Transient Stability Assessment using ANN Considering Power System Topology Changes

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***Abstract*— This paper presents an application of Artificial Neural Network (ANN) for monitoring transient stability assessment (TSA) considering system topology changes. Offline trained ANN makes use of the advance of online TSA in specifying the proper remedial action for real time power system operation to counteract the system instability. The training of ANN is executed using important selected features as inputs and critical fault clearing time (CCT) at pre-selected set of critical contingencies as desired target. CCT is considered as an indicator for system transient stability criterion. Multilayer feed forward neural network trained with back-propagation algorithm is used to provide the CCT. To demonstrate the effectiveness of the ANN in estimation of TSA considering various system topologies, the method is verified on 66-bus power system and the results are compared with time domain simulation (TDS). The simulation results indicate that the ANN provides a fast and accurate tool to evaluate online power system transient stability with acceptable accuracy.**

Keywords- power system transient stability; neural network applications; power system security

I. INTRODUCTION

Transient stability as a part of power system dynamic security aspects is having a significant importance in the power system operation with the continuing growth in system interconnection sizing and loading near to the limits leading to system blackouts. For the effective use of power system automation and control environment to safely drive the power system away from unstable operating regions, Independent System Operator (ISO) evaluates the transaction based on TSA. On the other side, Transient stability constrained optimal power flow contains a large number of variables and constraints and solved iteratively thus it consumes a lot of time. In order to reduce the computation time, TSA must be computed fast and accurately. The conventional transient stability measure of a system's robustness to withstand a large disturbance is its corresponding CCT which requires computational effort and consumes time. CCT is the maximum time duration for which the disturbance may act without the system losing its capability to recover a steady-state (i.e., stable) operation. In modeling nonlinear relationships, ANN models have recently become important alternative tool to conventional methods. The literature survey has shown that ANN is representing a feasible technique for TSA [1-3]. ANN has a specific feature of storing the knowledge in the synaptic weights of the processing elements (artificial neurons) thus ANN can be treated as a black-box with specific characteristics to achieve certain task. This feature allows ANN to deal with complex nonlinear problems such TSA [2-3]. ANN can be trained to map the power system operating conditions in order to simulate the dynamic system behavior. However, there is no a significant effort to apply the ANN for online TSA in large scale power system considering system topology changes. ANN is trained offline based on a given operation states so that the heavy computational burden is avoided in online application and thus allows TSA to perform in a very short time.

ANN can be interpolated well within the range of the data used for calibration but is poor at extrapolating so that their weight need to be updated when major changes occur in the power system such as transmission lines or generation equipment re-connection or disconnection. In order to maximize the benefits from estimating TSA using ANN, we have to train different neural network models for each system topology and to use in real-time the one corresponding to the actual configuration or train a single ANN model to deal with all the expected system configurations during all load states. In this paper, we suggest to train a single ANN based on all expected system configurations and loading states.

II. TRANSIENT STABILITY BASED CCT

Power system dynamic model is composed of linear and nonlinear equations, involving many discrete and continuous state variables with sophisticated models. TDS, direct and pattern recognition learning are the usual methods used in power system TSA [4]. These evaluations aim to assess the dynamic behavior of the rapidly changing electrical values of a power system subjected to a sequence of credible disturbances. TDS provides an accurate calculation of TSA involving repeatedly solving large, sparse, time varying nonlinear state space differential equations of power networks over thousands of time steps. This iterative calculation can not be applied in online applications. Direct methods such as transient energy function and extended equal area criteria are used to reduce the time consumed in TDS avoiding all repetitive runs. They aim to identify when the system leaves its stability domain without further integration of the system trajectory. These methods require significant approximations that limit the modeling complexity for multi-machine power system. These approximations reduce the accuracy and reliability of TSA.

Pattern recognition learning method such as ANN is used for online monitoring of TSA to overcome the required computation time and mathematical complexity requirements. ANN has to be trained based on suitable input/output pattern for good generalization of the entire application. CCT based angle stability as index for TSA measures the proximity of the system to be unstable due to loss of synchronism. The CCT depends on the system configuration and the loading level at the instant of fault occurrence. The most accurate way to assess transient stability is the step by step TDS to accommodate system complexity modeling and stability conditions by observing its electromechanical angular and voltage swings during simulation time. To reach this aim, power system dynamic simulation package (PSD) approach based upon TDS method is presented and applied at all system operating points during contingencies in order to prepare input/output pattern during training process [5].

III. Study Power System

The implementation of ANN for TSA is illustrated through the Power Stability Test 16-machine network (PST16) [6]. The single line diagram of the test system is shown in Fig. 1.

The test system contains 66-bus and is divided into three areas (A, B and C) connected through tie lines and fifty distributed loads with (2460+15450) MVA (Mega Volt Ampere) at the base case. System topology is assumed to be occurred with disconnecting transmission lines or generators which may be disconnected due to overloading operation, permanent fault or maintenance scheduling process.

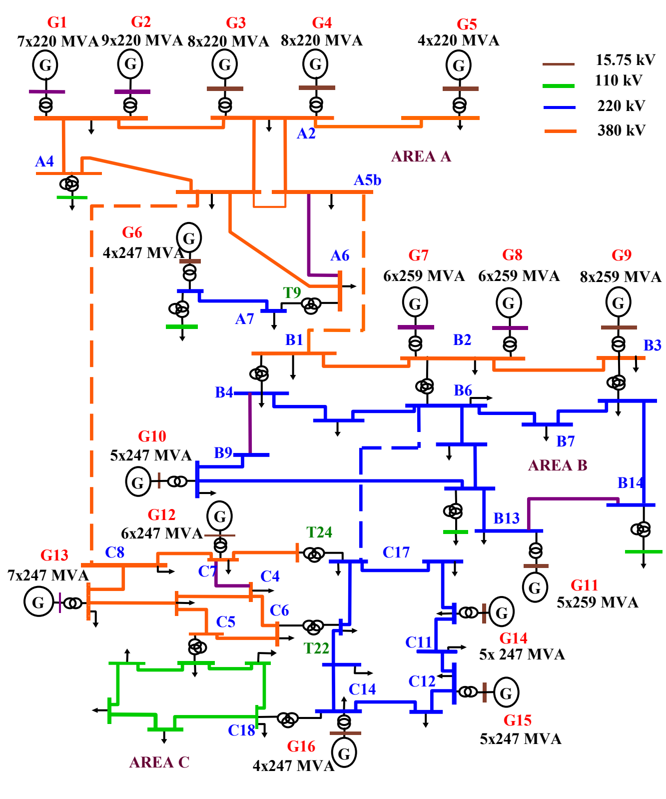

Figure 1. Single line diagram of the sixteen-machine, 66-bus test system

Nine system topologies are considered during preparing Input/output pattern. Table I lists the terminals of the disconnected transmission line and Table II lists the name of disconnected generators in each system topology.

TABLE I. Disconneted Transmission Lines.

Topology Number	**1**	**2**	**3**	**4**	**5**
Disconnected Transmission Line	Base case	A5b/A6	B13/B14	B13/ 14 B4/ B9	C4 / C7

TABLE II. Disconneted Geerators During Topology Changes

Topology Number	**6**	**7**	**8**	**9**
Disconnected Generators Name	G1-G2	G7-G8	G13	G1-G2-G7-G8- G13

IV. Data Preparation and Features Selection

A. Data Preparation

A large number of input/output patterns are generated either from historical stored data or by perturbing both real and reactive loads randomly in a wide range of loading states. In this paper, input/output pattern is generated by randomly varying active and reactive loads at all load buses using equations (1) and (2) in the range from 50% to 125% of their base case operating point [7].

$$P_L(k) = P_L^0(k) * \Delta L(k) + 2 * P_L^0(k) * \Delta P(k) * [0.5 - \varepsilon_p^k] \qquad (1)$$

$$Q_L(k) = Q_L^0(k) * \Delta L(k) + 2 * Q_L^0(k) * \Delta Q(k) * [0.5 - \varepsilon_q^k] \qquad (2)$$

Where P_L and Q_L are the base case operating point load; ΔL is the required loading ratio; ΔP and ΔQ are the acceptable random variation of each load; ε_p and ε_q are random generated number between 0 and 1.

The optimal power flow (OPF) is used to adjust each operating point and obtain the required data. Transmission Losses minimization is used as a target during OPF. One hundred and thirty different operating points for each system configuration are used in data preparation. System constraints and limits should be satisfied during OPF for all selected dispatched operating points. Load and generation pattern for which the power flow does not meet steady state operating requirements were removed. All generators in the system are assumed to share in the increase in system loading with controlled generator terminal voltage.

Twenty-one contingencies distributed in all system areas were selected based on CCT less than 400 milliseconds are considered as critical contingency set. For each operating point, PSD software is used to get all the required data during simulation and calculate the corresponding CCT for the predefined set of critical contingencies.

B. Feature Selection

Feature selection is a process used to identify an optimal combination of features which contain valuable information that efficiently characterizes and represents all system data and generates input/output pattern of the ANN. As the size of power system is increased, the number of features is substantially increased so that the assignment of deciding which system quantities to choose as input features is a difficult task. Feature selection is important to minimize required training time, memory requirements and the number of weight factors during training. Accurate selection of input/output pattern is an important key to the success of ANN applications for effectively map the desired output and the set of selected features with acceptable accuracy. Input features are carried out in two stages as shown in Fig. 2.

In the first stage, an initial feature set is selected based on the knowledge of power system and the required target to be estimated. These features should be adequately characterizing all operating state of a power system from transient stability point of view and system topology changes. The proposed initial selected features in the first stage are listed as follows in Table III.

The second stage of the feature selection is used to find the final features from the pre-selected initial feature set. Generators dynamic behavior during contingencies and fault locations play an important role in system stability during and after fault clearance. In order to characterize the severity of the contingencies on the generators and specify the fault location, the generator terminal voltage drop immediately after the fault occurrence is considered as important ANN input features.

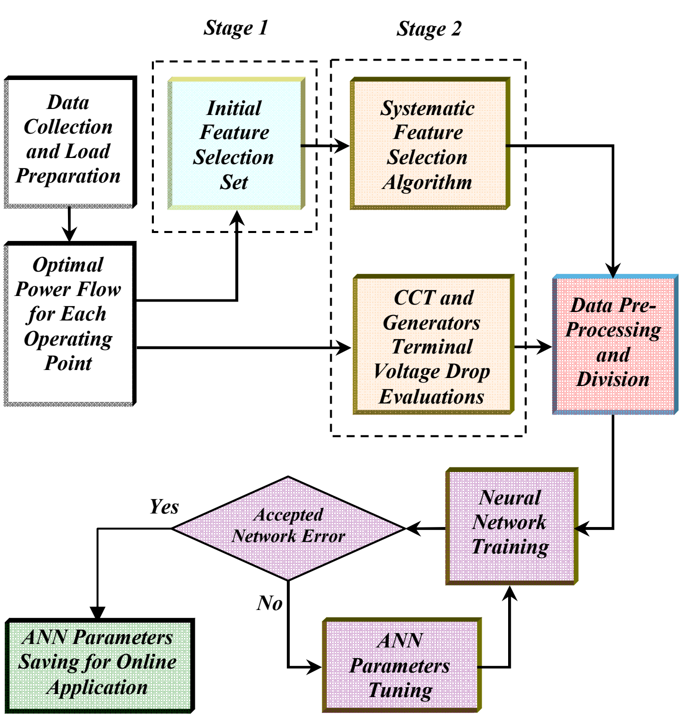

Figure 2. Feature selection stages and ANN training for TSA monitoring.

According to the author's field experience, these features are the most important for CCT assessment by ANN and therefore preferred as ANN selected input features. It can be estimated very fast e.g. by using a simple short circuit calculation algorithm.

TABLE III. INITIAL SELECTED FEATURE SET

Number	Features Name	Features Number
1	Total active and reactive power in each area	6
2	Generator active and reactive power	32
3	Voltage magnitude and angle of each bus except the slack bus and generator terminal voltages	115
4	Transformers tap sittings	28
5	Active and reactive power demand at each load bus	100
6	Active and reactive power of tie line	6
7	Generators terminal voltage drop immediately after the fault	16

Beside the generators terminal voltage drop, a systematic feature selection algorithm is used to select the most important features from the initial selected set of features to characterize the system topology changes and varying loading levels. In this paper the k-means clustering algorithm is used to group the system features into a certain number of clusters such that features in the same cluster have similar characteristics and then one feature from each cluster picked out as a selected feature based on the distance from the cluster-centroid or field experience [8].

All selected features are combined together and represent input pattern. The output pattern is simply the TSA as the CCT corresponding to the pre-selected critical contingencies at each operating point of all expected system topologies.

V. NEURAL NETWORK MODEL DEVELOPMENT

A. Network Architecture

Many researchers have proven that a single hidden layer of neurons, operating a sigmoid activation function, is sufficient to model any solution [9]. In this paper, a single hidden layer feed-forward structure which is based on pattern matching technique with the back-propagation training network is implemented to relate the input/output pattern. The number of input neurons depends on the total number of selected features. The number of output neurons is equal to one for CCT estimation. The number of hidden neurons depends on the complexity of the problem under implementation and the quality of available data. For single hidden layer networks, there are a number of rules-of-thumb to obtain the best number of hidden layer nodes [10-11]. For example, it should never be more than twice as large as the input layer nodes and it should be between the average and the sum of the nodes in the input and output layers [9]. In this paper, the optimal number is obtained by starting from a small number of nodes and slightly increasing the number to minimize the root mean square error (RMSE) during training process.

B. Training and Performance Evaluation

The input/output pattern is merged, shuffled and normalized to avoid saturation and memorization problems during the training process. The normalized data then divided into training, testing and validation subsets beside a set for testing as unforeseen data. The training algorithm should provide ANN the ability of generalization.

MATLAB toolbox is used as a computing tool to implement the ANN. Among all back-propagation training algorithms, Levenberg-Marquardt optimization based for weight and bias updating algorithm is selected because it provides a fast convergence and a better performance. All information about the trained ANN is saved to be used through the online applications. The trained network is tested for its performance on a test set of unseen patterns.

VI. EXPERIMENTAL RESULTS

K-means algorithm is used to select the proper features from the initial selected set starting from 5 to 40 features. These features combined with the experimental selected generators terminal voltage drop immediately after the contingency by short circuit calculation to form the input pattern. The credible contingency was taken to be a three phase to ground self-clearance fault without change in the specified system topology. ANN is implemented for each selected set of features with a variable number of hidden neurons in order to select the proper features and the corresponding number of hidden neurons. The training input/output pattern is normalized, shuffled and divided with different random splits into training, testing and validation samples (60% for training, 20% for testing and 20% for validation). All the input/output pattern is deemed equally significant and scaled on [0.1, 0.9] to remove the effect of large values and avoid saturation problem.

The performance of the TSA using the developed ANN is evaluated by calculating the relative estimation error (E), average estimation error (AE), standard deviation (σ) of the relative estimation error, Pearson correlation coefficients (PCC) and mean absolute percentage error (MAPE) between estimated CCT and target CCT. The correlation coefficient determines the extent to which the values of two variables are "proportional" to each other. The definitions are given as follow:

$$RMSE = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}\left(y_k - \tilde{y}_k\right)^2} \quad (3)$$

$$E_k = \left(\frac{y_k - \tilde{y}_k}{y_k}\right) \quad (4)$$

$$AE = \frac{1}{N_d}\sum_{k=1}^{N_d} E_k \quad (5)$$

$$\sigma = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}\left(E_k - AE\right)^2} \quad (6)$$

$$PCC = \frac{N_d \sum_{k=1}^{N_d} y_k \tilde{y}_k - \sum_{k=1}^{N_d} y_k \sum_{k=1}^{N_d} \tilde{y}_k}{\sqrt{N_d \sum_{k=1}^{N_d} y_k^2 - \left(\sum_{k=1}^{N_d} y_k\right)^2}\sqrt{N_d \sum_{k=1}^{N_d} \tilde{y}_k^2 - \left(\sum_{k=1}^{N_d} \tilde{y}_k\right)^2}} \quad (7)$$

$$MAPE = \frac{1}{N_d}\sum_{k=1}^{N_d}\left|E_k\right| \quad (8)$$

Where y is the calculated CCT by TDS; ỹ is the estimated CCT using ANN; N_d is the number of input patterns.

A. ANN Training using a Single Contingency

The suitability of ANN for TSA to account for the change in system topology is investigated using input/output pattern corresponding to a single contingency. A contingency at Bus C9 in area C with 1100 operating points in all selected system topologies is used in ANN modeling. 1000 operating points are used in the training process and the remaining 100 operating points are used in testing as unforeseen operating points. The best number of selected features for minimum RMSE and high PCC is 42 features with 37 neurons in the hidden layer. The ANN selected input features are listed in Table IV.

TABLE IV. SELECTED FEATURES IN THE SINGLE CONTINGENCY CASE

Name of Features	Selected Features	Number
Terminal voltage drop	Terminal voltage drop of all generators after the fault	16
Total power in each area	ΣPA - ΣPC - ΣQC	3
Generator power	PG2 - QG2 - PG5 - QG6 - QG9 - QG11	6
Magnitude of bus voltage	VA4 - VB9 - VC6 - VC11	4
Load power	PA2 - PA7 - QB1 - QB2 - QB4 - QB9 - PC7 - PC14 - QC5 - QC6	10
Tie-line power	PA5b / B1 - PB6 / C17 - QB6 / C17	3

Linear regression between target CCT and estimated CCT during training process is shown in Fig. 3.

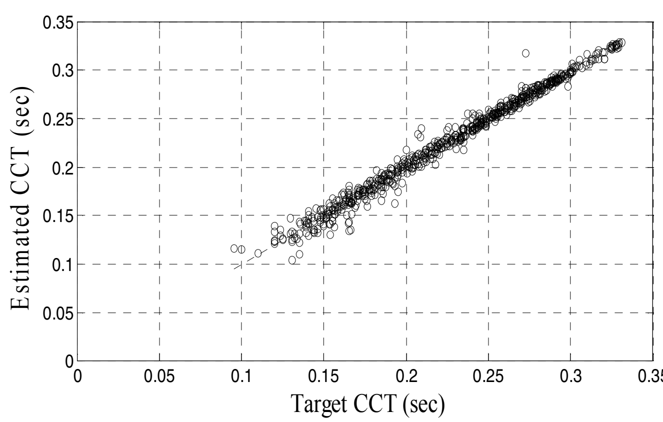

Figure 3. The plot regression between target CCT and estimated CCT

The percentage relative estimation error for 600 selected input/output patterns after training process is shown in Fig. 4. Fig. 5 presents the target CCT calculated by TDS relative to the estimated CCT using ANN for the remaining 100 operating points as unforeseen operating points.

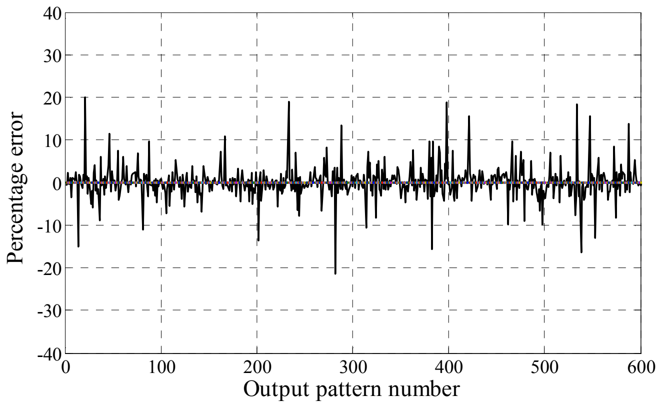

Figure 4. The percentage error between the target CCT and estimated CCT

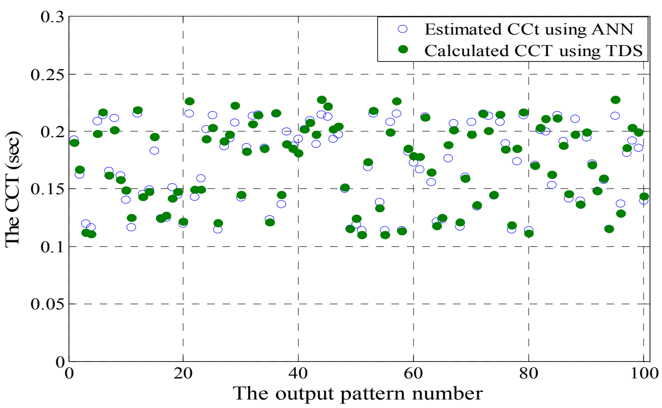

Figure 5. The estimated CCT and the target CCT during testing process

The performance of the trained ANN is given in Table V. The low standard deviation, together with the very small average estimation error, leads to the conclusion that ANN is accurate enough for monitoring of the system transient stability when trained based on multi system topologies.

TABLE V. PERFORMANCE OF ANN IN A SINGLE CONTINGENCY CASE

Emax (%)	Emin (%)	AE (%)	σ (%)	PCC p.u.	MAPE (%)
19.9	-21.3-	0.12	3.79	0.964	5.65

B. *ANN Training using Multi-contingency*

All the input/output patterns of twenty contingencies are used to select the best number of elected features and the number in neurons in the hidden layer in order to develop a general ANN. The remaining contingency is left for testing as unforeseen input/output set. During the training process, there are some operating points observed to have a high estimation error because these points are away from the harmony of the input/output pattern. To solve this problem a number of operating points are created around each operating point to improve the accuracy. RMSE during training process with varying the number of hidden neurons at each selected features is shown in Fig. 6. From Fig. 6, we can realize that the best number of features for minimum RMSE is 46 with 55 hidden neurons in the hidden layer.

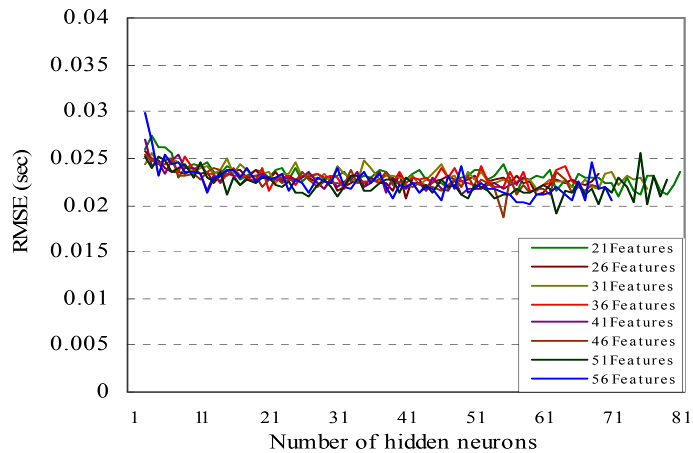

Figure 6. RMSE with variable ANN architecture and input features

The ANN selected input features are listed in Table VI. The performance of the selected ANN is presented in Table VII.

TABLE VI. SELECTED FEATURES IN THE MULTI-CONTINGENCY CASE

Name of Features	Selected Features	Number
Terminal voltage drop	Terminal voltage drop of all generators after the fault	16
Total power in each Area	ΣPA - ΣPB - ΣQC	3
Generator power	QG3 - QG6 - PG8 - PG9 - QC13 - PG14	6
Magnitude of bus voltage	VA4 - VA7 - VB7 - VC6 - VC8	5
Transformer taps	T24 - T22 - T9	3
Loads power	PA2 - PA7 - PB3 - PC4 - PC7 - PC14 - QB1 - QB2 - QC12 - QC18	10
Tie-line power	PA5b/B1 - PB6/C17 - QB6/C17	3

TABLE VII. PERFORMANCE OF ANN IN MULTI-CONTINGENCY CASE

Emax (%)	Emin (%)	AE (%)	σ (%)	PCC p.u.	MAPE (%)
16.47	-17.12	-0.1343	7.088	0.954	3.467

The high correlation coefficient between ANN output and desired CCT target indicates that the ANN has modeled the application problem well and can be used in TSA. After training, input/output pattern of the remaining contingency is used for testing the performance of trained ANN to monitor uncovered operating points during the training process. Fig. 7 depicts the target CCT and estimated CCT for randomly selected one hundred unforeseen operating points after training process. The Linear plot regression between the target CCT and the estimated CCT using ANN of all unforeseen operating points during testing process are shown in Fig. 8.

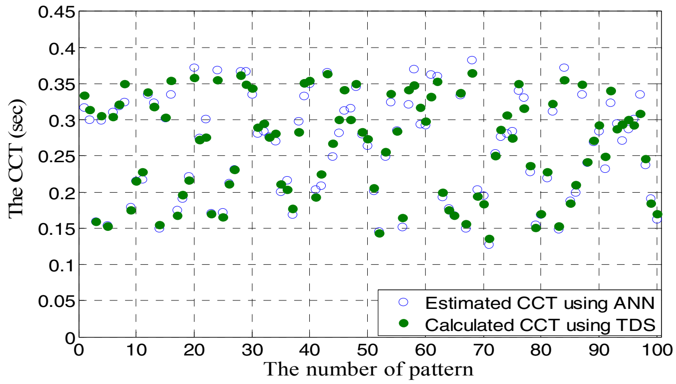

Figure 7. The estimated CCT and the target CCT during testing process

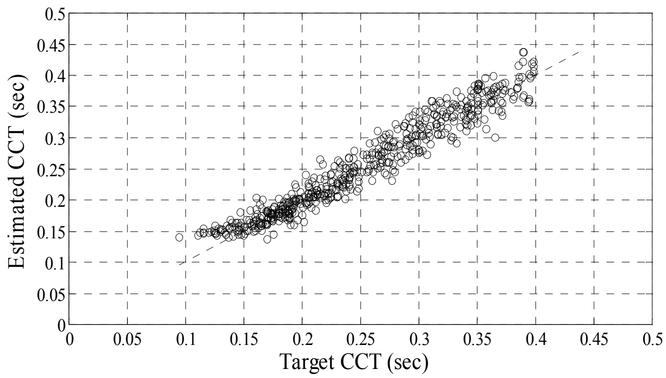

Figure 8. The plot regression between targets CCT and to estimated CCT.

The performance coefficients during ANN testing are given in Table VII.

TABLE VIII. PERFORMANCE OF ANN IN TESTING STAGE

Emax (%)	Emin (%)	AE (%)	σ (%)	PCC p.u.	MAPE (%)
19.40	-21.58	-0.32	7.525	0.9452	4.60

The RMSE is 16.03 milliseconds and the standard deviation is 7.525 % with average relative error -0.23 %. Therefore, once trained, the ANN is able to estimate the CCT as index for TSA of all the critical contingencies under any loading condition almost instantaneously. The required action by ISO can be executed to improve the system transient stability if a contingency analyzed is shown to be potentially insecure.

VII. Conclusion

The estimated results obtained from the case study system has achieved that ANN is successfully implemented to estimate TSA with a reasonable degree of accuracy. ANN is a very fast tool for TSA compared to traditional methods but should be trained carefully over a wide hyperspace in order to avoid over-fitting. The results emphasize ANN capability of handling TSA with system topology changes. The ANN based TSA can then be used to initiate the online remedial action. The preliminary results show that the most sensitive parameters were found to be the post fault generators terminal voltage drop which represent the system state at post fault so that the experimental feature selection plays a crucial role in the ability of ANN to achieve a better performance in TSA.

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IX. Biographies

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István Erlich (1953) received his Dipl. Ing. degree in electrical engineering from the University of Dresden/Germany in 1976. After his studies, he worked in Hungary in the field of electrical distribution networks. From 1979 to 1991, he joined the Department of electrical Power Systems of the University of Dresden again, where he received his PhD degree in 1983. In the period of 1991 to 1998, he worked with the consulting company EAB in Berlin and the Fraunhofer Institute IITB Dresden respectively. During this time, he also had a teaching assignment at the University of Dresden. Since 1998, he is Professor and head of the Institute of Electrical Power Systems at the University of Duisburg- Essen/Germany. His major scientific interest is focused on power system stability and control, modeling and simulation of power system dynamics including intelligent system applications. He is a member of VDE and senior member of IEEE.