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Probabilistic Neural Network Based Transient Security Assessment of Power Systems

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Abstract: Transient security assessment is a significant part of power systems operation. In particular, on-line assessment is a present necessitate in large power systems. In this paper, a feasible method for transient security assessment of power systems using Probabilistic Neural Network (PNN) based classifier has been presented. A PNN is a feed forward neural network often used in various classification problems. PNNs are much faster, accurate and relatively insensitive to outliers and hence generate accurate predicted target probability scores. The PNN technique provides better performance with large data set. The data collected from the time domain simulations are then used as inputs to the PNN. This classifier has the capacity to adapt to different network configurations, becoming independent of the power system model. Genetic algorithm (GA) based Feature Selection Technique is then integrated to lessen the number of features to the PNN based classifier to conclude whether the proposed power system is secure or insecure. The prospective of the proposed technique is verified using an IEEE 30 - bus system. The results acquired from the simulation reveals that the PNN based classifier provides practically higher classification accuracy and a reduced amount of misclassification rate. Furthermore, PNN with the incorporation of GA based feature reduction technique, takes less time to train the PNN with increase in accuracy of the classification results.

Key words: Artificial neural networks · Genetic Algorithm based Feature Selection · Probabilistic Neural Network · and Transient Security Evaluation

INTRODUCTION

The modern power system is a complex one, consisting of a large number of units of energy production, interconnected by a transmission and distribution network. Over ninety percent of the time, it is found that the system is operating in its normal state, i.e., all loads are met, frequency is constant, voltage magnitudes are within prescribed limits and no component is overloaded. However, inevitable disturbances may affect production as well as transmission systems, deteriorating the electric power quality delivered to the customers. Thus, there exists a pressing need to develop an on-line security monitoring system, which helps the operating engineer to detect conditions which may lead to possible failures or deteriorations of the quality of the power supply, before they actually occur [1, 2].

With the expansion of power systems and complexity existing in power systems, transient security assessment of large sized power systems has become extremely complex. The complexities arises from the numerous nonlinear equations that have to be determined for every disturbance leading to deferred conclusions in offering the essential control measures for controlling the system under secure level. Hence, there exists an urgent requirement to design a trustworthy and quick online Transient Security Assessment (TSA) classifier to predict the status of a power system when subjected to all possible unforeseen events [3, 4].

At present, computational intelligence (CI) techniques for solving TSA problems have attained more interest in the midst of researchers because of their capability to perform parallel data processing, high precision and quick response [5]. In past days, ANN technique based on multi layer perceptron neural network

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has been used for solving TSA problems [6]. With multi layer perceptron neural network, the time taken for training the network gets worsens with large power systems. Other ANN methods that have been used are radial basis function neural network [7] and fuzzy ARTMAP architecture [8].

In this research work, a Probabilistic Neural Network (PNN) [9] based classifier for evaluating transient security state of a large sized and practical power system has been presented. PNN has been adopted to overcome the weaknesses of the other ANN methods in terms of its accuracy and training time. Genetic Algorithm based feature selection method has been incorporated for solving TSA [10] problem in order to enhance the overall performance of the PNN based classifier. To prove the effectiveness of the proposed PNN based classifier, it has been implemented on a standard IEEE 30 bus system.

Transient Security Assessment: In power system, Security assessment is a most important concern in design, operation and control of electric power systems[10]. Security assessment is the analysis performed to determine whether, and to what extent, the system is reasonably safe from serious interference to its operation [11]. It includes three types static, transient and dynamic. The conventional method used in static security analysis engages AC load flow equations for each unforeseen event. This is highly inadequate and time consuming for real time applications.

Certain severe faults occur in the power system that may cause the system to go to an undesirable emergency state. If the system is said to be insecure, take immediate control action must be taken to retain the power system in normal operating state.

Transient security analysis estimates the performance of the power system after a disturbance. Analysis of power system rotor angle stability is an important part in TSA. This has made the security evaluation more important and demands the investigation of fast and reliable techniques to allow on-line transient security assessment. Transient security is the ability of a power system to operate consistently within the limits imposed by the stability phenomena. A set of most probable contingencies needs to be first specified for security evaluation. This set may include single line outage, generator outage, sudden increase in load or a three phase fault in the system [12].

In this paper, the power system operating condition is evaluated by increasing or decreasing the load and checking the limits of voltages and the line flows. If they are within limits, the system said to be steady state secure, otherwise insecure. Steady state secure condition is then checked for transient security condition by introducing three phase fault at an all buses and removing transmission line from corresponding faulted bus one at a time and absorbing oscillations of rotor angle using Time Domain Simulation (TDS). If the relative rotor angle of generators with respect slack generator does not exceed 180 electrical degree following fault clearing, the system status is categorized as Transient secure (1). Otherwise, the power system status is categorized as transient insecure (0). Repeated simulation is carried out and the system status is observed.

Data Generation: In general, the variables of all the power system would be collected together as an input data set, but the classification will become difficult with large set for a large power system. Hence, some general variables, independent of the size of the power system are preferred for TSA. The post fault states of the system characterizes the stability status of a power system, hence the post fault variables provide the obvious choice as input variables for TSA [13]. Initially, a vast number of load flow simulations for a variety of power systems operating conditions are carried out. A group of post-fault variables are selected as input data, based on experience and expert knowledge. The collected data set have been normalized between 0 and 1 before presented to the PNN classifier. These generated data samples are then randomly split into training data set and testing data set.

Classifier Design (PNN): Probabilistic Neural Network (PNN) is a neural network with multi layer utilized for pattern classification problems. The PNN is a non-linear, nonparametric pattern recognition algorithm based on probability density function of the train set optimized kernel width parameter [14, 15]. The PNN has four layers namely input, pattern, summation and output layers as shown in Figure 1. The input layer consists of distribution units that offer analogues values to the complete pattern layer. RBF has been utilized as the activation function in the pattern layer for the proposed TSA. The pattern layer of the PNN is given in Figure 1.

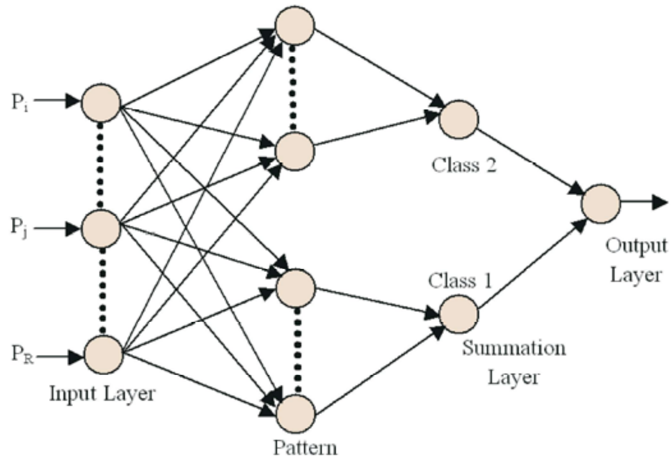

Fig. 1: Pattern layer of the PNN

The output a is given by,

$$a= radbas\ (\|IW_{1.1} - p\|b) \quad (1)$$

where *radbas* is the radial basis activation function in general form radial basis activation function is expressed as

$$radbas\ (n) = e^{n^2} \quad (2)$$

The orthogonal least squares method is used for training the RBF which offers methodical move towards the selection of RBF centers [16]. The summation layer sums the inputs from the pattern layer which correspond to the category from which the training patterns are classified as class 1 or class 2. The classification decisions are produced by the output layer of the PNN, which is a binary. For this proposed TSA problem, the classification is 1 for secure cases or class 0 for insecure cases.

The PNN execution procedures are given as follows [17]:

- For PNN input data, the training data are normalized and given as input.
- The training data are passed through the pattern layer and then the Euclidean distances of the training data are calculated.
- The calculated Euclidean distances of each element are multiplied with the bias and provided as input to the RBF. The RBF is trained with orthogonal least squares method to provide a systematic approach to the selection of RBF centers.
- Train the network in the pattern layer by setting each pattern in the training data equals to the weight vector in one of the pattern neurons and connecting its output to the appropriate summation neurons.
- At the summation layer, by referring to the desired output of the training data, the calculated RBF centers are separated between class 1 and class 0. The number of neurons in the summation layer is equal to the number of classes. Each neuron in the summation layer corresponds to the calculation of an estimate of probability density for class 1 and 2. The output of the summation neurons as written as follows:

$$S_k(x) = \sum_{i=1}^{n_k} \phi_i(\| x - c_{ki} \|^2) \quad (3)$$

where

$$\phi_i(\| x - c_{ki} \|^2) = \exp\left(-\frac{\| x - c_{ki} \|^2}{\sigma_i^2} \right) \quad (4)$$

S_k, the output of summation neuron, k =1,2, ... , N. N is the total number of neurons in the summation layer; x, input data; C_{ki}, ith hidden RBF center vector for the kth pattern class of the pattern layer; nk, number of the hidden center vector for the kth pattern class of the pattern layer. $\|\cdot\|$ is Euclidean distance. $\phi_i(\cdot)$, RBF activation function is σi, smoothing factor.

- The output layer is the decision layer used for implementing the decision rule by selecting the maximum posteriori probability of each class from the outputs preceding the summation layer. The output layer neuron decides the classification of the training data by using the following classification criterion,

$$d(x) = C_j, \text{ if } S_j(x) > S_l(x) \text{ and } j \neq l \qquad (5)$$

where $d(x)$ is decision of the output layer, Sj(x) and $S_l(x)$ is summation neurons for class j and class l; C_j is class j.

- Testing of the trained PNN by using the testing data to classify the test system according to class 1 (secure) or class 0 (insecure).

Implementation of Classifier in Tsa: Modern power systems are often huge, complex and highly unpredictable in the context of restructuring and increasing penetration of renewable energy. This makes the off-line generated knowledge base insufficient for accurate real-time complex classification problems. PNN technique can carry out learning at a very high rate. Based on it a PNN based TSA classifier model has been presented in this paper.

An initial data set is generated off-line from the past TSA records and off-line illustration simulations, and then significant features as input for training are selected using suitable feature selection process. The selected important feature data set not only enhances the accuracy of PNN classifier but also provides sufficient information regarding the critical system parameters.

During training stage, PNNs are trained by means of selected features with possible contingencies and this process is completed quickly. For real-time TSA, PNN-based model developed the system dataset as input and predicts the TSA results within a very short duration of time. From the TSA status, if insecure status is predicted, preventive control measures are initiated to preserve system security.

Feature Reduction Technique: For PNN, the selected numbers of input features depend on the size of power systems under consideration. Larger the size of power system, the larger will be the number of input features. Nevertheless, with all the initially selected features, some features are not needed and they do not contribute for the discrimination among the features. Hence, feature reduction technique is required to decrease and optimize the initial input feature set. In this work, Genetic algorithm based feature reduction technique has been proposed.

The Genetic algorithm is a search and optimization algorithm derived from the ideologies of natural evolution. For large data classification, Genetic Algorithm has been established to be an effective means. Even though the solutions might not always be the global optimum, GA naturally makes out a good solution in a realistic period of time. Owing to its effortlessness of applicability, GA applications are established in various disciplinary. This paper employs GA based feature selection for transient security assessment of an IEEE 30 bus system, which has enormous number of input features and logical estimation measures are not as much of effective due to large numbers of variables that are influenced in each iteration stage. In GA, at every generation, the process of choosing variables in proportion to their fitness generates new sets of approximations, which then breed together. This process leads to better selection of input features that suits the power system environment. This work uses the benefits of GA in obtaining the optimal solution that is an optimal feature subset [18].

The following section shows the steps of GA feature subset selection [19].

- For any optimization problem, GA requires an initial population for the solution. Randomly generate the initial population and assume the probability of crossover, probability of mutation, maximum number of generations.
- Evaluate the initial population using the fitness function.
- Selection and generation of the offspring. The objective of this step is to find the optimal chromosome to minimize the fitness value. Roulette wheel method is used to select good chromosomes for the next generation.
- Alteration: Alteration contains both crossover and mutation. As per the crossover rate, pick two chromosomes for one-position crossover. Depending on the fitness values among the offspring prior to and past crossover, the superior chromosomes will be reserved. The mutation provides a possibility to evade ending up in a local optimum solutions.
- An iterative procedure to find the optimal feature subset. The maximum number of generations is the stopping criteria. Else step 2 to step 5 are repeated till the stopping criteria is reached.

For this transient security assessment problem, the feature extraction based on GA has been performed with the following assumptions. In GA approach, a large population size acquires a larger computational cost, while smaller population sizes generate insufficient computational accurateness. An optimal population size of around 150–250 is a fine balance among the computational necessity and accuracy. Hence in this case, the population size has been selected as 200. The probability of crossover is 0.8, probability of mutation is 0.1 and the maximum number of generation is 100. The number of variables in this TSA problem is 329. Each of the 200 chromosomes has 329 genes. The initial population for GA is generated randomly and evaluated using a fitness function. The fitness value for each initial population chromosome is computed using KNN-based classification error [20]. The process of selecting variables according to their fitness creates new sets of approximations, which leads to better individuals that suit the environment resulting in optimal feature set. Using the GA, 16 variables are selected from the 329 original variables.

Performance Evaluation of Classifier: The performance of a classifier is judged by evaluating the subsequent parameters for test data, training data and overall data set [21].

Classification Accuracy (CA):

$$\text{CA (\%)} = \frac{\text{Number of samples classified correctly}}{\text{Total number of samples in data set}} \text{x}100 \qquad (6)$$

False Dismissal (FD):

$$\text{FD (\%)} = \frac{\text{Number of insecure classes classified as secure}}{\text{Total number of insecure classes}} \text{ X}100 \qquad (7)$$

False Alarm (FA):

$$\text{FA (\%)} = \frac{\text{Number of secure classes classified as insecure}}{\text{Total number of secure classes}} \text{X}100 \qquad (8)$$

In power system security evaluation, the false alarms are not much harmful. In case of false dismissals, failure of control events may lead to a rigorous blackout. It is, for that reason, essential to make certain that false dismissals are kept at minimum. The classifier must be professionally planned to satisfy this condition.

RESULTS AND DISCUSSION

Initially, load flow analysis is carried out by rising and lessening the values of generation and load among 130% to 70% of base value. From the simulation data, steady state security analysis is conducted and the system is classified as steady state secure or steady state insecure. Then steady state secure states are subjected to transient security analysis by introducing three phase fault at each bus and removing line from the faulted bus.

Table 1: Steady state operating scenario

Number of Operating Scenarios	1302
Static secure	1111
Static insecure	191

Table 2: Generation of data set and features for transient security assessment

Total number of Operating Scenarios	2160
Total numbers of training data (80%)	1728
Total numbers of testing data (20%)	432
Transient Secure	1754
Transient insecure	406
Total number of input variables	329
Features selected after feature selection process	16

The proposed PNN based classifier is used in a standard IEEE 30 bus test system for transient security assessment [22, 23]. The load flow simulation is performed by using Newton Raphson method for increased and decreased base values of generation and load. It has been found from the simulation that total data set has 1302 states, among the total data set, 1111 states are secure and 191 states are insecure. For transient security analysis, the 191 insecure states are left out and the remaining 1111 steady state secure states are considered for transient analysis and three phase fault is simulated at all buses. Table 1 shows the results of Steady state operating scenario.

Three phase fault has been initiated in all buses one at a time and transmission line to be removed from faulted bus. The three phase fault is initiated at time t=0 seconds and cleared at time t=0.25 seconds. Table 2 shows the results of data generation obtained by off-line simulation and GA based feature selection of the pattern recognition system for the proposed test case.

For transient security assessment, a total of 2160 operating scenarios have been considered. From this, 80% of the 2160 operating scenarios (i.e.) 1728 operating scenarios have been used as training data and remaining 432 operating scenarios have been used as test data. The feature chosen by the GA feature selection method shown in Table 2 are quite less and is obvious from the figure of Dimensionality Reduction. The list of optimal features selected serves as an input database for the design of classifier function.

Table 2 shows the reduced set of features before and after implementation of GA feature selection method. The PNN based classifier is trained and tested with features obtained before and after feature extraction and the performance of the classifier is evaluated. Table 3 shows the GA parameters used for the proposed TSA problem.

Table 3: GA parameters

Population size	200
Genome length	329
Population type	Bit strings
Fitness Function	kNN-Based Classification Error
Number of generations	300
Crossover	Arithmetic Crossover
Crossover Probability	0.8
Mutation	Uniform Mutation
Mutation Probability	0.1

Table 4: Selected features of IEEE30 bus system

1	Voltage of bus 10
2	Voltage angle at bus 26
3	Real power demand at bus 3
4	Reactive power of generator at bus 2
5	Real power flow in transmission line 10
6	Real power flow in transmission line 4
7	Real power flow in transmission line 2
8	Real power flow in transmission line 5
9	Real power flow in transmission line 13
10	Reactive power flow in transmission line 7
11	Real power loss in transmission line 27
12	Reactive power loss in transmission line 11
13	Reactive power loss in transmission line 19
14	Relative rotor angle of generator 3
15	Relative rotor angle of generator 5
16	Electrical power output of generator 2

Table 5: Transient security classification results for IEEE 14 bus system

	Without feature selection		With feature selection	
Performance Evaluation	Training	Testing	Training	Testing
Classification accuracy (CA)%	100	81.33	100	96.2
False Dismissal (FD)%	0	0	0	0
False Alarm (FA)%	0	18.77	0	3.8

It shows that there were 329 features before feature extraction and the number of features has been reduced to 16 after feature selection. The selected features are tabulated as shown in Table 4

Table 5 shows the performance evaluation of proposed PNN classifier. It has been observed that the PNN classifier provides better results in terms of classification accuracy and false alarm. The false dismissals are treacherous and will lead to a rigorous blackout. Hence, the classifier should make certain that false dismissals are kept at minimum. In Table 5, it has been observed that the false dismissals are zero with the proposed technique and false alarms are also minimum which proves the robustness of the PNN classifier.

CONCLUSION

In this paper, Transient Security Assessment for large power system by means of probabilistic neural network has been presented. The Transient Security Assessment of the test system by PNN is done by means of classifying the system into either secure or insecure states in the test system. The PNN based classifier is examined using a standard IEEE 30 bus test system. Transient security analysis has been done by initiating three phase faults at all buses and by removing transmission line corresponding to the faulted bus. An additional significant feature is that the proposed technique can rapidly assess the transient security status levels for diverse fault clearing time and load levels of the system. Results demonstrate that the number of input features and data influence the time taken to train the PNN for both with and without reduced input features. GA based feature selection technique adopted in this work successfully decreases the number of input feature set. The proposed technique has better classification in terms of accuracy, speed and less misclassification rate.

REFERENCES

1. Kundur, P., 1993. Power System Stability and Control, McGraw-Hill.
2. Rahimi, F.A., M.G. Lauby, J.N. Wrubel and K.L. Lee, 1993. Evaluation of the transient energy function method for on-line dynamic security analysis,IEEE Transactions on Power Systems, 8(2): 497-507.
3. Balu, N., T. Bertram, A. Bose, V. Brandwajn, G. Cauley, D. Curtice, A. Fouad, L. Fink, M.G. Lauby, B.F. Wollenberg and J.N. Wrubel, 1992. On-line power system security analysis, Proceedings of the IEEE., 80(2): 262-82.
4. Stott, B., O. Alsac and A.J. Monticelli, 1987. Security analysis and optimization, IEEE Proceeding, 75(12): 1623-1644.
5. Wang, X., S. Wu, Q. Li and X. Wang, 2005. V-SVM for transient stability assessment in power systems, Proceedings of Autonomous Decentralized Systems, pp: 356-363.
6. Niazi, K.R., C.M. Arora and S.L. Surana, 2004. Power system security evaluation using ANN: Feature Selection using Divergence, Electric Power Systems Research, 69(2-3): 161-167.
7. Bettiol, A.L., A. Souza, J.L. Todesco and J.R. Tesch, 2003. Estimation of critical clearing times using neural networks, In Power Tech Conference Proceedings, IEEE Bologna, 3(6): 635-647.

8. Silveira, M.C.G., A.D.P. Lotufo and C.R. Minussi, 2003. Transient stability analysis of electrical power systems using a neural network based on fuzzy ARTMAP, IEEE Power Tech Conference Proceedings, 3: 223-245.
9. Abdul Wahab, N.I., A. Mohamed and A. Hussain, 2007. Transient stability assessment of a power system using PNN and LS-SVM methods, Journal of Applied Sciences, 7(21): 3208-3216.
10. Sivanandam, S.N. and S.N. Deepa, 2008. Introduction to Genetic Algorithms Springer-Verlag , Berlin, Heidelberg.
11. Shahidehpour, M., 2003. Communication and Control in Electric Power Systems. Wiley Interscience, John Wiley and Sons, Publication.
12. Pang, C.K., A.J. Kovio, H. Ahmed and El. Abiad, 1973. Application of Pattern Recognition to Steady State Security Evaluation in a Power System, IEEE Transactions on Systems, Mans and Cybernetics, 3(6): 622-631.
13. Se-Young, O.H., 1986. Pattern Recognition and Associative Memory Approach to Power System Security Assessment, IEEE Transactions on Systems, Mans & Cybernetics, 16(1): 62-72.
14. Haykin Simon, 1998. Neural Networks-A Comprehensive Foundation, Prentice Hall, Second Edition.
15. Burrascano, P., 1991. Learning vector quantization for the probabilistic neural network, IEEE Transactions on Neural Networks, 2(4): 458-461.
16. Chen, S., C.F. Cowan and P.M. Grant, 1991. Orthogonal least squares learning algorithm for radial basis function networks, IEEE Transactions on Neural Networks, 2(2): 302-309.
17. Abdul Wahab, N., A. Mohamed and A. Hussain, 2002. Fast Transient Stability Assessment of large power system using Probabilistic Neural Network with feature reduction techniques, Expert system with Applications, 22(4): 295-302.
18. Wang, Y.Z., 2002. An application of genetic algorithm methods for teacher assignment problems, Expert Systems with Applications, 22(4): 295-302.
19. Lee, Y. and C. Hung Wei, 2010. A Computerized Feature Selection Method Using Genetic Algorithms to Forecast Freeway Accident Duration Times, Computer-Aided Civil and Infrastructure Engineering, 25: 132-148.
20. Oluleye, B., A. Leisa, L. Jinsong and D. Deen, 2014. A Genetic Algorithm-Based Feature Selection, International Journal of Electronics Communication and Computer Engineering, 5(4): 889-905.
21. Kalyani, S. and K.S. Swarup, 2009. Study of Neural Network Models for Static Assessment in Power Systems, International Journal of Research and Reviews in Applied Sciences, 1(2): 104-117.
22. Pai, M.A., 1989. Survey of Practical Direct Methods of Stability Analysis in Power Systems, Electric Machines and Power Systems.
23. http://www.ee.washington.edu/research/pstca/ (Power System Test Case Archive).