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Application of Artificial Neural Network for Automatic Contingency Analysis in Power Security Assessment

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ABSTRACT

Several incidents that occurred around the world involving power failure caused by unscheduled line outages were identified as one of the main contributors to power failure and cascading blackout in electric power environment. With the advancement of computer technologies, artificial intelligence (AI) has been widely accepted as one method that can be applied to predict the occurrence of unscheduled disturbance. This paper presents the development of automatic contingency analysis and ranking algorithm for the application in the Artificial Neural Network (ANN). The ANN is developed in order to predict the post-outage severity index from a set of pre-outage data set. Data were generated using the newly developed automatic contingency analysis and ranking (ACAR) algorithm. Tests were conducted on the 24-bus IEEE Reliability Test Systems. Results showed that the developed technique is feasible to be implemented practically and an agreement was achieved in the results obtained from the tests. The developed ACAR can be utilised for further testing and implementation in other IEEE RTS test systems particularly in the system, which required fast computation time. On the other hand, the developed ANN can be used for predicting the post-outage severity index and hence system stability can be evaluated.

Keywords: *Artificial Neural Network, contingency analysis and ranking, voltage stability*

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Introduction

Current scenario has intensely witnessed the progressing restructuring of electric utilities mainly driven by rapid regulatory environments and market demands. In such situation, unpredictable events may occur if adequate precaution procedures are not properly outlined when power system network is subjected to disturbance. The emergence of various analytical approaches in voltage security assessment enabled the power system operator to analyze, perform status prediction led the power system experiencing changes in dramatic manner in the sense of fast analysis, status prediction and proper remedial action can be arranged as a result of the disturbances. Disturbance caused by line outage is known to be one of the contributing factors in power system instability problem. This has led to various analysis concerning line outage contingencies; in the sense of screening, selection and filtering in order to determine the possible credible contingencies. The incidents could lead to system instability and voltage collapse in the whole system. Most discussions in past researches reported that computation burden faced in performing contingency analysis can be alleviated by employing contingency selection, screening, filtering and ranking. Since most line outages occurrences in power transmission system are merely unpredictable, therefore prediction of post-outage severity is needed in order to know the status of system stability condition. Artificial Neural Network (ANN) has been widely exploited in solving contingency problem. The work carried out by Wan *et al.* [1] indicated that ANN is feasible to solve contingency problems for predicting the occurrence of voltage collapse. The solution of ANN can also be utilised to handle the non-linear relationship between the reactive support index (RSI) and voltage stability margin to be used for on-line voltage stability contingency selection [2]. ANN can be employed in its stand alone form or combinatorial form such as cascaded and/or hybrid network as can be seen through the work conducted by Lo *et al.* [3], Srivastava *et al.* [4] and Singh *et al.* [5]. Other AI technique implemented for contingency ranking was the fuzzy-set contingency ranking technique as reported by Hau *et al.* [6]. Other type of ANN technique namely the radial basis function network in the ANN hierarchy was also utilised for analysing contingencies in bulk power system, which has indicated the flexibility of AI technique [7]. In this work, non-linear mapping capabilities in radial basis function was exploited for estimating line loading and bus voltage as a consequence of contingency. ANN technique was employed for dynamic security contingency screening and ranking indicating that ANN application is very broad [8]. In this work, a large power system network employing ANN technique in performing the contingency screening and ranking was able to produce the energy margin calculation module.

This paper proposes a new algorithm for automatic line outage contingency analysis and ranking technique in power security assessment. This has speeded up the contingency analysis and ranking process since all algorithms were conducted automatically. The algorithm was utilised to generate the training and testing data for an ANN for the prediction of post-outage severity index. The input patterns for the ANN were generated from the pre-outage load flow analysis using the Newton-Raphson load flow program cascoded with line outage indicator while the targeted outputs are the line outage severity index obtained from the post-outage contingency analysis noted as *FVSI* [9]. The proposed technique has been tested on the IEEE 24-bus and results show that the proposed technique is able to predict line outage severity from a set of unseen data set within several pre-determined loading conditions.

Research Methodology

The research procedures cover the data preparation, development of the ANN, training process and testing process. Subsequently, a post-processing is also performed in order to assess the accuracy or the perfection of the developed network. The procedures involved the following steps:-

i. Implementation of pre-outage load flow analysis.
ii. Development of automatic line outage contingency analysis and ranking algorithm.
iii. Development of line outage indicator.
iv. Combination of pre-outage load flow results with the line outage indicator.
v. Implementation of automatic line outage contingency analysis and ranking at similar loading condition as in [i].
vi. Preparation of data for testing and training process.
vii. Development of ANN training programme.
viii. Development of ANN testing programme.
ix. Run training processes.
x. If solution is not converged, adjust ANN properties and repeat step[ix], otherwise go to [x]

xi. Save the developed ANN
xii. Run testing process.
xiii. Perform post-processing
xiv. If ANN is not accurate, adjust ANN properties and repeat step [ix] onwards, otherwise go to [xv]
xv. stop

The procedures are represented in the flow chart illustrated in Figure 1.

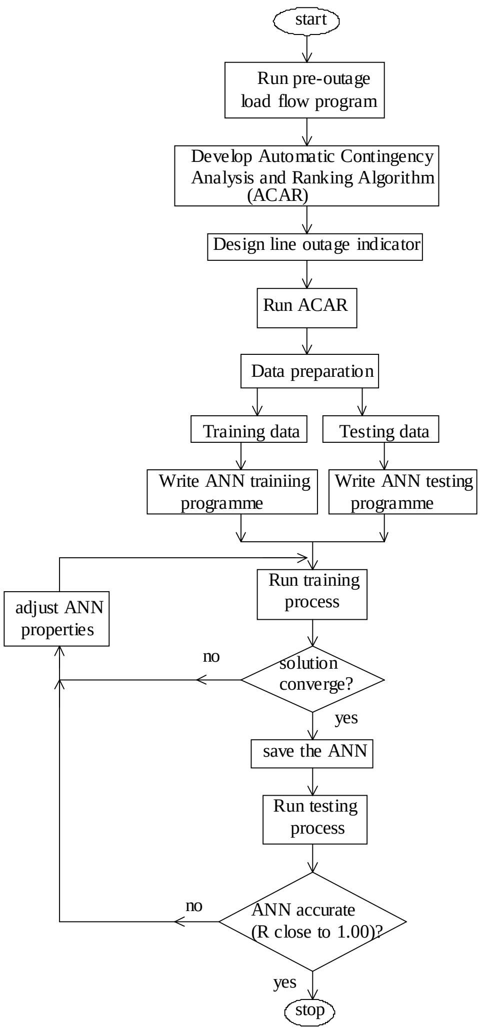

Figure 1: Flow Chart for the Research Development

Development of Automatic Contingency Analysis and Ranking

In this study, line outage contingency analysis was conducted by executing the load flow programme while removing one line at a time. The occurrence of the line outage is simulated by removing the respective line from the line data prior to executing the load flow programme. The results from the post-outage load flow were used to compute the *FVSI* values and the highest value of *FVSI* was recorded. This process was repeated for all lines in the system. The highest *FVSI* values from each line outage were sorted in descending order to rank the severity of each line outage in terms of voltage stability condition.

The proposed automatic line outage contingency analysis incorporated the line outage simulation and voltage stability analysis together. In order to identify the suitable operating loading condition for the contingency simulation, the maximum loadability at a particular load bus is first determined. For any line outage simulated which leads to non-convergence of the load flow, the proposed technique will assign an *FVSI* value of unity for the outage. This would indicate that voltage collapse has occurred in the system due to the outage. The steps of the procedures are as follows:

i. Select a load bus
ii. Set a loading condition (below Q_{max} of a load bus)
iii. Set maximum counter, λ = total line number
iv. Set a line counter ($k = 1$)
v. Read system data
vi. Remove line (k)
vii. Run Newton-Raphson load flow analysis
viii. Calculate *FVSI* values for all remaining lines, i.e.; for lines 1 to (l 1)
ix. Extract the highest *FVSI* for this outage. Outage number = (k)
x. Reinsert the removed line (k)
xi. Test counter, if $k \geq \lambda$, repeat steps e. to j for $k = k + 1$.; otherwise
xii. Sort all *FVSI* in descending order for line outage (k) for 1 to l.

The procedures are represented in flow chart shown in Figure 2.

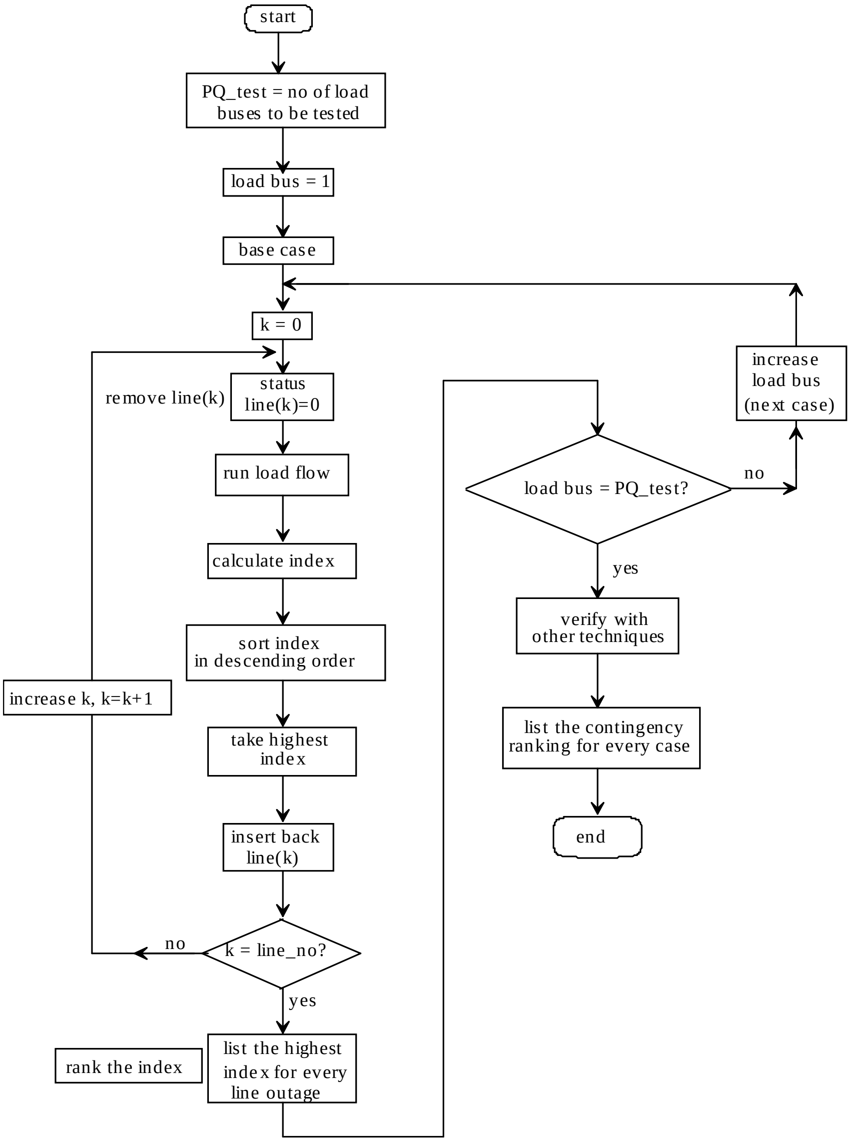

Figure 2: Flow Chart for Automatic Contingency Analysis and Ranking (ACAR)

Line Outage Severity Index

A pre-developed line-based voltage stability index termed as *FVSI* was utilised as the line outage severity indicator [9]. The mathematical formulation for *FVSI* is given by:

$$FVSI_{ij} = \frac{4{Z_{ij}}^2 Q_j}{{V_i}^2 X_{ij}} \tag{1}$$

where; Z_{ij} is magnitude of the line impedance connecting the sending bus i and the receiving bus j, X_{ij} is the line reactance, V_i is the voltage at the sending bus and Q_j is the reactive power at the receiving bus. *FVSI* value must be kept less than unity to maintain a stable system. In this study, it was assigned as the targeted output of the ANN in both the training and testing processes. Automatic contingency analysis was conducted for several loading conditions in order to generate the targeted output for the training and testing data sets.

Line Outage Indicator

Line outage indicator was introduced in order to indicate the line outage occurrence. It was found that by introducing the line outage indicator could speed up the convergence process of the ANN solution during the training phase. The line outage indicator is given by a square matrix with matrix size ($n \times n$) where n is the number of lines in the system.

Data Composition

The training and testing data are taken from the pre-outage data, which are the generated active and reactive power cascoded with the line outage indicator. The generated powers were obtained from the pre-outage ac load flow solution. When it is coupled with the line outage indicator, the number of patterns that can be generated for a particular loading condition will be appeared in the following configuration:

$$NN_{input} = \begin{bmatrix} pre-outage \;\; power \;\; data \\ line \;\; outage \;\; indicator \end{bmatrix} = \begin{bmatrix} P_{g11} \;\; P_{g12} \;\; P_{g13} \;\; P_{g14} \ldots\ldots P_{g1n} \\ Q_{g11} \; Q_{g12} \; Q_{g13} \; Q_{g14} \ldots\ldots Q_{g1n} \\ Q_{g21} \; Q_{g22} \; Q_{g23} \; Q_{g24} \ldots\ldots Q_{g2n} \\ \ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots \\ \ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots \\ Q_{gm1} \; Q_{gm2} \; Q_{gm3} \; Q_{gm4} \ldots\ldots Q_{gmn} \\ \overline{\qquad\qquad\qquad} \;\; \overline{\qquad\qquad} \\ 1 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; \ldots\ldots\ldots \;\; 0 \\ 0 \;\; 1 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; \ldots\ldots\ldots \;\; 0 \\ 0 \;\; 0 \;\; 1 \;\; 0 \;\; 0 \;\; 0 \;\; \ldots\ldots\ldots \;\; 0 \\ 0 \;\; 0 \;\; 0 \;\; 1 \;\; 0 \;\; 0 \;\; \ldots\ldots\ldots \;\; 0 \\ 0 \;\; 0 \;\; 0 \;\; 0 \;\; 1 \;\; 0 \;\; \ldots\ldots\ldots \;\; 0 \\ \ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots \\ 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; \ldots\ldots\ldots \;\; 1 \end{bmatrix} \qquad (2)$$

where:

m = no. of generator bus.

n = no. of lines.

P_{g1n} = the generated real power on the swing bus obtained from the pre-outage load flow solution.

$Q_{g11}, \; Q_{g21}, \; ..Q_{gn1}, \; Q_{gnm}$ = reactive generated power on the generators obtained from the pre-outage load flow solution.

Therefore, the general input pattern is given by:

$$P = [P_{g11} \; Q_{g11} \; Q_{g21} \; Q_{g31} \; \ldots Q_{gn1} \; L_{ijn}]^T \qquad (3)$$

L_{ijn} is the line outage indicator column for nth pattern. In this study, the IEEE 24-bus RTS was chosen as the test system, which has 11 PV buses and 38 lines. Therefore, the number of elements in a column is 50 (i.e. 11 PV buses + 1 slack bus + 38 lines). Thus making the matrix size for one loading condition in this system is (50 × 38). The exclusion of line outage indicator would cause the non-convergence of the training process since it was found that the pre-outage power data alone are not sufficient to train the ANN. The pre-outage load flow data were obtained from several loading conditions in order to allow wide coverage of input data.

The targeted outputs (*i.e.*, maximum *FVSI* value) for the ANN were obtained by performing the line outage automatic contingency analysis and ranking (ACAR) at the loading conditions similar to the pre-outage load flow. The ACAR performed on the IEEE 24-bus RTS gives 38 maximum *FVSI* values correspond to the respective line on outage for one loading condition. The matrix size for the targeted output at one loading condition is ($1 \times n$) and it is written in the following form:

$$t = [t_1\ t_2\ t_3\ t_4\ t_5 \ldots\ldots\ldots\ldots t_n] \tag{4}$$

Where; n is the number of lines in the system. Thus, the first input pattern will correspond to the first targeted output denoted by t_1. The number of hidden layers and the number of neurons in each hidden layer characterize the complexity of a neural network. There are no general rules for the selection of the number of middle layers and the number of neurons in each layer. Thus, the choice of number of neurons in the hidden layer is rather based on heuristic technique. The output layer has only one neuron with *FVSI* as the output of the respective line outage.

The ANN input given in (4) from several loading conditions are combined together to form the overall data sets or data patterns and similarly to the targeted outputs. These data patterns were grouped into two groups in order to be utilized for the training and testing processes. Conventionally, the number of training patterns is larger than the testing patterns in order to allow sufficient information to the ANN during the training process. Insufficient training patterns imply less information to the ANN, which may result in significant error during the training and testing processes.

Training Process

Training process is implemented in a computer programme written in MATLAB. This process involves data loading, data normalisation, network creation, parameters initialisation, network simulation, data denormalisation and display of results. The training process is implemented using the algorithm given in the following step-by-step procedures:

i. Load input data into the training program.
ii. Normalise the input and targeted output data within a pre-defined range.
iii. Create the network and specify the number of hidden layers, number of neurons and the suitable transfer function to suit the normalised range.
iv. Set the network parameters *i.e*. learning rate, momentum rate, maximum iteration number and training goal (accuracy).

v. Train the network.
vi. Simulate the network.
vii. Denormalise the results.
viii. If the training process converges, save the network and proceed with the testing process. Otherwise, repeat steps [iv] to [vii].

Testing Process

Testing process allows the developed network to enumerate a set of unseen data, which produces the output in the form of post-outage severity indices. A fully trained network should be able to produce outputs, which are closed to the targeted outputs. However, the developed ANN may not necessarily perform well during the testing process. A statistical regression analysis was implemented to the output of the testing process in order to evaluate the accuracy of the developed network. The correlation coefficient, R obtained from this procedure is a measure of the accuracy of the developed ANN. Unity correlation coefficient indicates zero absolute and rms errors. The training algorithm is represented by step-by-step procedures as follows:

i. Load testing data into the workspace.
ii. Normalise the testing data.
iii. Retrieve the developed network into the workspace.
iv. Set the minimum and maximum targeted outputs specified in the training process.
v. Simulate the network.
vi. Denormalise the results.
vii. Perform statistical regression analysis for network perfection evaluation.
viii. If correlation coefficient, R is closed to 1.00; display results. Otherwise, retrain and retest the network with adjusted network properties.

Results and Discussion

A new algorithm to simulate the contingency analysis and ranking automatically has been developed. With this newly developed algorithm, the computation burden and error due to human factor have been solved. Line outage simulation and voltage stability analysis are the two procedures incorporated together to perform the automatic contingency analysis and ranking by the proposed technique. Prior to the automatic contingency analysis and ranking, determination of maximum loadability has to be first conducted as proposed in [8] to identify the suitable operating loading condition margin. A constraint was considered in the algorithm by assigning *FVSI* values to unity for the non-converged load flow and *FVSI* values exceeding unity. Results obtained from the automatic contingency analysis and ranking process was assigned as the targeted output of the developed Artificial Neural Network (ANN). To establish the effectiveness of the proposed ANN, test was conducted on the IEEE 24-bus RTS. The training set discussed in the preceding section needed to be normalised in order to ensure the input data laid under the acceptable range specified in the network configuration. The achievement of the developed network can be seen from the rms error calculated using the following mathematical formulation

$$rms\ error = \sqrt{\frac{1}{P}\sum_{i=1}^{P}\left[T(i)-O(i)\right]^2} \qquad (5)$$

where P is the number of patterns, $T(i)$ is the targeted output and $O(i)$ is the actual output of ANN for the i^{th} pattern. Further evaluation of the develop network can be conducted by performing post processing using statistical technique called the regression analysis in which comparison is made between the outputs of ANN and targeted outputs. In achieving the ranking and classification processes using the proposed ANN, 239 patterns were generated by performing the pre-outage ac load flow studies with several loading conditions. The loading conditions were randomly selected at arbitrary load buses. For training process, 155 patterns were randomly selected and the remaining 84 patterns were utilised for the testing. The fully trained neural network consists of 2 hidden layers with [8,8,1] ‘logsig’,’logsig’,’purelin’ configuration. This network configuration consists of eight neurons in the first and second hidden layers, which were determined heuristically. In this study, 50 input variables and 1 output variable were accommodated. A reliable network was successfully developed with 0.7120 learning rate and 0.2700 momentum rate in order to achieve accuracy (goal) of 1×10^{-9}. The calculated rms error is 1.21 % and the maximum absolute error for the entire contingency numbers is 3.91 %. The properties of the developed network are summarised in Table 1.

Table 1: The Developed Neural Network Properties (IEEE 24-bus RTS)

Network configuration	[8,8,1]'logsig','logsig','purelin'
Learning rate	0.7120
Momentum rate	0.2700
Training technique	Levernberg-Marquardt
Epochs (iterations)	9
Training goal	10^{-9}
Correlation coefficient, R	0.988
Training patterns	155
Testing patterns	84
No of variables	50

The graphical representation is illustrated in Figure 4, which shows the neural network output and the targeted output. From the figure, it is observed that the deviations at every line outage for both outputs are very small. This implies that the developed ANN is reliable and able to predict the post-outage severity index from a set of unseen pre-outage data with high accuracy. Further evaluation on the developed network was implemented, in which a post processing or regression analysis is conducted in order to assess the perfection of the network. The results are shown in Figure 5. From the figure, it is observed that the value of the correlation coefficient, R is 0.988, which is very close to 1.00. This means that the error is very small i.e. 0.012 or 1.2 %. It is also observed that the targeted output points and NN output points are overlapped for most of the points.

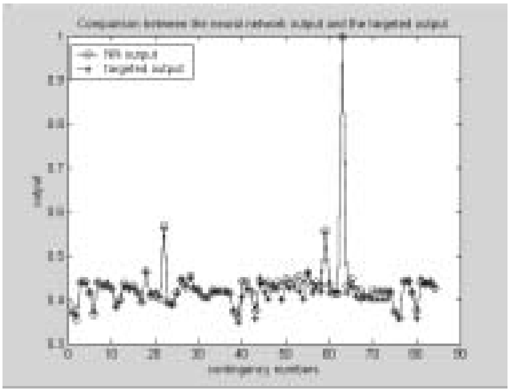

Figure 4: Difference between NN output and targeted output for IEEE 24-bus RTS during the testing process

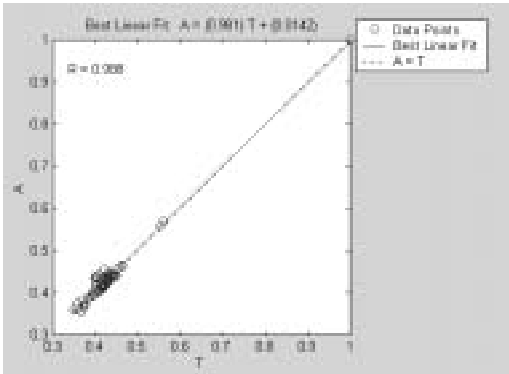

Figure 5: Post Processing Results for IEEE 24-bus RTS

Conclusion

A new automatic contingency analysis and ranking algorithm based on voltage stability condition and Artificial Neural Network (ANN) for post outage severity prediction have been presented in this paper. It incorporated the algorithm for automatic line removal, post-outage voltage stability analysis and ranking technique in a common cascading programme. The technique has successfully reduced the time taken in the contingency analysis and ranking which may cause misranking due to long computation time and human factor constraint. The developed automatic contingency analysis and ranking algorithm has been tested on the IEEE Reliability Test Systems to realise its effectiveness and has produced a remarkable improvement in automatic contingency analysis and ranking in terms of computation time. The findings from this study can easily recognise the line outage severity without having to go through a long process as implemented previously and it is viable to be implemented on-line.

Results showed that the proposed technique has its own advantage over the one appeared in the literature in references [6, 8, 9] which can only classify the contingencies into secure and non-secure, while in this method line severity can be accurately predicted ranging from 0 to 1.0. The tests conducted on the IEEE 24-bus indicated the proposed technique is reliable and can be used by the power system operators in Energy Management System (EMS).

Future Work

The work in this research can be further explored towards the line outage classification for the post-outage severity results. The essence of expert system or fuzzy logic could be recommended to enhance the scope and capability of the technique. Since ANN technique has known to be heuristic in nature, therefore the application of any optimisation technique in determining the optimal weights, ANN configuration and number of neurons towards minimising the rms error might be an advantage to reduce the computation time and avoidance of heuristic or uncertainty of the technique. Evolutionary Programming based optimisation technique would be a good choice for this purpose.

References

[1] Wan, H. B. and Ekwue, A. O. 2000. Artificial Neural Network Based Contingency Ranking Method for Voltage Collapse, *International Journal of Electrical Power and Energy Systems*, vol. 22, pp. 349-354.

[2] Zhang, Y. and Zhou, Z. 2002. Online Voltage Stability Contingency Selection Using Improved RSI Method Based on ANN Solution, *Proc. IEEE Power Engineering Society Meeting*, vol. 2, pp. 888-892.

[3] Lo, K. L., Peng, L. J, Macquen, J. F., Ekwue, A. O. and Cheng, D. T. Y. Fast Real Contingency Ranking Using a Counterpropagation Network, *IEEE Trans. On Power and Energy Systems*, vol. 13, no. 4, pp. 1259-1264.

[4] Srivastava, L., Singh, S. N. and Sharma, J. 2000. A Hybrid Neural Network Model for Fast Voltage Contingency Screening and Ranking, *International Journal of Electrical Power and Energy Systems*, vol. 22, pp. 35-42.

[5] Singh, S. N., Srivastava, L. and Sharma, J. 2000. Fast Voltage Contingency Screening and Ranking Using Cascade Neural Network, *International Journal of Electrical Power and Energy Systems*, vol. 22, pp. 197-205.

[6] Hau, Y. Y. and Kuo, H. C. 1992. Fuzzy-Set Based Contingency Ranking, *IEEE Transaction on Power Systems*, vol. 7, no. 3, pp. 1189-1196.

[7] Refae, J. A., Mohamdes, M. and Maghrabi, H. 1999. Radial Basis Function Networks for Contingency Analysis of Bulk Power System, *IEEE Trans. On Power and Energy Systems*, vol. 14, no. 2, pp. 772-778.

[8] Mansour, Y., Vaahedi, E. and El_Sharkawi, M. A. 2000. Dynamic Security Contingency Screening and Ranking Using Neural Networks, *IEEE Transaction on Neural Networks*, vol. 8, no. 4, pp. 942-947.

[9] Musirin, I. and Rahman, T. K. A. 2002. Estimating Maximum Loadability for Weak Bus Identification Using FVSI, *IEEE Power Engineering Review,* vol. 22, pp. 50-52.

[10] Lo, K. L., Peng, T., Maqueen, A. O., Ekwue, A. O. and Cheng, D. T. Y. 1995. Application of Kohonen Self-Organising Neural Network to Static Security Assessment, *Proc. IEEE Artificial Neural Network Conference*, pp. 387-392.

[11] Repo, S. 2001. On-Line Voltage Stability Assessment of Power System – An Approach of Black-Box Modelling, Ph.D. dissertation, Tampere University of Technology, Finland, 2001.