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5 - Conclusion

In this paper an Artificial Neural Network (ANN) based approach was presented for on-line power system Dynamic Security Assessment (DSA), i.e., estimation of the critical clearing time (t_{cr}) for transient stability analysis. A suitable topology for the ANN, based on the multilayer Perceptron was developed. The inputs of the proposed ANN are a set of directly monitorable variables in the pre-fault situations. The high performance of the approach was assessed on the New England test system. Simulation results indicated that the trained ANN can be used to estimate the t_{cr} for a particular contingency under different operating points with a high degree of accuracy. It is worth noting that this network could estimate the t_{cr} very fast, i.e., for the case of studied in Section 4, the t_{cr} estimation by the trained ANN took only a few milliseconds with a very small computation flops. Therefore, due to accuracy and computatinal efficiency the proposed appproach is well suitable for on-line dynamic security assessment. The most attractive scenario of the proposed approach is to remove the additional static and/or dynamic variables determined normally by supplementary software from the inputs of the ANN.

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this better, Table 1 lists the actual and estimated t_{cr} for 20 out of 1000 test vectors. From this table, it can be easily seen that the trained network can estimate the actual t_{cr} very well. This estimation just takes a few milliseconds with the corresponding computation flops of 1486, which shows how fast the designed neural network can determine the t_{cr}. So, the proposed approach is well suitable for on-line dynamic security assessment.

Table (1) Comparison of actual and estimated t_{cr}.

Test No.	Actual t_{cr} (sec.)	Estimated t_{cr} (sec.)
1	0.25	0.246
2	0.30	0.297
3	0.34	0.343
4	0.31	0.311
5	0.26	0.253
6	0.30	0.298
7	0.36	0.353
8	0.28	0.276
9	0.34	0.333
10	0.30	0.301
11	0.31	0.309
12	0.22	0.233
13	0.26	0.259
14	0.33	0.337
15	0.22	0.212
16	0.27	0.280
17	0.24	0.235
18	0.23	0.229
19	0.26	0.256
20	0.22	0.213

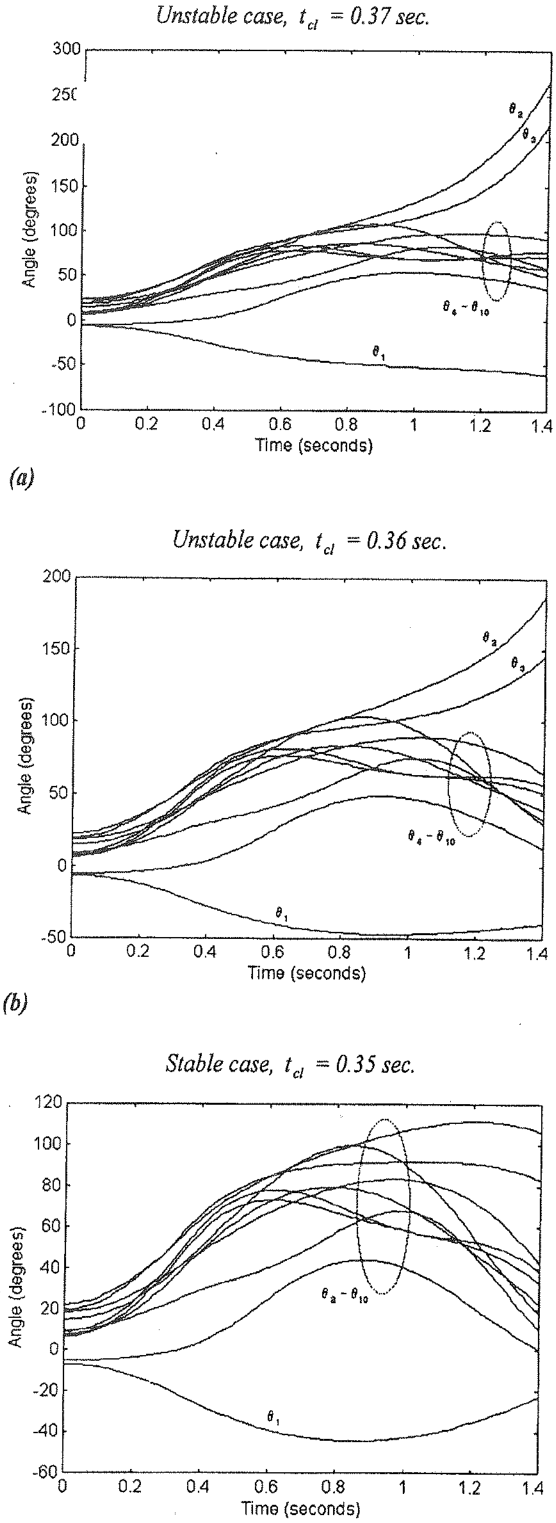

Fig. (3) Rotor angle plots for a three-phase fault at a point very close to bus 15 cleared by tripping the line 15-16: (a) Unstable case, t_{cl} = 0.37 sec.; (b) Unstable case, t_{cl} = 0.36 sec; (c) Stable case, t_{cl} = 0.35 sec.

For obtaining a training data vector we proceed as follows:

1-The minimum and maximum limits for generated reactive power in all PV buses are set to -0.2 and 0.7 times of their nominal generated active power, respectively.

2-It is assumed that the following pre-fault conditions vary over some specified ranges independently:

- generated active power of all PV buses
- active and reactive powers of all electrical loads
- generated reactive power of the shunt capacitor located at bus 25

It is further assumed that the range of variations of each of the above mentioned variables is bounded form 0.7 to 1.0 times of their corresponding nominal value.

3-A random number with uniform distribution is assigned independently to each of the variables mentioned in step 2.

4-With the above prepared data and assumed specific voltage magnitude for PV buses, a load-flow analysis is perfomed. The results may show that some PV buses may be treated as PQ buses. However, the voltage magnitude of all violated and non-violated PV buses are used as the inputs of the proposed ANN.

5-The TEF method described in Section 2 is employed to calculate the t_{cr}.

To illustrate the application of the TEF method for obtaining the t_{cr} data set, here we consider some plots related to the time variations of rotor angle of synchronous generators in the test system. These plots are based on the COI frame of reference and have been obtained by the time domain simulation of the system dynamic equations. For the sake of brevity, we focus on three plots corresponding to a specific random pre-fault operating point and three values of the fault clearing time (t_{cl}).

The first plot shown in Fig. 3a, is related to t^{*}_{cr} = 0.37 sec; that is the critical clearing time estimated by the PEBS method (i.e. t_{cl} = 0.37sec.) . It is clear that the system is unstable and the PEBS method has failed to predict the actual value of t_{cr}. Thus, the t_{cl} is reduced to 0.36 sec. As seen from Fig. 3b, the system is still unstable . Therefore, further reduction for t_{cr} is necessary (i.e. t_{cl} = 0.35 sec.). The rotor angle-time plot related to this value for t_{cl} is shown in Fig. 3c. It is evident that the system is stable in this case. This means that the exact value of t_{cr} is 0.35 sec.

4-The simulation Results

With the procedure presented in Section 3, we generated 2000 training data vectors in order to train an ANN with 57 inputs corresponding to 57 elements of vector x, and only one linear output neuron corresponding to t_{cr} for the previously mentioned three-phase fault in the test system, (see Fig. 2). This ANN has only one hidden layer with sigmoid transfer function. The hidden layer has 5 neurons. The MATLAB Neural Networks Toolbox [22] was used to train this ANN, and function TRAINRP (Resilient Backpropagation) was employed for this purpose. Before training, the input and output data vectors were scaled so that they fell in the range [-1,1]. The error goal, the mean-squared errors between desired and estimated outputs in the training phase was set to 0.00002.

In order to test how good the trained network generalizes, we generated another set of 1000 data vectors as a test set. The mean-squared errors for this data set became 0.000032. This proves the generalization accuracy of the trained network. To see

(V_2- V_{10})

- generated active power of all 9 PV buses (PG_2-PG_{10})
- active power of all 19 electrical loads acting on different buses (P_{D1}, P_{D2}, ..., P_{D37})
- reactive power associated with above 19 electrical loads (QD_1, QD_2, ..., QD_{37})
- generated reactive power of the single shunt capacitor installed at bus 25 (QC_{25})

Hence, the vector x consists of 57 elements. It should be noted that, all variables included in vector x are, in general, directly monitored in Energy Control Centres (ECC). As we pointed out earlier, for a particular fault, t_{cr} is a function of only pre-fault system operating point. However, this operating point can be adequately characterized by the pre-fault conditions contained in vector x. Consequently, t_{cr} can be considered as a function of vector x as:

$$t_{cr} = f(x) \tag{3}$$

The main objective of this paper is to approximate this function with a feedforward ANN. To employ the ANN, we are required to provide the ANN with an appropriate set of training data vectors. By using a given good enough number of pre-fault conditions data vectors, as the inputs, we may use the corresponding t_{cr}'s as the outputs, in order to train the ANN. Since the inputs are a set of directly monitorable variables, it is worth noting that after successfully training the network, t_{cr} can be estimated as fast as possible at the output of the trained network. This is a very attractive goal, which is always looked for. Furthermore, due to the fact that the variables included in vector x are the minimum required number variables that can adequately characterize the prefault system operating point, the size of both ANN and training data set are remarkably reduced.

Figure 2 shows the general architecture for the multilayer Perceptron ANN adopted in this paper for the New England test system. It should be noted that the selected architecture for the ANN shown in Fig. 2, can be used for all fault scenarios in the test system. Because , as we pointed out earlier, for a particular fault t_{cr} is a function of vector x. However, we should be careful that we are required to train a separate ANN for each fault scenario. This is due the fact that a different data training set for t_{cr} is needed for each contingency.

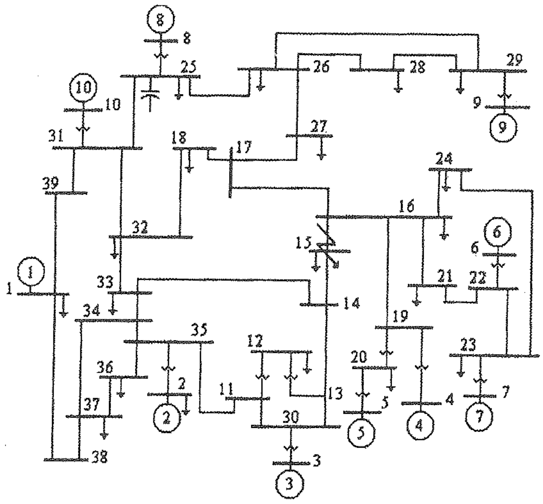

Fig. (1) One-line diagram of the New England test system

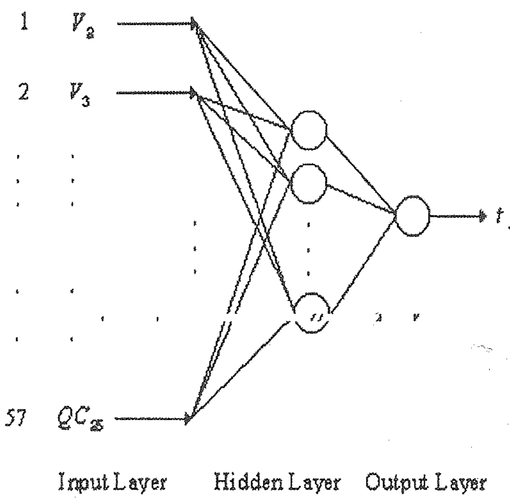

Fig. (2) Selected architecture for the proposed ANN.

In this paper Kakimoto's Potential Energy Boundary Surface (PEBS) method is used for fast evaluation of V_{cr}. This method has been fully described in Ref. [2]. However, it has been shown in [3, 21] that the V_{cr} and therefore the t_{cr} obtained by the PEBS method may be less or greater than their actual values. To remedy this drawback, PEBS method along with the time domain simulation of the system equations of motion is employed to obtain the actual value of t_{cr}. The procedure can be described as the following steps:

Step 1: Integrate the faulted system dynamic equations until the transient potential energy reaches a maximum along the faulted trajectory (i.e. until PEBS crossing is detected). This maximum value denoted by V_{cr}^* provides a good estimate of actual V_{cr} [2].

Step 2: From the faulted trajectory find the time instant, t^*_{cr} , at which transient energy V reaches V^*_{cr} . The t^*_{cr} is viewed as an estimate of the actual t_{cr} [2].

Step 3: Find actual t_{cr} by using t_{cr}^* as an initial guess in the time domain simulation technique accompanied by a trial and error.

3 -The Problem Statement

Consider the 10 machines and 39 buses New England test system shown in Fig. 1. The system data is given in [2]. Assume that a three-phase fault occurs at a point on the transmission line between buses 15 and 16 very close to bus 15 far from generation buses. The fault clearing policy is to isolate the fault by tripping the transmission line from bus 15 to bus 16.

It is obvious that the critical clearing time is a complex function of pre-fault system operating point, fault type and location, and post-fault system configuration. But, for a particular fault such as the fault mentioned above, the critical clearing time is indeed a function of only pre-fault system operating point. Therefore, we try to focus mainly on determination of this operating point from the huge number of variables that may characterize the pre-fault system. To deal with this problem, it would be necessary to extract a proper set of pre-fault system conditions. This can be done as below:

Here bus 1 represents the slack bus whose voltage magnitude and phase angle are known. The remaining generation buses (i.e. buses 2-10) are considered as PV buses whose generated active powers and voltage magnitudes are denoted by PG_i and V_i ($i = 2, 3, \dots, 10$). Besides one slack bus and 9 PV buses, the test system consists of additional 29 PQ buses (i.e. buses 11-39). However, the loads are acting only on 19 distinct buses. The active and reactive load powers of these buses are denoted by PD_j, and QD_j (j is the bus number). Note that the shunt capacitor installed at bus 25 is treated as a load whose generated reactive power is known as QC.

Knowing the fact that the slack bus whose voltage magnitude and phase angle are fixed, the pre-fault operating point can be determined by the above mentioned pre-fault conditions. Because, all the other variables in the pre-fault situations such as voltage of PQ buses, generated reactive power of PV buses, rotor angle of synchronous generators, etc., are dependent on the above mentioned variables. These variables in the New England test system can be arranged in a vector x with the following elements:

- voltage magnitude of all 9 PV buses

ping a transmission line. Thus, pre-fault and post-fault topologies are not the same.

3 -In the test system, the limits of generated reactive power are considered for all PV buses. Therefore, PV buses may be treated as PQ buses.

In order to obtain t_{cr} data set for training purpose, the Potential Energy Boundary Surface (PEBS) method, which is one of the fastest TEF methods, accompanied by the time domain simulation technique is employed [2, 3, 21]. The remainder of paper is organized as follows: The TEF method is presented in Section 2. In Section 3, we propose our approach and introduce some case studies. Section 4 presents the simulation results, and Section 5 concludes the paper.

2 -The Transient Energy Function Method

Consider a power system consists of n synchronous generators. The system equations of motion for the ith generator using the classical model and internal Center of Intertia (COI) frame of reference are given by [1-3]:

$$M_i \dot{\tilde{\omega}}_i = P_{mi} - P_{ei} - \frac{M_i}{M_T} P_{COI} \tag{1}$$

$$\dot{\theta}_i = \tilde{\omega}_i$$

where,

$$P_{ei} = \sum_{j=1 \neq i}^{n} (C_{ij} \sin \theta_{ij} + D_{ij} \cos \theta_{ij}) + E_i^2 G_{ii}$$

$$P_{COI} = \sum_{i=1}^{n} (P_{mi} - P_{ei})$$

$$M_T = \sum_{i=1}^{n} M_i$$

$$C_{ij} = E_i E_j B_{ij}$$

$$D_{ij} = E_i E_j G_{ij}$$

$$Y_{ij} = G_{ij} + jB_{ij}$$

and:

Y_{ij} = elements of reduced admittance matrix

E_i = internal generator voltage magnitude

P_{mi} = mechanical input power of generator

M_i = intertia constant of generator

$\tilde{\omega}_i$ = angular velocity of rotor with resepect to COI

θ_i = rotor angle with respect to COI

$\theta_{ij} = \theta_i - \theta_i$

The transient energy function V associated with Eq. 1 can be written as:

$$V = V_{KE} + V_{PE} \tag{2}$$

This function consists of two components: transient kinetic energy V_{KE} and transient potential energy V_{PE}. The expressions for V_{KE} and V_{PE} are given in [1-3].

Computing two values of the transient energy makes the stability assessment feasible. The first value of the transient energy is normally determined at the fault clearing time, V_{cl}. The other value denoted by V_{cr}, is the critical value of transient energy which extensively determines the accuracy of the transient stability assessment. In fact V_{cr} is the transient energy function evaluated at the controlling Unstable Equilibrium Point (UEP), for the particular disturbance under investigation. The system is stable (unstable), if $V_{cl} < V_{cr}$ ($V_{cl} > V_{cr}$).

Due to complexity of exact computation of the controlling UEP, the evaluation of V_{cr} at the controlling UEP is a very hard task.

ed active and reactive powers, active and reactive load powers, active and reactive powers flow on a branch, transient kinetic energy, and some other static and dynamic features were used in [19].

In all of the methods seen in [13-19], determination of the inputs of the ANNs is itself a time-consuming task. Because, the determination of the inputs requires the supplementary tools such as load-flow and/or transient stability software. Thus, the high speed solution capability of ANNs has not been fully exploited in the neuro-based techniques seen in the literature. In addition, because some previously designed neural networks inputs are dependent on some specific variables in the pre-fault situations, using these dependent variables does not provide any additional information about the state of the pre-fault system.

The main objective of the present investigation is to propose a new neuro-based approach for on-line DSA (i.e. t_{cr} estimation). The basic idea is that for a particular fault scenario, t_{cr} is a function of only pre-fault system operating point, which can be adequately characterized by a proper set of directly monitorable conditions (variables) in the pre-fault situations. On the other hand, if we denote this set of directly monitorable pre-fault conditions by vector x, and knowing that the t_{cr} is indeed a function of vector x as : $t_{cr} = f(x)$, the principle goal of the present approach is to approximate this function by a multilayer ANN with the vector x as the input and t_{cr} as the output. In fact, we face with a function approximation problem associated with feedforward ANNs for DSA. The great achievement of the present investigation is to remove the additional static and/or dynamic variables from the inputs of the proposed ANN. The removal of these variables from the inputs of the ANN reduces remarkably the size of both ANN and training data set. Moreover, t_{cr} can be estimated as fast as possible, because there are no extra calculations for ANN inputs generation.

In [20], the authors of this paper have briefly demonstrated the results corresponding to the application of the present ANN approach to a small size power system. In paper [20] , the following conditions were considered:

1-Self clearing three-phase fault was assumed at a point close to the terminal of a specific synchronous generator. Therefore, the pre-fault and post-fault configurations of the underlying system were the same .

2 -There was no limit on the generated reactive power of each synchronous generator. Thus, all generation buses (PV buses) were never treated as load buses (PQ buses).

The present paper demonstrates the proposed neuro-based approach more precisely. In fact in the present study we show the effectiveness of our proposed ANN approach in a medium size power system (i.e. the New England test system). The salient features of the present study which distinguishes the present investigation with our latest report [20] are:

1 -The New England test system consists of 10 synchronous generators and 39 buses, while the small system reported in [20] includes only 3 generators and 9 buses.

2- A three-phase fault is assumed at a point very close to a specific bus located far from generation buses. It is further assumed that the fault is cleared by tripthe major and necessary topics to be investigated. The results will show that following a contingency, the synchronous machines would be transient stable (i.e. settling in a new stable operating point) and/or proper and necessary preventive control actions are required.

The conventional method for DSA is based on repetitive time domain simulations of a given power system dynamic equations. In this method a great number of simulations for a large number of credible fault locations are to be performed to assess the system security and the critical clearing time (t_{cr}). This method yields the most accurate and reliable results. However, for online applications this method has the following major drawback: it is very slow because of lot of time-consuming computations which are inherent to the method.

As an alternative method for transient stability analysis in electric power systems, we may cite the Transient Energy Function (TEF) method [1-3]. The main advantages of TEF method are computational speed and the transient energy margin (ΔV) determination. However, fast calculation of the ΔV will be achieved at the expense of accuracy. Furthermore, especially in stressed power systems, the TEF method may fail to provide any practical results because of non-convergence problems related to iterative nature of relevant Unstable Equilibrium Point (UEP) determination [4] . Thus, several methods were proposed to determine the ΔV or the t_{cr} by analyzing the results of the time domain simulation technique through the TEF methods [4-12]. However, these methods still need considerable computations for stability assessment, and they are not fully suitable for online DSA.

Interest in applying Artificial Neural Neworks (ANNs) to dynamic security assessment began in 1989. Sobajic and Pao proposed a feedforward neural network for estimating the t_{cr} [13]. The application of feedforward and functional link neural networks were reported in [14]. Jeyasurya used a feedforward neural network to evaluate the ΔV [15]. Zhou et. al. used ANNs for estimating a power system vulnerability [16]. Hobson and Allen [17] developed the approach of Sobajic and Pao [13] and applied their method on a practical power system. Aboytes and Ramirez reported the application of feedforward neural networks to a real longitudinal power system [18]. The application of ANNs for dynamic security contingency screening and ranking was reported by Mansour et. al. [19] in order to evaluate the energy margin and maximum swing angle.

The following steady state and/or dynamic state variables were used as the inputs of the ANNs designed in the above mentioned approaches: Initial angular rotor positions, initial acceleration and acceleration energy were used in [13] and later with small enhancements in [17]. Generated active and reactive power during a fault, mechanical power, angular rotor position and machine inertia were reported in [14]. Transient kinetic energy, transient potential energy, rotor angle deviation, rotor speed deviation, mechanical power and terminal voltage of a specific generator were employed in [15]. The UEP angles and the ΔV were used in [16]. Generated active and reactive powers, relative angular position, number of synchronized generators and load levels were analyzed in [18]. Generat-

On-line Dynamic Security Assessment in Electric Power Systems Using Artificial Neural Networks

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Abstract

This paper presents a new Artificial Neural Networks (ANNs) based approach for on-line power system Dynamic Security Assessment (DSA). The paper represents an application of feedforward neural networks in estimating the critical clearing time (t_{cr}) for transient stability analysis. Knowing that for a particular fault scenario, t_{cr} is a function of only prefault system operating point, the main objective of the paper is to show how one may develop an ANN based method for estimating t_{cr} by considering the smallest set of directly monitorable variables characterizing this operating point adequately. The proposed technique does not require any supplementary tools such as load flow and/or transient stability software for input determination of ANN. Here it has been attempted to just convert the DSA to a function approximation problem which is well-suited to be tackled by multilayer feedforward neural networks. So, we adopted a multilayer ANN with the pre-fault directly monitorable variables as the inputs and t_{cr} as the output. In order to obtain the necessary training data set for t_{cr}, we have used the Potential Energy Boundary Surface (PEBS) method accompanied by the time domain simulation technique. The proposed approach has been successfully applied to the New England test system, and it has been shown that the t_{cr} can be estimated by the trained network in a few milliseconds. Our technique has the following two main advantages:1) t_{cr} is estimated as fat as possible;2) the size of both ANN and training data set are remarkably reduced.

Keywords

Dynamic Security Assessment, Critical Clearing Time, Potential Energy Boundary Surface Method, Artificial Neural Networks.

1 - Introduction

In recent years electric utilities are increasingly facing with the transient stability problem. In electric power systems, Dynamic Security Assessment (DSA) is one of