the contingencies. The effectiveness of the proposed method is demonstrated by contingency screening and ranking on a standard 6-bus and IEEE 14-bus systems. The performance of the proposed method is compared with a traditional Newton Raphson (NR) method and the results discussed. The proposed methodology was implemented using the MATLAB Neural Network Toolbox. The generalization capability of the trained neural network was able to identify unknown contingencies with large range of operating conditions and changes in network topology. The proposed approach to contingency analysis was found to be suitable for fast voltage and line-flow contingency screening and ranking.

Keywords: Contingency analysis; Evaluation; Screening; Ranking; Neural network; Multi-layer perceptron; Performance index; Voltage and MW ranking

1. Introduction

Power System Security and Contingency evaluation is one of the most important tasks encountered by planning and operation engineers of bulk power systems. In power system planning, contingency analysis is used to examine the performance of a power system and the need for new transmission expansion due to load growth or generation expansion. In operation, contingency analysis assists engineers to operate the power system at a secure operating point where equipment are loaded within their safe limits and power is delivered to customers with acceptable quality standards. In this type of analysis the objective is to find overloads or voltage violations under such contingencies and the proper measures that are needed to alleviate these violations. Identification of these contingencies and the determination of corrective actions often involve exhaustive load flow calculations.

Contingency analysis is an important aspect of power system security assessment. As various probable outages compose a contingency set, some cases in the contingency set may lead to transmission line over loads or bus voltage limit violations during power system operations. Such critical contingencies should be quickly identified for further detailed evaluation or, where possible, corrective measures taken. The process of identifying these critical contingencies is referred to as "*contingency selection*". The traditional procedure of contingency selection is based on the results of a full AC load flow solution. A variety of algorithms were developed for contingency analysis, the most popular being the performance index (PI) based method. Performance Index based method utilizes a system side scalar PI to quantify the severity of each case by

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calculating their PI values and to rank them accordingly. To achieve accurate ranking, each PI value would need to be calculated from the results of a full AC load flow. This process is time consuming and is not suitable for on-line use.

Artificial neural network (ANN) methods are efficient computing models with the ability to solve nonlinear pattern matching problems. They can capture the inherent non-linearity in the input patterns and use them for classification. Therefore, ANN based-method for contingency screening is a good alternative. The paper presents the design of an ANN for fast line-flow and voltage contingency screening. A three-layer perceptron network with back propagation learning technique has been used for line flow and voltage contingency screening. The proposed method has been tested on the standard 6-bus system and IEEE 14-bus systems. Results of the contingency screening and rankings by the proposed method are compared with those obtained by the classical performance index method. The paper is organized as follows. Section 2 described the various contingency analysis methods. Various Performance Indices used for contingency analysis are presented in Section 3. Section 4 described the neural networks approach to contingency screening and ranking. Implementation aspects are discussed in Section 5, while the simulation results are presented in Section 6. Important observations and conclusions are finally provided in references.

2. Contingency analysis methods

Contingency analysis is a software application run in an energy management system to give the operators an indication of what might happen to the power system in the event of an unplanned (or unscheduled) equipment outage [2]. The contingency list to be processed within the energy management system (EMS) comprises those cases whose probability of occurrence is deemed sufficiently high, and is specified by the utility company at system element level. The list, which is normally large, is automatically translated into electrical network changes: normally generator and/or branch outages. Contingency evaluation using full AC load flow is then performed on the successive individual cases in decreasing order of severity. The process is continued up to the point where no post-contingency violations are encountered, or until a specified time has elapsed.

Contingency selection is the process that offers the greatest potential for computational saving, and has received most development effort. Its purpose is to shorten the original long list of contingencies by eliminating that vast majority of cases having no violations. It invariably uses an approximate power system model with approximate computational techniques, to give relatively rapid but limited-accuracy results. On the basis of these results, the contingency cases are ranked in rough order of severity [3].

The two main approaches to contingency selection are direct and indirect methods [15]:

(a) *Direct methods:* Direct methods involve screening and direct ranking of the contingency cases. Screening involves the fast approximate power-flow simulation of each contingency case. By monitoring the approximate post-contingent quantities (flows, voltages), the case's severity can be quantified directly in some heuristic manner for ranking purposes. The severity measure is often a single number, the severity or performance index.

(b) *Indirect methods:* Indirect methods produce the values of the contingency-case severity indices for ranking, with out calculating the monitored contingent quantities. Contingency analysis is difficult because of the conflict between accuracy with which the power system is modeled and the speed required to model all contingencies that the operator specifies. If the contingencies can be evaluated fast enough, then all cases specified on the contingency list are run periodically and alarms reported the operators. This is possible if the calculation for each outage case can be performed very fast or else the number of contingencies to be run is very small. With modern energy management systems the number of contingency cases to be solved is usually varies from a few hundred to a few thousand cases. This coupled with the fact that results are to be as accurate as if run with a full power flow program make the execution of a contingency analysis program with in an acceptable time frame extremely difficult.

2.1. Conventional methods for contingency analysis

(i) Complete bounding method.
(ii) Concentric relaxation method.
(iii) 1P-1Q Method.
(iv) Zero mismatch method.
(v) Expert Systems.

(i) *Complete bounding method*: Complete bounding methods [4] determine the parts of the network in which branch MW flow limit violations may occur. A linear incremental solution is performed only for the selected system areas rather than for the entire network. The accuracy of the bounding methods is only limited by the accuracy of the incremental linear power flow.

(ii) *Concentric relaxation method*: The concentric relaxation method [17] can be considered as the earliest localization attempt. The main idea behind the method is to solve a small portion of the system in the vicinity of the contingency, while treating the remainder of the network as an infinite expanse. The area to be solved is concentrically expanded until the incremental voltage changes along the last solved tier of buses are not significantly affected by the inclusion of an additional tier of buses. Possibility of missing severe problems outside the selected solution pocket due to the use of the small cutoff network and the exclusion of the boundary buses from outage severity considerations.

(iii) *1P-1Q method*: The fundamental idea behind 1P-1Q method [10] is to take advantage of the speed and reasonably fast convergence of the fast-decoupled power flow by limiting number of iterations to one. The approximate first iteration solution can be used to check for major limit violations and the calculation of different contingency severity measures. Because of the approximation in the convergence this method was not found to perform a well as it is supposed to do.

(iv) *Zero mismatch method*: The zero mismatch method [1] extends the application of localization ideas from contingency screening to full iterative simulation. The zero mismatch method is significantly different from the concentric relaxation approach. The main difference between the two methods is in the network representation. The zero mismatch method uses the complete network model while a small cutoff representation is used in the later one (concentric relaxation).

(v) *Expert systems*: Expert systems [13] were also developed to heuristically estimate the severity of MW and voltage contingencies. However, this approach suffers from slow execution, knowledge base in sufficiency, dependency on specific system, etc.

2.1.1. Contingency analysis procedure

Fig. 1 shows the traditional contingency analysis process. The post-contingency state of the system must be obtained for each contingency, so that performance index can be calculated. This calculation has been done by performing full AC load flow for each contingency case [5]. The contingency ranking is accomplished by ordering these performance index values from the smallest to the lowest. Contingency analysis does not explicitly indicate whether a contingency is going to give bus voltage or line over load problems. Rather, it indicates the severity of each contingency relative to the others. To obtain the voltage violations at generators and line overloads we have to go for corrective action analysis. In corrective action analysis, severe cases are easily determined by simply running the full AC load flow for each case starting at the top of the list and stopping when the cases do not give problems.

2.1.2. Adaptive contingency processor

Fig. 2 shows adaptive contingency processor [6], which has been developed for the automatic ranking and selection of contingency cases for a power system contingency analysis study. In this methodology a contingency list is build, containing line and generator outages which are ranked according to their expected severity as reflected in voltage level degradation and circuit overloads. An adaptive contingency processor can be setup by performing sequential contingency tests starting with the most severe

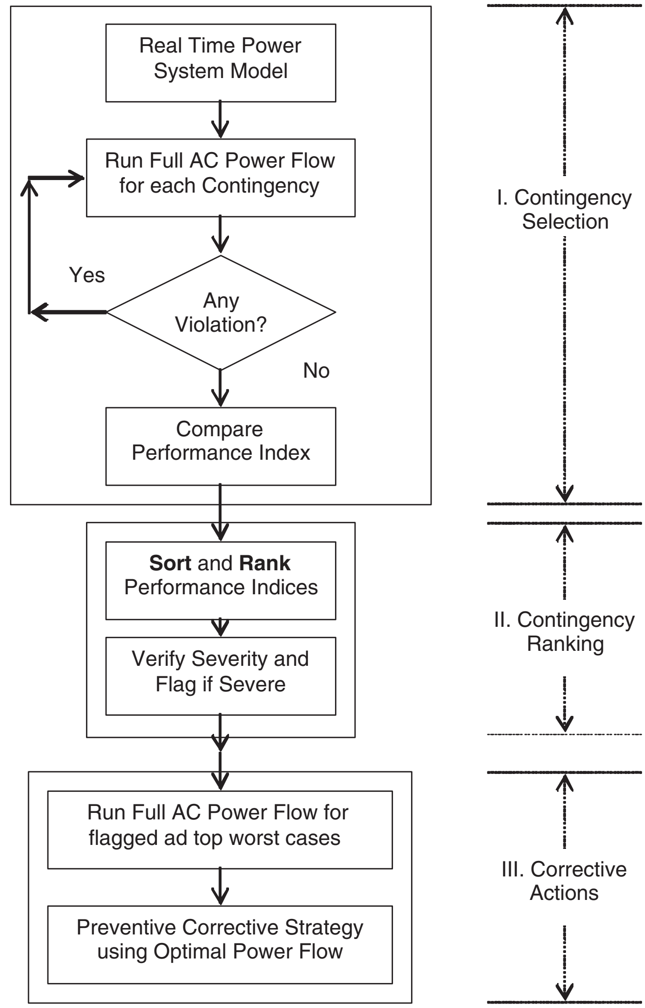

Fig. 1. Flowchart of contingency analysis procedure.

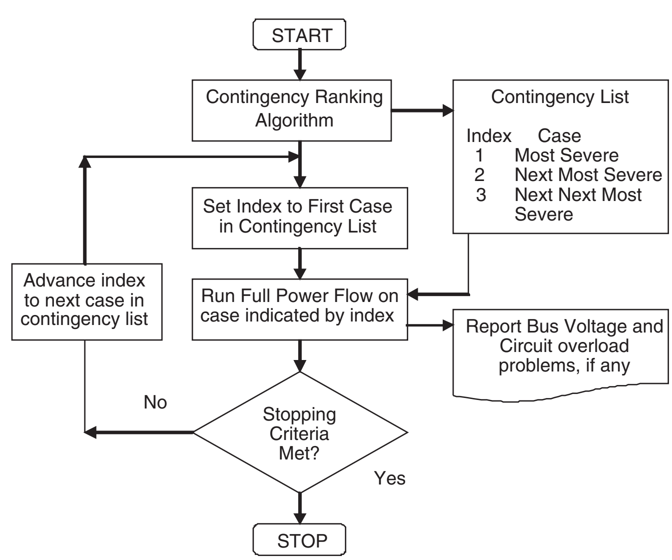

Fig. 2. Adaptive contingency processor.

contingencies at the top of the list and proceeding down the list, stopping when the severity goes below a threshold. An adaptive contingency processor was developed, because the number of cases solved will vary depending upon system conditions.

2.2. Drawbacks and limitations of conventional methods

1. These methods involve heavy computation, because these methods have to run the full AC load flow for all contingency cases in the contingency set.
2. Analytical methods are time consuming because to identify severe cases full AC load has to run for all contingencies in the contingency set.
3. These methods take long time to find the severity in the power system so analytical methods are not suitable for on-line applications.
4. Problem of misclassification. Misclassification arises when an active contingency classified as an inactive contingency or vice-versa.

Table 1 shows the comparison of Conventional and Neural Computation of Power System contingency analysis. The ANN approach is found to be more suitable than the conventional method in many aspects and therefore was used in this research.

A reliable power system should be operated so that it can withstand the outage of any system component or a set of components. To this end, most power systems are operated on the first contingency basis. A contingency is a set of hypothetical network equipment outages or breaker operation such as the loss of a generator, transmission line, a transformer or a combination of these events. In contingency analysis, user specified outage is then examined to assess the effect of contingencies and then alert the system operators to the potentially harmful ones that violate the equipment operating limits and/or drive the system to voltage and phase angle instability or excessive frequency deviations. The most common limit violations include transmission line and/or transformer thermal overloads, abnormal voltages and excessive voltage deviations. Given this information, a system operator can judge the relative severity of each contingency and decide if preventive actions should be initiated to mitigate the potential problems.

The traditional contingency selection and ranking approach is to use some type of automated contingency selection (ACS) or contingency screening (CS) method [8]. In either case, the key to a good ACS or CS method is that it is fast in computation and accurate in correctly identifying the harmful contingencies, that is quickly reducing the contingency list by eliminating the irrelevant (or harmless) contingencies [9]. Moreover, it must rank the contingency in relative severity and if possible predict the post-contingent line flows, voltages, frequency, and system stability. To achieve this, various algorithmic methods have been proposed, each of which uses an approximate system performance (ASP) model, which are computationally efficient to either identify the insecure contingencies and/or estimate the enhancement strategy. The ASP model can be either a scalar performance index or a linearized system model (such as distribution factors), or a simplified dynamic model.

2.3. Suitability of ANN for contingency screening

The analytical methods are usually time consuming and therefore not always suitable for on-line applications. Moreover, many PI based analytical methods suffer from the problem of misclassification or/and false alarm. Misclassification arises when an active contingency is classified as non-critical. A false alarm occurs when an inactive contingency is classified as critical. Expert systems and fuzzy system base methods are fast, but they lack versatility as many expert system and fuzzy system based rules are system specific. With recent advancements in learning techniques, ANN based-methods for contingency screening can be a good alternative [7,12].

Table 1
Comparison between conventional and neural network approach for contingency analysis

No	Task	Conventional approach	Neural network approach
1	Contingency analysis	Selection of Approximate System Performance (ASP) model & Algorithm	Selection of Neural Network Architecture & processing rule
2	Input data	Data from State Estimation Network data; Injections; Contingency List & Operating constraints (Numerical form only)	Processed injection & network data to reduce the input data set plus operator data (Both numerical & perceptual data)
3	Knowledge acquisition	Programming	Weight determination, i.e. training set & learning rule
4	Knowledge retrieval	Sequential computation	Fast parallel computation
5	Computation	High-precision arithmetic to determine if ASP model predicts limit violation	Low precision, non-linear mapping to predict the level of insecurity; on a low precision contingency filter
6	Stored parameters	ASP model parameters are estimated & held constant	Values of weights are adapted via a learning rule

Recognized shortcomings of the ANN based approach:

(i) A large number of training samples are required for the training of the neural network.
(ii) ANNs are found to be good at interpolating within the training set, but do not extrapolate accurately outside it because of the non-linear relationship between the input and output, and multiple correlated inputs [11].
(iii) The solution of the ANN is represented in the correction of the problem weights, and hence is difficult for interpretation and comprehension by an ANN operator.

3. Performance indices

The standard approach for steady state contingency checking is to run a load flow for the post-transient steady state condition following each outage. Some of the outages may result in system constraint violations such as load bus voltages outside their normal limits and transmission line (transformer) overloads. The voltage constraints at the load buses are usually expressed in terms of a high and low limit. The high limit is imposed by maximum voltage value of the system, and the low limit is a value below which it is assumed that the load can no longer be supplied. Flows on transmission lines are usually constrained by thermal limits and sometimes by stability considerations on long lines. In light of these constraints, the system performance may be quantitatively evaluated in terms of indices reflecting the severity of out-of-limit voltage values or line overloads resulting from a particular contingency. In defining the system performance indices, we treat the constraints on the load bus voltage and the line flows as soft constraints, i.e., the violation of these constraints, if not excessive may be tolerated for short periods of time. The system performance index is defined as a penalty function to penalize severely any violation of bus voltage constraints or line flow constraints. There are two performance indices widely used, namely the Voltage Performance Index and the Line Flow (MW) performance Index.

3.1. Voltage performance index PI_V

The voltage performance index chosen to quantify system deficiency due to out-of limit bus voltages [6] is defined by

$$PI_{\mathrm{V}} = \sum_{i=1}^{NB} \left(\frac{W_{\mathrm{v}i}}{2n}\right) \left(\frac{(|V_i| - |V_i^{\mathrm{sp}}|)}{\Delta V_i^{\lim}}\right)^{2n}, \tag{1}$$

where $|V_i|$ is the voltage magnitude at bus i, $|V_i|^{\mathrm{sp}}$ the specified (rated) voltage magnitude at bus I, $|\Delta V_i|^{\lim}$ the voltage deviation limit, above which voltage deviations are unacceptable, n the exponent of penalty function (= 2 preferred), NB the number of buses in the system, $W_{\mathrm{v}i}$ the real non-negative weighting factor (= 1).

The voltage deviation $\Delta V_i^{\lim}$ represents the threshold above which voltage level deviations are outside their limits, any contingency load flow with voltage levels outside this limit yields a high value of the index PI_{V}. When all the voltage level deviations from the rated voltage are within $|\Delta V_i|^{\lim}$, the voltage performance index PI_{V} is small. Thus, this index measures the severity of the out-of-limit bus voltages, and for a set of contingencies, this index provides a direct means of comparing the relative severity of the different outages on the system voltage profile.

It is pertinent to note, that since the bus voltage levels depend mainly on the reactive power flows, and therefore, on the reactive power production of the generators (and reactive power production units, e.g., synchronous condensers), the performance index PI_{V} provides a good measure of the severity of abnormal voltages, as long as the generating units remain with in their reactive power limits. However, it is possible to encounter a contingency for which some generator reactive powers are driven to their limits. In this situation, the standard full AC load flow computes the bus voltage using the limiting reactive powers at generator buses as specified independent variables, and their voltages as dependent variables, as a consequence, there is a voltage deviation from the scheduled voltage at these generator buses. Therefore, in order to reflect the reactive power capability constraints of the generators in the contingency selection for voltage analysis, we define a generalized voltage-reactive power performance index by

$$PI_{\mathrm{VQ}} = \sum_{i=1}^{NB} \left(\frac{w_{\mathrm{V}i}}{2n}\right) \left(\frac{(|V_i| - |V_i^{\mathrm{sp}}|)}{\Delta V_i^{\lim}}\right)^{2n} + \sum_{i=1}^{NG} \left(\frac{w_{\mathrm{G}i}}{2n}\right) \left(\frac{Q_i}{Q_i^{\mathrm{MAX}}}\right)^{2n}, \tag{2}$$

where Q_i is the reactive power produced at bus i, Q_i^{MAX} the reactive power production limit, NG the number of generating (reactive production) units, $W_{\mathrm{Q}i}$ the real non-negative weighting factor.

The second summation, takes over all reactive production units, penalizes any violations of the reactive power constraints. The reactive power weighting factors are set to zero if the effect of the reactive power deficit is not required. t is perhaps important to emphasize here that the contingency selection procedure developed in the proposed approach is not concerned with computing the system performance index PI_{VQ}. The proposed method is concerned with computing the voltage performance index (PI_{V}) and MW performance index (PI_{MW}) with respect to outages.

3.2. MW performance index PI_{MW}

An index for quantifying the extent of line overloads [6] may be defined in terms of MW performance index:

$$PI_{\mathrm{MW}} = \sum_{l=1}^{NL} \left(\frac{W_{\mathrm{l}i}}{2n}\right) \left(\frac{P_l}{P_l^{\lim}}\right)^{2n}, \tag{3}$$

where P_l the MW flow of line l, $P_l^{\lim}$ the MW capacity of line l, NL the number of lines of the system, W_{li} real non-negative weighting factor$(=1)$, n exponent of penalty function $(=2$ preferred).

The performance index PI_{MW} contains all line flows normalized by their limits. These normalized flows are raised to an even power (by setting $n=1,2\ldots$), thus, the use of absolute magnitude of flows is avoided. This index PI_{MW} has a small value, when all line flows are with in their limits, and a high value when there are line overloads. Thus, it provides a measure of the severity of line overloads for a given state of the power system.

It is observed from simulation that for $W_{vi}=1$ and $n=2$, masking effect has been removed for the tested sample systems. Here summation is carried out only for limit-violated buses. A number of line/generator outages having no bus voltage violation and line flow violations give zero value of system performance index for all the load patterns. Such lines are not selected for training of the neural network. It is observed that the list of critical contingent cases is dynamic in nature depending upon the loads at various buses i.e. a critical contingency may be a non-critical one at some other loading condition. Similarly the ranking order of critical contingency cases may be different at different loading conditions.

4. Neural network approach to contingency screening and ranking

ANNs have been utilized for contingency screening. However, most of these applications use ANNs as a tool to classify the system states under contingency to secure or insecure states. This approach is used mainly for on-line operation at power control centers where the objective is to provide the operator with an indication about the state of the power system.

4.1. Hopfield neural network

Hopfield neural network [16] was used in power system security to classify the contingency by learning to recognize the number and type of limit violations associated with each contingency. It uses a linear programming technique to optimize the ANN classification accuracy. The violation pattern that results from each contingency is constructed using a binary matrix in which violations are assigned a binary code.

4.2. Kohonen's self-organizing feature map

The application of Kohonen's self-organizing feature map provides a fast contingency assessment tool for on-line operations. The operating point of the system is presented to the ANN as a vector of line active and reactive power flows obtained from running load flow under different conditions. The state of the system can be determined by estimating how far the operating point is away from the self-operating boundaries of the system. Kohonen's self-organizing feature map was also used to identify similarities in system state variables (line flows and bus voltages) under different contingency. The network is trained to produce a feature map that relates each contingency and pre-contingency state parameter to contingency attributes.

4.3. Multi-layered perceptron

The multi-layered perceptron (MLP) [14] has been chosen because of its excellent training convergence characteristics, particularly on such a huge dimensionality. Another feature that makes the MLP more ideal for this type of problems is its ability to recognize unknown patterns with out retraining the neural network.

4.4. Neural network design

The neural network used in these studies was of the feed-forward structure. It consisted of three layers, one for the input, one hidden and one for the output. The size of the input layer was determined by the size of the input pattern. For an input pattern of size n, the number of input neurons was n plus one neuron for biasing neuron. Similarly, the size of the output layer was determined by the number of outputs-each output neuron was assigned to one performance index. The size of the hidden neurons was selected to provide the best test results for the given system. It was found that 4–6 hidden neurons were adequate for screening module for standard 6-bus system and 6 to 8 hidden neurons were adequate for screening module for the IEEE 14-bus system.

The input neurons of the feed forward structure are potential nodes. They pass the information to the neurons in the hidden layer in a weighted form. The neurons in the hidden layer process this information with a nonlinear function. The hidden neurons pass the information to the output neurons, which are linear current nodes. The data of each study was normalized before training the neural network. This was done to enhance the randomness of the data and eliminate the sequential bias effect. After the data normalization, it was divided into two groups, one used for training and the other for testing. For proper neural network performance, test data and training data must be different although belonging to the same source.

During the training, the neural network was closely monitored to prevent network over-training, or saturation. The presence of any of these problems would have resulted in unreliable results. When a neural network memorizes the training data, it reproduces acceptable results for patterns that have used during the training, but unacceptable results with high errors when tested on unseen patterns. Such a neural network is useless for the contingency applications but may find applications in areas where over training is the goal. There are different techniques to ensure that a neural network has learned and not memorized. They are all based on the fact that a properly trained neural network should respond with equal error measures to both training and testing patterns.

4.5. Feature selection

The performance of any neural network mainly depends upon the input features selected for training. It is essential to reduce the number of inputs to a neural network and to select the optimum number of inputs, which are able to clearly define the input-output mapping. In the event of line outage in a power system, line-flows are affected on a number of lines. It is observed that line flows at the contingent line, change drastically. System loading conditions greatly influence the real power at different lines, and hence the MW performance index. So, pre-outage real power flows at the contingent line are considered as input features for the ANN.

In the event of generator outage in power system, bus voltages and reactive power flows are affected at a number of buses and lines. It is observed that the terminal voltages and reactive powers at the contingent generator change a lot. System loading conditions greatly influence the voltage magnitudes and reactive powers at different buses, and hence the voltage performance index. So, pre-outage bus voltages are considered as input features for the ANN.

5. Implementation

5.1. Methodology

The block diagram of the proposed model is shown in Fig. 3. A large number of patterns are generated randomly at each bus for a wide range of load variation. Full AC load flow is performed for each case to compute pre-outage line-flows and terminal voltages at the contingent line or generator, and also corresponding to single line and generator outages to compute the voltage and MW performance indices. The proposed method was designed and tested on a windows environment with the help of ANN toolbox using MATLAB.

5.2. Full AC load flow study

To obtain pre contingency line flows, terminal voltages of the contingent line as input features training/testing of the neural network. A large number of load patterns are generated by perturbing the load on all the buses randomly in wide range of system operating conditions and a full AC load flow is performed for each case. Single line outage corresponding to each load pattern are also simulated by full AC load flow to calculate the PI_V and PI_{MW}.

5.3. Power system operating state

This block modifies the full AC load flow results into a matrix form and supplies line flows to MW screening module and all bus voltages to the voltage-screening module.

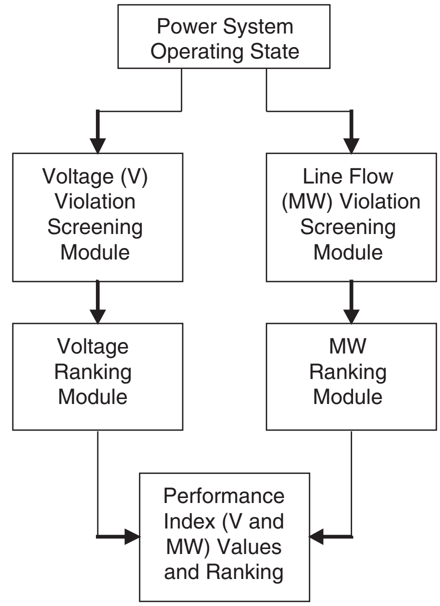

Fig. 3. Block diagram of proposed approach to contingency analysis using neural networks.

5.4. Voltage screening module

Voltage screening module is a three-layered feed-forward ANN used to classify contingencies as critical or non-critical. The voltage screening module is trained using BP algorithm The voltage performance index (PI_V) is calculated by considering the limit violated buses only, and it is the output of the neural network. Pre contingency terminal voltages of the contingent element are selected as input features for training of the neural network.

5.5. MW screening module

MW screening module is a three-layered feed-forward ANN, used to classify contingencies as critical or non-critical. The MW screening module is trained using BP algorithm. The MW performance index ($\mathrm{PI}_{\mathrm{MW}}$) is calculated by considering the limit-violated lines only, and it is the output of the neural network. Pre contingency line flows of the contingent element are selected as input features for training of the neural network. The calculated PI values from voltage and MW screening modules are passed to the voltage and MW ranking modules respectively for ranking of the contingencies.

5.6. Voltage ranking module

The screened critical contingencies from voltage screening module are passed on to the voltage-ranking module for ranking of the contingencies.

5.7. MW ranking module

The screened critical contingencies from MW screening module are passed on to the MW ranking module for ranking of the contingencies.

5.8. Solution algorithm

The solution algorithm for contingency screening and ranking can be summarized in following steps:

1. A large number of load patterns are generated by perturbing loads randomly at all the buses.
2. Full AC load flow is performed for each case to compute pre outage line flows, terminal voltages at the contingent element.
3. The line outages and generator outage cases having zero or very small values of PI_{MW} and PI_{V} for all the load patterns are not considered for training of neural network.
4. The input data as well as output are normalized between 0.0 and 1.0.
5. The normalized input data along with PI_{MW} and PI_{V} value corresponding to the contingent line or generator are used for training of the screening module.
6. The training of screening module is continued till the error for testing patterns is minimum.
7. Only those contingency cases belonging to critical class are passed to the ranking module for ranking of the critical contingency cases.

5.9. Generation of training data

Once the selection of the input and output parameters is done, the next step is to prepare the training data set. Many system variables change during operation of a power system and these variables include:

1. Topology of the power system.
2. Total load.
3. Total generation.
4. Capacitor/reactor at different locations.
5. Transformer taps.
6. Phase shifter angles.

Ideally, variations of all of the above parameters should be considered for generating the training data. However, for the sake of simplicity and to keep the training data set to a minimum length, only the total load of the system was altered during the generation of the training data. For MW contingency screening and ranking, 600 training patterns showing 24 load scenarios were generated in the range of 75–175% of their base case loading and for voltage contingency screening and ranking, 600 training patterns showing 24 load scenarios were generated in the range of 75–175% of their base case loading.

Fig. 4 shows methodology used in generating data for training and testing of the neural network. Contingency set consists of various probable outages (line and generator), some cases in the contingency may lead to transmission line overloads and bus voltage limit violations during power system operations. Full AC load flow selects one contingency from contingency set and supplies the line flow results to the PI_{MW} block (program to calculate MW performance index) and all the bus voltages supplies to the PI_{V} block (program to calculate voltage performance index) and full AC load flow repeats the same process for all contingencies in the contingency set. To generate large data and to cover entire power system operating conditions in practical load has been varied from 75% to 175% in steps of 5% for each contingency in the contingency set.

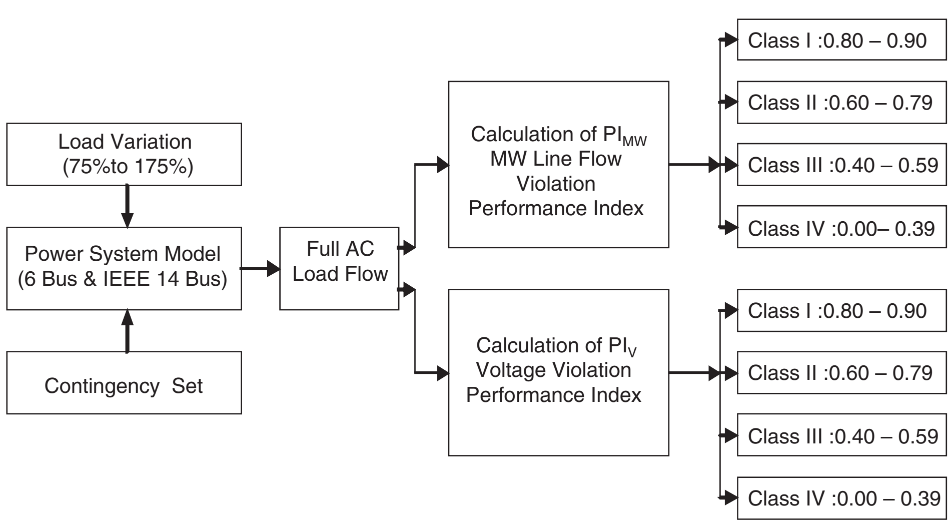

Fig. 4. Methodology for data generation for the contingency analysis using neural network.

The blocks PI_{MW} and PI_V calculate the power system performance indices MW performance index (PI_{MW}) and voltage performance index, respectively.

5.10. Data normalization

Normalization of the data is an important aspect for training of the neural network. Without normalization, there is a risk of the simulated neurons reaching saturated conditions. If the neurons get saturated, then the changes in the input value will produce a very small change or no change in the output value. This affects the learning a great extent. One popular method of normalization is to normalize all the data so that the values lie between 0 and 1. This is done by dividing each training variable by its maximum value. In this proposed method, all training parameters are normalized by this method.

5.11. Selection of training and testing patterns

The training and testing patterns are created while loads are varied between 75% and 175% of the base case in the 29 randomly selected steps. These variation changes are typical for a large power system. The power system state in each step will be defined by a set of variables as a pattern. The corresponding accurate PI values of the 25 contingencies in each step are obtained from full AC load flow solutions. These training and testing patterns are automatically created by means of a MATLAB program. The loads are varied from 75% to 175% in 5% step and 725 patterns are generated for training and testing of the ANN. From that 600 patterns are selected for training and the remaining 125 patterns are used as testing patterns for the ANN to evaluate its performance.

Table 2 shows training testing statistics for the MW screening module and voltage screening module for the standardn6bus system and the IEEE 14 Bus System.

6. Simulation results

6.1. Case study 1: Six-bus system

The standard 6-bus system shown in Fig. 5 was selected to demonstrate the use of ANN to calculate system performance indices with single line and generator outages under different system demand levels. The system consists of 6 buses, 3 of them are generator buses and 11 transmission lines.

A total of 18 base cases with different load levels were used to create data for training the neural network. A total of 236 (contingencies) load flow cases were selected for these load scenarios using different lines and generation outages. After training the ANN was tested using different sets of load flow cases that were not used during the training process. For testing 16 load flow cases are selected using different transmission and generation outages.

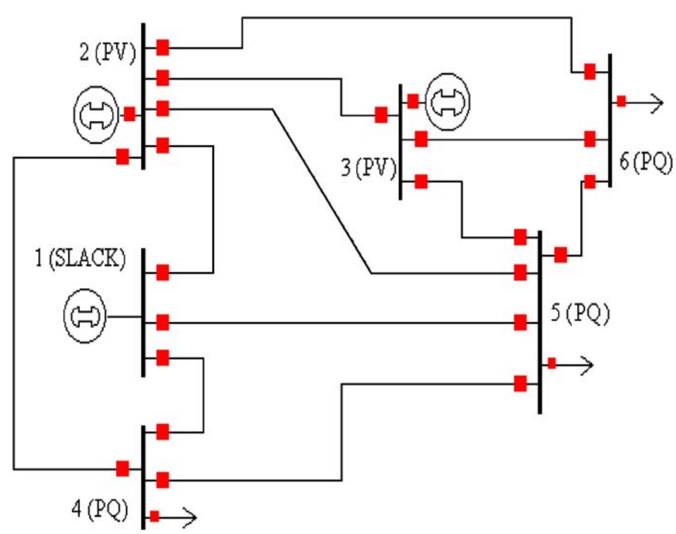

Fig. 5. Six bus model power system.

Table 2
NN parameters for standard 6-bus and IEEE 14 bus system for MW and voltage screening

		6-bus system		IEEE 14-bus system	
No.	NN features	MW screening	Voltage screening	MW screening	Voltage screening
1	Inputs	14	14	20	20
2	Outputs	1	1	1	1
3	Hidden layers	1	1	1	1
4	Hidden neurons	5	6	8	8
5	Iteration step	100	100	100	100
6	Momentum factor	0.97	0.97	0.97	0.97
7	Learning rate	0.005	0.005	0.005	0.005
8	Sum squared error	0.005	0.005	0.007	0.007
9	Training patterns	175	156	470	276
10	Iteration count	2×10^5	2×10^5	2.2×10^6	2.2×10^6
11	Testing data	16	16	125	125

Table 3
MW screening and ranking at different loading conditions for 6 bus system

Sl. No	Loading		Line/Gen	PI_{MW} values		Contingency ranking	
	P (MW)	Q (MVAR)	From–To	NR	ANN	NR	ANN
1	40	40	2–4	0.514	0.664	11	12
2	40	50	3–6	3.019	3.291	*5*	*5*
3	40	60	G1	0.236	0.411	15	13
4	45	45	3–6	3.276	3.497	*4*	*4*
5	50	50	G3	0.236	0.374	15	14
6	50	70	1–5	0.428	0.202	13	16
7	55	55	2–5	0.428	0.332	13	15
8	60	40	3–6	4.09	4.228	*3*	*3*
9	60	50	1–5	0.492	1.261	12	10
10	60	60	G3	2.184	2.28	*9*	*9*
11	60	70	2–4	1.135	1.076	10	11
12	65	65	1–5	2.634	2.749	*7*	*7*
13	70	70	1–4	6.616	6.751	*2*	*2*
14	75	75	2–4	2.484	2.894	*8*	*6*
15	80	80	1–5	12.012	13.159	*1*	*1*
16	80	80	2–6	2.933	2.46	*6*	*8*

It can be observed from Table 3 that the column corresponding to the contingency ranking obtained by Artificial Neural Network (ANN) for different loading conditions is almost the same as that obtained by the Newton Raphson (NR) (shown as italics). The contingency ranking for line 1–5 corresponding to 80 MW and 80 MVAR loading (Sl.No 15) obtained by NR method is 12.012, while that obtained by ANN is 13.139, which is the highest and is given as index *1*.

For instance there the contingency ranking by both NR and ANN methods from ranks *1* to *9* (shown as italics) and having high PI_{MW} values, is in complete agreement whereas there is a slight mismatch from ranks 10 to 16 (very small values of PI_{MW}).

Similar matching of the contingency ranking by ANN method verified by the NR method can be observed corresponding to the voltage screening and ranking provided in Table 4. It can be inferred that the result indicate the verification with conventional NR method and correct working of the ANN method for contingency screening and ranking.

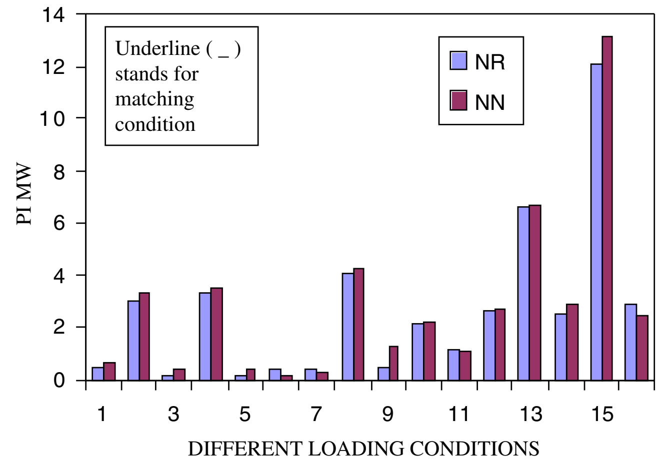

Fig. 6. Comparison of results obtained using the proposed ANN-method and the traditional NR-method at different loading conditions.

Table 4
Voltage screening and ranking at different loading conditions for 6 bus system

Sl. No	Loading		Line/Gen outage	PI_V values		Contingency ranking	
	P (MW)	Q (MVAR)		NR	ANN	NR	ANN
1	45	45	3–6	6.949	5.994	4	4
2	55	55	3–6	16.843	13.537	3	3
3	60	60	GEN3	4.24	3.772	5	5
4	60	60	2–4	23.203	21.793	2	2
5	65	65	1–5	0.118	0.382	7	6
6	70	70	1–4	0.589	0.224	6	7
7	75	75	2–4	40.516	41.025	1	1
8	80	80	2–6	0.118	0.132	7	8

The "ANN contingency analysis" models were able to produce results that are with in the desired accuracy level as compared with those obtained from a standard AC load flow program. In this example the line flow neural network has 14 inputs, 5 hidden neurons and one output. The inputs represent all line flows (in MW values) and the three generator bus voltages and the output is the system MW performance index (PI_{MW}) at that particular contingency case. The bus voltage neural network has 14 inputs, 6 hidden neurons and one output. The input represents all line flows (in MW values) and the three generator bus voltages and the output is the system voltage performance index (PI_V at that particular contingency case.

Table 3 shows the comparison of results obtained using the proposed ANN-method and the traditional NR-method at different loading conditions.

The standard 6-bus system was tested for 11 single line outage cases and three generator outage cases. The rankings produced by the ANN are displayed in comparison with the traditional NR-method for the MW ranking. The most severe contingencies being those that have a higher performance index value 1,2, 3,4,7,9 and 6 & 8 are interchanged. It can be seen that the MW performance index values are almost the same for both the methods. Also for both methods, the top 9 contingencies are with the same sequence in the ranking list. For other contingencies such as 10, 11, 13, 14, and 15, they have close performance indices, which are about one-tenth of the highest PI value, so their effects on the system can be neglected. Fig. 6 shows the comparison of PI_{MW} values of NR-method and ANN-method.

Table 4 shows the comparison of results obtained using the proposed ANN-method and the traditional NR-method at different loading conditions.

The standard 6-bus system was tested for 11 single line outage cases and three generator outage cases. The rankings produced by the ANN are displayed in comparison with the traditional NR-method for the voltage ranking. The most severe contingencies being those that have a higher performance index value. It can be seen that

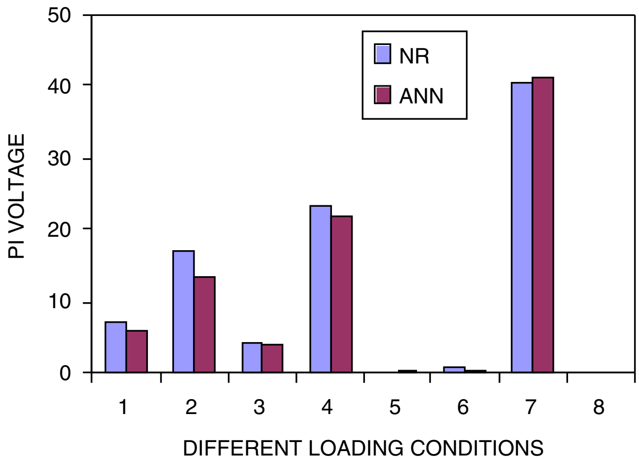

Fig. 7. Comparison of results obtained using the proposed ANN-method and the traditional NR-method at different loading conditions.

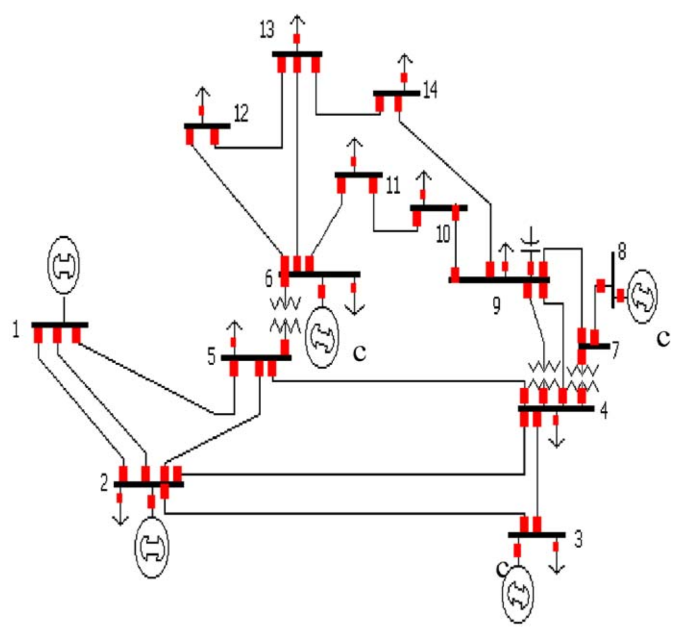

Fig. 8. IEEE 14 bus system.

the voltage performance index values are almost the same for both the methods. Also for both methods, the top 5 contingencies are with the same sequence in the ranking list. For other contingencies such as 6, 7 and 8, they have close performance indices, which are about one-thirtieth of the highest PI value, so their effects on the system can be neglected. Fig. 7 shows the comparison of PI_V values of NR-method and ANN-method.

6.2. Case study 2: (IEEE 14-bus system)

The IEEE 14-bus system given in Fig. 8 was selected to demonstrate the use of ANN to calculate system performance indices with single line and generator outages under different system demand levels. The system consists of 14

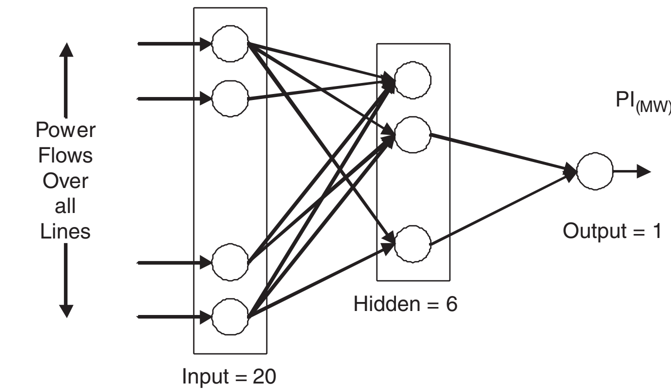

Fig. 9. Block diagram of ANN for MW screening.

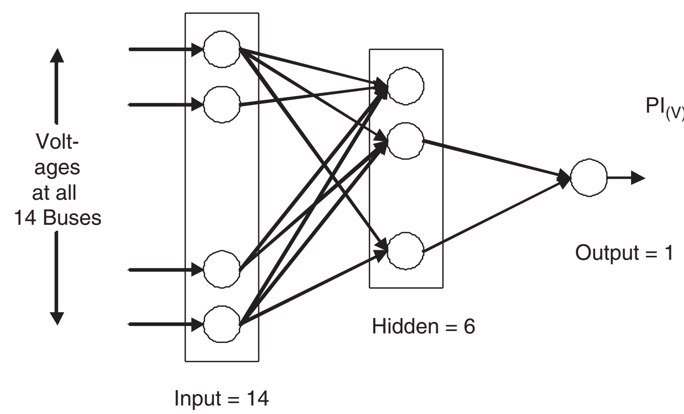

Fig. 10. Block diagram of ANN for voltage screening.

buses, five of them are generator buses and 20 transmission lines.

A total of 24 base cases with different load levels were used to create data for training the neural network. The base cases used for training are 75% (a, b, c), 100%, 110%, 115%, 125% (a, b, c), 135%, 140%, 145%, 150% (b, c), 160% (b, c), 170%, 175%, (a, b, c), ((a)—load applied at buses 4,5,9; (b)—load applied at buses 10,11; (c)—load applied at buses 12, 13, 14 of base case load, for all other case load applied at all load buses). A total of 725 load flow cases were generated for these load scenarios using different lines and generation outages. After training the ANN was tested using different sets of load flow cases that were not used during the training process. The load levels used to generate the test cases are 90%, 130%, 150%(a), 160%(a), and 165%. These load scenarios were used to generate 125 load flow cases using different transmission and generation outages.

The ANNs contingency analysis models were able to produce results that are in accordance with the desired accuracy level as compared with those obtained from a standard AC load flow program. In this example the MW screening module has 20 inputs, six hidden neurons and one output. The inputs represents all line flows (in MW values) and the output is the system MW performance index (PI_{MW}) at that particular contingency case. Fig. 9 shows the diagram of the ANN architecture used for MW screening.

The bus voltage neural network has 14 inputs, six hidden neurons and one output. The input represents all bus voltages (in p.u. values) and the output is the system voltage performance index (PI_V) at that particular contingency case. Fig. 10 shows the diagram of the ANN architecture used for voltage screening.

Table 5
MW screening and ranking at 130% loading for IEEE 14 bus system

Sl. No	Lines/Gen outage	PI_{MW} values		Contingency ranking	
		NR	ANN	NR	ANN
1	Base Case	0.74	1.126	21	20
2	2–3	42.345	42.818	*1*	*1*
3	2–4	2.513	2.804	*8*	*8*
4	1–5	4.763	4.934	3	4
5	2–5	1.368	1.573	*11*	*11*
6	3–4	1.085	1.021	15	24
7	4–5	2.65	2.836	*6*	*6*
8	5–6	32.72	32.677	*2*	*2*
9	4–7	4.457	4.955	4	3
10	4–9	2.598	2.466	7	9
11	7–9	4.172	4.251	*5*	*5*
12	9–10	0.687	1.098	24	21
13	6–11	1.129	1.382	14	13
14	6–12	1.167	1.327	13	14
15	6–13	2.116	2.825	9	7
16	9–14	1.344	1.454	*12*	*12*
17	10–11	0.933	1.14	*19*	*19*
18	12–13	0.747	1.068	20	23
19	13–14	0.987	1.168	17	15
20	GEN 1	1.977	1.936	*10*	*10*
21	GEN 2	0.997	1.076	16	22
22	GEN 3	0.728	1.164	22	16
23	GEN 6	0.941	1.143	*18*	*18*
24	GEN 8	0.699	1.163	23	17

6.3. MW and voltage screening and ranking at 130% loading

Table 5 shows the comparison of results obtained using the proposed ANN-method and the traditional NR-method at 130% loading condition at all load buses when one line at a time in the 14-bus system outaged. For example, rows 2 and 3 show the performance indices when lines 2–3 and 2–4 are outaged, respectively.

The performance index is computed using the proposed ANN and the traditional approach. The contingencies are also ranked; the most severe contingencies being those that have a higher performance index value. It can be seen that the performance index values are almost the same for the both methods. Also for both methods, the top 12 contingencies are with the same sequence in the ranking list. For other contingencies such as 13, 14–24, they have close performance indices, which are about one-fortieth of the highest PI value, so their effects on the system can be neglected. Fig. 11 shows the comparison of PI_{MW} values of NR-method and ANN-method.

6.4. MW and voltage screening and ranking at 150% loading at buses 4, 5 and 9

Table 6 shows the comparison of results obtained using the proposed ANN-method and the traditional NR-method at 150% loading condition at buses 4, 5 and 9, when one line at a time in the 14-bus system outaged. For example, rows 2 and 3 show the performance indices when lines 1–2 and 2–3 are outaged, respectively. The performance index is computed using the proposed ANN and the traditional approach. The contingencies are also ranked; the most severe contingencies being those that have a higher performance index value. It can be seen that the performance index values are almost the same for the both methods. Also for both methods, the top 8 contingencies are with the same sequence in the ranking list. For other contingencies such as 9, 10–25, they have close performance indices, which are about one-tenth of the highest PI

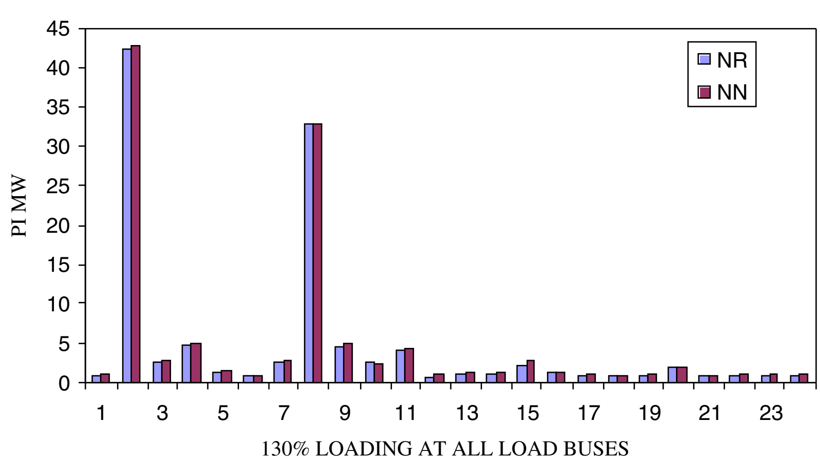

Fig. 11. Comparison of results obtained using the proposed ANN-method and the traditional NR-method at 130% loading condition (at all load buses).

value, so their effects on the system can be neglected. Fig. 12 shows the comparison of PI_{MW} values of NR-method and ANN-method.

6.5. Observations and discussions

The trained neural network was tested to determine if performance indices could be estimated for various system operating conditions. Results obtained from the ANN and the traditional Newton Raphson method was compared. It was observed that both methods provide very similar results indicating that the trained ANN can operate in generalized manner and is able to handle new topologies and operating conditions.

Table 6
MW screening and ranking at 150% loading for IEEE 14 Bus system

Sl. No	Line/Gen outage	PI_{MW} values		Contingency ranking	
		NR	ANN	NR	ANN
1	BASE	0.387	0.568	20	19
2	1–2	14.518	15.384	3	2
3	2–3	15.793	14.753	2	3
4	2–4	1.843	1.67	7	8
5	1–5	3.282	3.14	5	6
6	2–5	0.875	0.792	13	12
7	3–4	0.406	0.529	17	23
8	4–5	1.839	1.869	8	7
9	5–6	16.8	16.283	*1*	*1*
10	4–7	3.429	3.687	*4*	*4*
11	4–9	1.764	1.332	9	10
12	7–9	2.978	3.141	6	5
13	9–10	0.355	0.57	23	18
14	6–11	0.926	0.661	12	14
15	6–12	0.406	0.636	17	15
16	6–13	1.142	1.414	11	9
17	9–14	0.295	0.666	25	13
18	10–11	0.796	0.563	15	20
19	12–13	0.392	0.525	19	24
20	13–14	0.787	0.596	*16*	*16*
21	GEN1	1.312	1.044	10	11
22	GEN2	0.374	0.532	*22*	*22*
23	GEN3	0.383	0.578	21	17
24	GEN6	0.837	0.561	14	21
25	GEN8	0.32	0.326	24	25

7. Conclusions

The analytical method for contingency analysis consists of the computation of the performance indices by running full AC load flow for all contingencies which is both time consuming and susceptible to screening and mis-ranking effects. The neural network approach to contingency analysis consists of training the screening module for different contingencies corresponding to voltage violated buses and Power Flow (MW) violated lines. The screening module provides accurate values of performance indices (PI_V, PI_{MW}) for unknown load patterns, which are compared with Newton Raphson method. The screened performance indices are passed on to the ranking module for ranking of the contingencies. The ANN approach to contingency analysis has been illustrated for a standard 6-bus system and extensively tested for the IEEE 14-bus system.

Based on the above simulation results obtained, it was observed that

(i) The ANN approach provides fast computation of voltage performance index, MW performance index and can generate unknown load patterns.
(ii) The proper construction of performance indices avoids the effect of masking of contingencies.
(iii) Once the network is trained and evaluated, this method can provide a fast contingency screening and requires much less calculations as compared to the traditional method.
(iv) The ANN based approach to contingency analysis would be most suitable as a decision making tool for on-line applications in Energy Management Systems.

7.1. Scope of the future work

In the present study contingency selection has been done for single line/generator contingencies, it can be extended to multiple contingencies (usually double contingencies). In the multiple contingencies approach the number of neurons in the input and middle layers should be changed. The

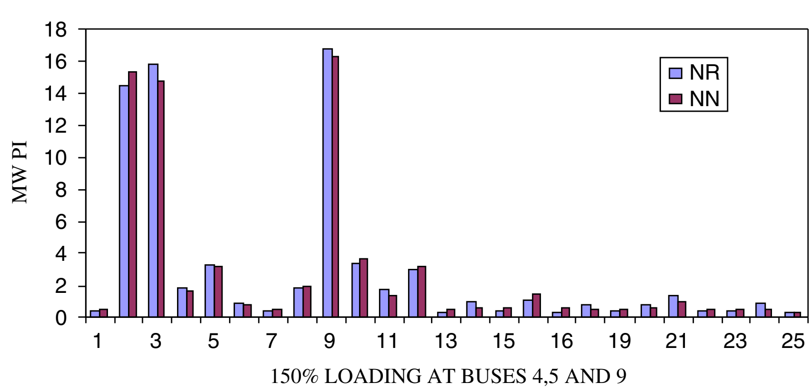

Fig. 12. Comparison of results obtained using the proposed ANN-method and the traditional NR-method at 150% loading condition (at buses 4, 5 and 9).

proposed method can be extended to any standard systems like IEEE-30, 57, 118, 300 bus systems.

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