A Comparison between ANN Based Methods of Critical Clearing Time Estimation

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Abstract

This paper presents a methodology based on Artificial Neural Network (ANN) structures for the dynamic security assessment (DSA) of power systems. Proposed methodology involves, ANN approach for fast and accurate estimation of critical clearing time (CCT) values of credible faults occurring in the system, considering changes in the loading conditions and system topology. CCT is an important indicator that measures the transient stability of the system against critical contingencies. Offline trained ANNs can monitor online DSA without suffering from excessive computational burden of time domain simulations (TDS). Decision Trees are used as a feature selection tool to reduce the training time and ANN complexity, increasing the CCT estimation performance of the ANN applications studied in this work, Multi-Layer Perceptron, Radial Basis Neural Network, Generalized Regression Neural Network and Adaptive Neuro-Fuzzy Inference Systems. The proposed approach is applied to 16 generator-68 bus test system operating at various loading conditions and system topologies.

1. Introduction

Economic considerations and continuously increasing demand on electricity force electric power systems to operate near their security limits. The system can lose synchronism and move to an unstable operating point after the occurrence of large disturbances if no control action is taken. Therefore, dynamic security assessment (DSA) earns more importance and becomes a mandatory task for power systems to maintain reliable and continuous operation under critical contingencies.

Critical clearing time (CCT) is one of the important indicators that measure the transient stability margin of the system against critical contingencies. CCT can be defined as the longest clearing time which can be allowed before the generators lose synchronism [1]. There are various approaches for the calculation of CCT. A common method based on time domain simulations (TDS) offers the accurate solution but requires substantially high computational effort [2]. Direct methods based on transient energy functions and equal area criteria, reduces the computational effort under a level of assumptions which also prevent the complexity and reduce the applicability for real power systems [3, 4]. Therefore, CCT based DSA methodology requires faster methods which also provide high level of accuracy. As a pattern recognition method, Artificial Neural Networks (ANNs) show promising results in estimating the CCT values and can be considered as an alternative to traditional methods [5-7]. In this study, CCT estimation performance of various ANN structures such as Multi-Layer Perceptron (MLP), Radial Basis Neural Network (RBNN), General Regression Neural Network (GRNN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are investigated [8-10].

The knowledge base (KB) created for the training of ANNs involves various measurements (features) taken from several elements of the power system. When dealing with large scale power systems, the number of features in the KB increases dramatically. Therefore, feature selection methods are required to identify sufficient number of features to represent the valuable information in the KB [11]. Since the number of features for the input pattern of ANN is reduced by feature selection process, the required training time and complexity of ANN structure also reduced and performance of ANN on mapping the target output increases. In this study, decision trees (DTs) are used a feature selection method to increase the CCT estimation performance of various ANNs.

Although, ANNs can calculate CCT values very fast for online DSA applications, this approach requires a sufficient amount of training data to make an accurate calculation for each critical contingency. The time required for the offline training process increases with the size of the power system. During this process, the system topology and loading level can change. Therefore, ANN based DSA application must cover these changes. In this study, the proposed methodology also considers various loading conditions and system topologies of the power system to increase the applicability of the approach. The proposed approach is applied to 16 generator-68 bus test system and the results are investigated.

2. Methodology

2.1. CCT Estimation by ANNs

For DSA of power systems, pattern recognition is a common technique to imitate the dynamic behavior of the system without suffering from complexity and computational burden. This study presents various ANN based pattern recognition techniques for estimating CCT which is a reliable indicator to measure the transient stability margin of the system against critical contingencies. The number of CCT values for each operating point of the system is equal to the number of critical contingencies. ANN based DSA can be performed using one of the two possible approaches, either estimation of each CCT values by separate ANN structures or estimation of minimum CCT value for all contingencies by one ANN structure. When separate ANN structures are used, high estimation accuracy can be achieved even if ANN structures are simple such as using a small input pattern consisting of just a few significant features related with a particular contingency. The main drawback of this approach is the increasing number of ANN structures to be trained with the size of the power system and the number of contingencies. When a single ANN structure is used, the structure becomes more complex in case the accuracy is to be to improved, therefore the required training and execution time increases. In this study, CCT estimation performance and applicability of single ANN structures are investigated by covering all contingencies, topologies and loading conditions. The methodology of this study is described with a flowchart given in Fig. 1.

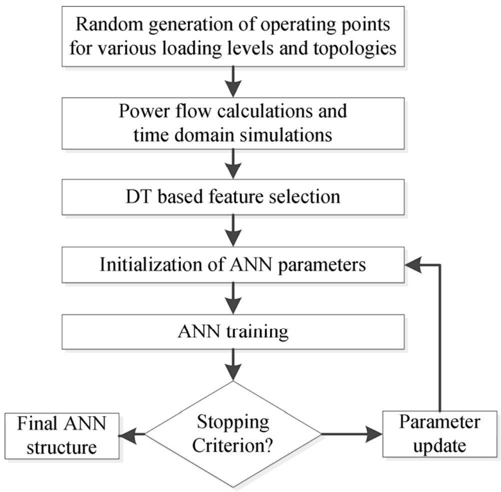

Fig. 1. Flowchart of the methodology

2.2. Creation of Knowledge Base

For the training of ANNs, we generate a KB which involves a large number of possible operating points (OPs) considering various active and reactive load values in a sufficiently wide range of loading levels. In this study, active and reactive power demands at all load buses are generated in a specified range of their initial values, by using (1). This procedure is repeated for each predefined system topology.

$$S_{L,i} = \left(P_{L,i}^{0} + jQ_{L,i}^{0}\right)\left(l + m(1-2r)\right) \tag{1}$$

where $P_{L,i}^{0}$ and $Q_{L,i}^{0}$ represent the initial value of loads at ith bus, l indicates the loading level, m is the allowed variation of loads and r is a random number generated by standard uniform distribution. For each OP, the power flow computations and DSA via time-domain simulations are performed by the software DSAToolsTM [12]. After the offline calculation procedure, KB involves OPs which are represented by features such as active and reactive power outputs of each generator, active and reactive power flows at each transmission line, magnitude and phase angle of the bus voltages, active and reactive power demands at all load buses and CCT value for each critical contingency.

2.2. Creation of Knowledge Base

The created KB involves a large number of features and using all features for the training and implementation of ANNs is not practical due to increased complexity of ANN structures and computational tasks. Therefore, feature selection process is applied for determining significant features to obtain the valuable information from the large sized KB and represent the dynamic behavior of the power system by a feature set with an acceptable size for ANNs. In this study, DTs are used for feature selection process.

Before constructing the tree structure by the DT approach, the OPs in the KB are classified into two classes, secure and insecure based on their CCT values. The number of CCT values associated with each OP is equal to the number of critical contingencies selected. When the class of each OP is detected, the minimum value of CCTs of each OP is considered.

In the following step, an orthogonal tree is developed through Classification and Regression Trees (CART) methodology [13]. All features in the KB are potential splitters for the tree structure constructed by a node splitting criterion based on improving the purity of the child nodes. For the calculation of purity, different impurity functions can be defined [14]. If the proportions of J classes in a node is given by the vector p = ($p_1, \ldots, p_J$), the entropy based impurity function $I(p)$ of that node can be defined as

$$I(p) = -\sum_{i=1}^{J} p_i \log p_i \tag{2}$$

Then, the split improvement of the split of a node, leading to a left and a right child node, is calculated as

$$\theta = I(p) - P_L I(p_L) - P_R I(p_R) \tag{3}$$

where p_L and p_R are the proportions of the classes in the left and right child nodes, respectively. P_L is the proportion of the population of left child node sent by the split and P_R = 1- P_L. For the sake of illustration, an example tree structure is given in Fig. 2, where number of classes is 2, N_M, N_L and N_R are the size of main node, left child node and right child node respectively. $N_{M,i}$, $N_{L,i}$ and $N_{R,i}$ represents the size of ith class in the main node, left child node and right child node respectively. For the calculation of variable importance, all main splitters as well as surrogates, which mimic or predict the split of the primary variable, along with the resulting improvements are listed and this list is aggregated by variable accumulating improvements [14]. Each improvement value can be scaled according to the largest value in the list.

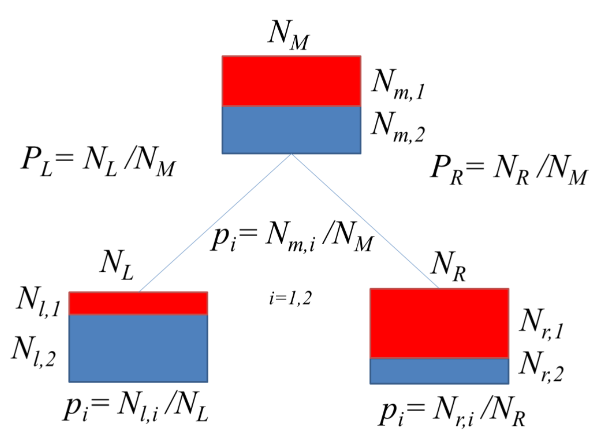

Fig. 2. Example tree structure

3. Results

3.1. Test System

The proposed methodology is applied on a 16 generator-68 bus test system given in Fig. 3. Each generator unit includes a two-axis generator model equipped with a power system stabilizer and a speed governor [15]. The critical contingencies, which are 3-phase-ground faults cleared 5 cycles after their occurrences by a single line tripping but causing transient instabilities, are listed in Table 1.

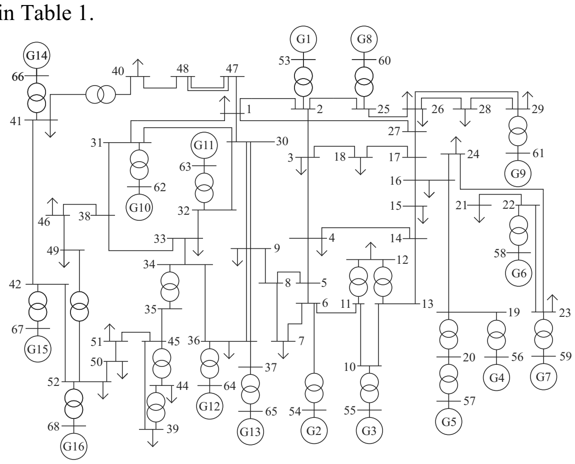

Fig. 3. 16 generator-68 bus test system

Table 1. Selected critical contingencies

Contingency no.	3 Phase Fault at Bus no.	Tripped Line (Between Buses)
1	22	22-21
2	29	29-26
3	29	29-28
4	51	51-45
5	52	52-50
6	50	50-51
7	40	40-48
8	40	40-41

While creating a KB for the training of ANNs, OPs are generated by considering 8 credible topologies of the system. Also, for each topology, the loading level is increased from %60 to %110. The disconnected generators and lines from the system in each topology are given in Table 2 where the 8th topology indicates the base case.

Table 2. Disconnected generators and lines in topologies

Topology no.	Generator Bus no.	Line (Between Busses)
1	67	-
2	61	-
3	58	-
4	-	34-36
5	-	1-27
6	-	25-26
7	58	25-26
8	-	-

The generation of OPs as described in methodology, creates initial KB involves 410 features. DT based feature selection technique ranks the features by their variable importance values which are calculated by using (2) and (3) in each node of the tree structure. Features with the 30 highest variable importance values are listed in Table 3. The variables with high scores are the values of the system elements which are topologically closer to the busses related with critical contingencies. This result confirms the success of DT on selecting the proper features for the estimation of CCTs by ANNs.

Table 3. Variable importance values of features

Feature name	Variable imp.	Feature name	Variable imp.	Feature name	Variable imp.
P_{li50_52}	100	P_{li26_28}	47,6896	Q_{li5_8}	3,1559
Q_{li39_44}	98,0208	P_{li26_27}	37,1742	V_{m1}	3,1559
P_{li50_51}	94,8973	P_{li21_22}	17,8328	V_{m9}	3,1559
Q_{li43_44}	94,7451	P_{li23_24}	15,1680	Q_{li31_62}	3,1559
V_{a68}	90,7938	Q_{g58}	10,7510	V_{m6}	2,2359
V_{m50}	87,3911	P_{li16_21}	9,5055	Q_{li23_24}	2,2359
P_{li28_29}	84,2056	P_{li22_58}	6,4765	Q_{li1_31}	2,2359
P_{g61}	82,6608	P_{g58}	6,4765	Q_{li22_58}	2,2359

3.2. Estimation of CCT

The CCT estimation performance of ANN methods significantly depends on the parameter values related with their structures. In the CCT estimation problem, experience shows that 1 hidden layer structure, Levenberg-Marquardt back propagation method and Gradient Descent learning method is the most efficient choices for MLP, and the size of the hidden layer and the input layer must be optimized for best performance. For RBNN and GRNN structures, spread values (variances) of activation functions and size of the input layer significantly affect their performances. For ANFIS structure, cluster size for the features of the data and again size of the input layer are the most important parameters.

The KB consisting of 1344 OPs and is randomly divided into two sets such as training (80%) and testing (20%). The performance of ANNs on estimating the CCT is evaluated by the calculation of mean absolute error (MAE), root mean square error (RMSE) and correlation (C) between real and estimated CCTs.

$$MAE = \frac{1}{N_t}\sum_{i=1}^{N_t}\left|y_i^* - y_i\right| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\left(y_i^* - y_i\right)^2} \tag{5}$$

$$C = \frac{\sum_{i=1}^{N_t}\left(y_i - \bar{y}_i\right)\left(y_i^* - \bar{y}_i^*\right)}{\sqrt{\sum_{i=1}^{N_t}\left(y_i - \bar{y}_i\right)^2 \sum_{i=1}^{N_t}\left(y_i^* - \bar{y}_i^*\right)^2}} \tag{6}$$

where $\bar{y}_i$ and $\bar{y}_i^*$ are the means of y and y^* which are the real and estimated CCT values respectively, and N_t is the number of samples in the test set. A Performance evaluation is done for each critical parameter of all ANN approaches and each evaluation is repeated 5 times and the averages of the results are considered to investigate the reliability of the methods and minimize the chance effect. As seen from the Fig. 4, the parameters of ANNs including the numbers of input features significantly affect their CCT estimation performances. Optimum ANN structures are determined by considering the RMSE values which are calculated by changing the critical parameters of each ANN structure. Also, the average performance evaluation of multiple attempts for the best structure of each ANN are presented in Table 4.

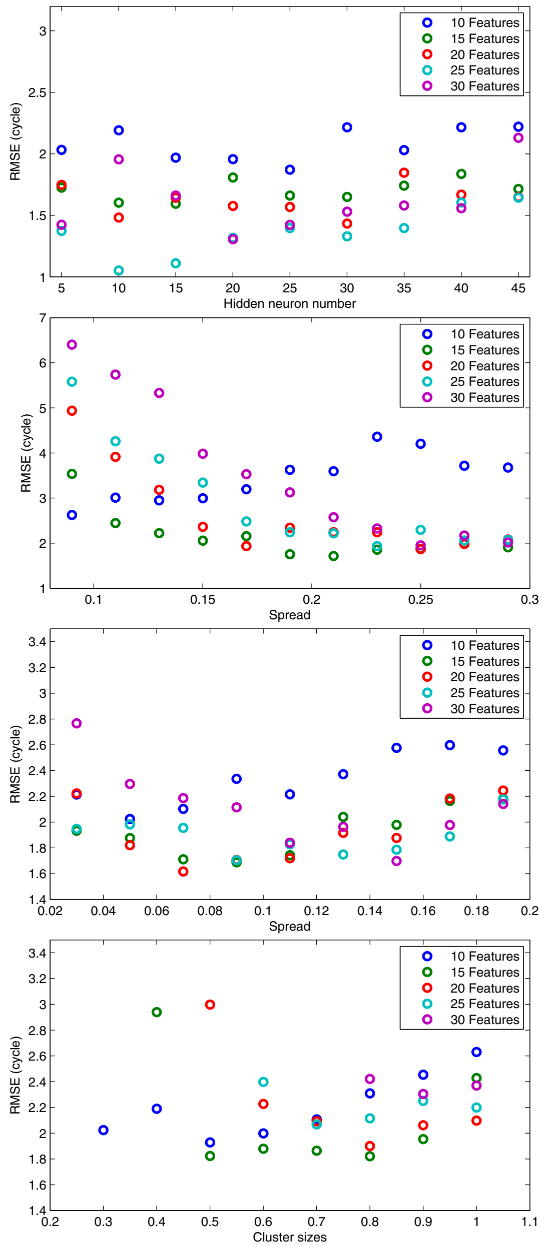

Fig. 4. Best RMSE values of each performance evaluation try for a) MLP, b) RBNN, c) GRNN, d) ANFIS

DSA methodology in this study is planned to be integrated into a security constrained optimization problem. Depending on the penalty function to be used for the optimization, CCT estimation problem can be converted into a two class (secure/insecure) classification problem by using a simple statement,

If $CCT_i > T$ cycles, sample i is secure, otherwise insecure.

where CCT_i is the minimum CCT value for ith test sample (OP) considering all the critical contingencies and T is the threshold value determined for each contingency considering the clearing time values of circuit breakers. In this study, for each contingency T is selected as 9 cycles. For each ANN we calculate the classification success which is the ratio of the number of successfully classified OPs to the number of all OPs in the test set and results are given in Table 4.

Table 4. Disconnected generators and lines in topologies

	MAE (cycle)	RMSE (cycle)	Correlation	Classification Success (%)
MLP	0.82	1.2731	0.9774	97.744
RBNN	1.2167	2.0263	0.9462	96.616
GRNN	0.8885	1.7989	0.9547	98.12
ANFIS	1.2821	2.0274	0.944	97.774

Fig. 4 and Table 4 show that MLP approach gives the most reliable result for the estimation of CCT due to low error values and high correlation. On the other hand, each ANN based approach gives promising results for classification success.

The actual CCT values calculated by TDS and the estimated CCT values by MLP are given in Fig. 5. The CCT values close to zero are mostly occurred in new topologies which are created by disconnecting generators and transmission lines from the system. Although, in Fig.5, limited number of cases with relatively high error, the overall CCT estimation performance is satisfactory.

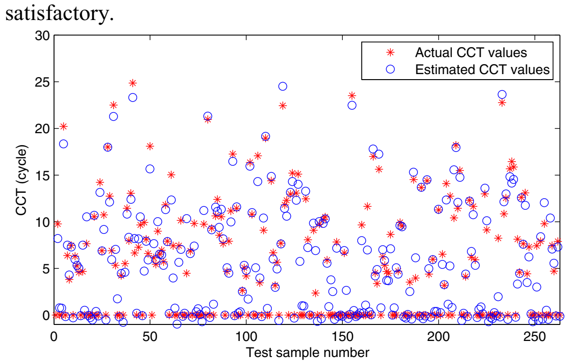

Fig. 5. Actual CCT values calculated by TDS and CCT values estimated by MLP

The computational burden for the NN based methodology can be divided into two tasks such as, execution of NN and training of MLP which includes generation of KB by time-domain and power flow computations. Table 5 gives the computational time requirements for the 16-generator test system in case of using a workstation with Intel i7 2600 CPU 3.4 GHz. TDS based CCT calculation, requires multiple simulation tries for each contingency on a single OP. Therefore, main computation requirement of the proposed method is due to the generation of KB and can be shared by multiple by computers to reduce the computation time. Since TDS based CCT calculation procedure, calculates all CCT values for one contingency and requires substantially computational effort for numerical integration, the time required for the execution of offline trained MLP for the estimation of minimum CCT value for all selected contingencies is negligible. While required execution time for TDS based method increases with the number of critical contingencies as well as the size of the system, total execution time of the MLP is not affected by the size of the system.

Table 5. Computation requirements

Execution for 1 OP		Generation of KB (TDS and power flow computation)
MLP	TDS	
0.48 sec	24 sec.	433 min.

6. Conclusions

In this paper, a methodology for the design of ANN based DSA is presented. For the proper training and execution of ANN structures, proposed DT is successfully applied as a feature selection tool to represent the dynamic behavior of the power system by a feature set with an acceptable size for ANNs. The ANN based approaches give promising results for the estimation of CCT, considering changes in the loading condition and topology of the test system. Real power systems have a large number of critical contingencies and possible topologies which can decrease the CCT estimation accuracy and also may prevent applicability of a single ANN based estimator. To deal with large scale power systems for DSA, a range of loading levels, a set of possible topologies and critical contingencies can be shared by several ANN structures and additional parameters related with the dynamic behavior of generators and faults has to be considered as new features in the future work.

7. References

[1] J. Machowski, J. Bialek, and J. R. Bumby, "Power System Dynamics and Stability", Chichester: Wiley, 1998.

[2] P. Kundur, "Power System Stability and Control", New York: McGraw-Hill, 1994.

[3] M. Pavella, and P. G. Murby, "Transient Stability of Power Systems, Theory and Practice", New Jersey: Wiley, 1994.

[4] A. A. Fouad, and V. Vittal, "Power System Transient Stability Analysis Using the Transient Energy Function Method", New Jersey: Prentice Hall, 1992.

[5] D. J. Sobajic, and Y. H. Pao, "Artificial neural-net based dynamic security assessment for electric power systems," *IEEE Trans. Power Syst.*, vol. 4, no. 1, pp. 220–228, Feb. 1989.

[6] C. A. Jensen, M. A. El-Sharkawi, and R. J. Marks II, "Power System Security Assessment Using Neural Networks: Feature Selection Using Fisher Discrimination," *IEEE Trans. Power Syst.*, vol. 16, no.4, pp. 757–763, Nov. 2001.

[7] A. Hoballah, and I. Erlich, "Transient Stability Assessment Using ANN Considering Power System Topology Changes," in *Proc. 2009 15th International Conference on Intelligent System Applications to Power Systems,* pp. 1-6.

[8] L. Wehenkel, "Automatic Learning Techniques in Power Systems", Boston: Kluwer Academic, 1998.

[9] D. F. Specht, "A general regression neural network," *IEEE Trans. on Neural Netw.*, vol. 2, no. 6, pp. 568-576, 1991.

[10] J. S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Trans. Syst. Cybern.*, vol. 23, no. 3, pp. 665–685, 1993.

[11] R. D. Reed, and R. J. Marks II, "Neural Smithing: Supervised Learning in Feedforward Artificial Neural Networks", Cambridge, MA: MIT Press, 1999.

[12] DSATools Dynamic Security Assessment Software. [Online]. Available: http://www.dsatools.com/.

[13] Salford Systems, CART. [Online]. Available: http://www.salfordsystems.com/cart.php.

[14] "CART for Windows V5.0—User's Guide," Salford Systems, San Diego, CA.

[15] G. Rogers, "Power System Oscillations", Norwell, MA: Kluwer, 2000.