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# DYNAMIC SECURITY ASSESSMENT OF INTERCONNECTED POWER SYSTEMS

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## ABSTRACT

*Modern power systems continue to grow in size and complexity due to the high demand for electricity. Thus, dynamic security assessment (DSA) is becoming a necessary requirement in the system operation. The critical clearing time (CCT) is a key issue for DSA. Nonlinear time domain simulation (NTDS) is the most accurate method for computing CCT. Unfortunately, DSA is often confronted by the high nonlinearity of interconnected power networks. Thus, NTDS-based DSA is considered time consuming and needs heavy computational effort. In order to avoid these drawbacks, this paper deals with a new technique for online DSA of interconnected power system. Such technique is developed in two steps. Firstly, NTDS is used to compute CCTs for various loading conditions. Then, adaptive network based fuzzy inference systems (ANFIS) is used to establish the relationship between the operating conditions and the corresponding CCTs. The approach effectiveness is validated on two multimachine power systems under severe fault disturbances.*

**KEY WORDS**
*Power system faults; Power system stability; Nonlinear network analysis; Fuzzy neural networks.*

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## INTRODUCTION

Due to the increasing demand and requirement for electric power, dynamic stability is having a significant importance in the operation of power networks. Stability is the ability of the power system to return to a normal operating state when subjected to disturbances [1-2], such as, short-circuits, loss of a tie between lines or sudden variation of operating conditions. Due to the occurrence of faults one or more generators can be seriously disturbed causing an unbalance between production and demand. If a fault persists and is not removed within a predefined period of time, it may cause serious equipment damage and may result in loss of power. To deal with this problem, dynamic security assessment (DSA) based on stability studies has become one of the essential tools for planning, designing and improving electrical networks.

In recent years, several research works have focused on the stability analysis of power systems [3-10]. Critical clearing time (CCT) is one of the most important parameters that measure the stability limits of the power network against disturbances. It is defined as the longest fault clearing time which can be allowed before the generators losses the synchronism [4]. Several methods have been proposed in the literature in order to calculate the CCT [10-15]. These methods differ from each other in the assumptions adopted and the modeling techniques. They can be classified into four groups which are (i) energy based methods [13-15], (ii) numerical integration methods [16-17], (iii) stochastic methods [18-19] and (iv) hybrid techniques [20]. A direct energy method based on the Lyapunov energy function was proposed in [15] to study the transient stability of the power network system. The energy based approaches were used to determine the stability limits without resorting to resolution of the state space differential equations of the system which makes them fast. However, the main drawback of such approaches is the selection of the optimum Lyapunov function which may affect the accuracy of the stability assessment. Long Vu and Turitsyn [5] presented a semi definite programming based technique for the construction of the Lyapunov function used for the DSA problem.

Numerical integration consists in finding a mathematical model capable of representing the system dynamics during three important phases that are before, during and after disturbance. Differential equations are resolved in the time domain using numerical integration methods such as Euler method and Runge-Kutta technique [21]. Then, simulation results can be directly interpreted by users, and the mechanisms of instability can be examined in detail. In recent years, various research studies have demonstrated that techniques based on the nonlinear time domain simulation (NTDS) provide the most accurate CCT [6]. NTDS-based techniques have been implemented by using the numerical integration of the nonlinear state space differential equations of the power network. Unfortunately, these techniques cannot be applicable for the online assessment of the system dynamics and CCT calculation because they are time consuming and need heavy computational effort [6].

To overcome these difficulties, novel intelligent techniques based on artificial neural network (ANN) and fuzzy logic have been proposed for predicting CCT and assessing power system dynamics [11]. Approaches based on ANNs and fuzzy logic have the ability to learn and model complex and nonlinear relationships. Moreover, they don't impose any limitations on the number of inputs and outputs. A neural-based approach has been proposed for online CCT estimation [6]. The approach was based on a feedforward neural network trained off-line using an historical database. Other algorithm based on multi-layer feedforward neural network has been proposed in [8] for real-time stability assessment. In [9], a transient stability model based on back propagation neural network has been suggested to assess transient stability. The load pattern has been chosen as ANN input and CCT has been considered as output. To calculate CCTs necessary for the training set, the multimachine system has been converted into single machine infinite bus. Sulistiawati et al. [10] have presented a new technique based artificial intelligence for CCT prediction. Calculation of the CCT has been done using the critical trajectory method.

Within this context, this study presents a new technique for online assessment and enhancement of interconnected power system stability. To do so, this online assessment method is based on two steps. First, CCT are computed for various loading conditions using Runge-Kutta method and time domain simulation. The second step is based on adaptive network-based fuzzy inference system (ANFIS) training with the collected input-output data pairs which are stocked in the first step. The input data are operating conditions and the outputs are CCTs. In this study, operating conditions are described by load real and reactive powers. The proposed approach is tested on a multimachine power system under different loading conditions. Results show that the proposed method works effectively over a wide range of arbitrary operating conditions and can be applicable for real-time DSA.

## MATERIALS AND METHODS

### Machine classical model

In this paper, synchronous machines are described by the third-order model [5, 21]. Thus, each machine is modeled by two motion equations and the generator internal voltage equation.

$$s\delta_i = \omega_b\left(\omega_i - 1\right) \tag{1}$$

$$s\omega_i = \left(P_{mi} - P_{ei} - D_i\left(\omega_i - 1\right)\right)/M_i \tag{2}$$

$$sE'_{qi} = \left(E_{fdi} - (x_{di} - x'_{di})i_{di} - E'_{qi}\right)/T'_{do} \tag{3}$$

The electrical power $P_e$ can be expressed by the d-axis and q-axis components of the terminal voltage $V_t$ and the armature current *i* as follows [21].

$$P_{ei} = v_{di}i_{di} + v_{qi}i_{qi} \tag{4}$$

where,

$$v_{di} = x_{qi}i_q \tag{5}$$

$$v_{qi} = E'_{qi} - x'_{di}i_{di} \tag{6}$$

$$V_{ti}^2 = v_d^2 + v_q^2 \tag{7}$$

Using equations (4)–(6), the electrical power can be written as.

$$P_{ei} = E'_{qi}i_{qi} + \left(x_{qi} - x'_{di}\right)i_d i_q \tag{8}$$

### CCT computation using numerical integration

Let consider $t_a$ and $t_c$ the application and clearing times of the disturbance. The behavior of the faulted system is studied in the time interval [$t_a$,$t_c$]. On the other hand, the behavior of the post-fault system is studied between the fault clearance time and simulation end time, $t_f$. If $t_a$ = 0, the critical clearing time (CCT) is the maximum value of $t_c$ for which the system remains stable. In this study, the CCT is determined using Runge-Kutta method.

Step 1: Enter system data
Step 2: Iteration = 0.
Step 3: Load flow calculation for the pre-fault system
Step 4: Computation of the bus admittance matrices for the pre-fault (Y1), during fault (Y2) and post-fault cases.
Step 5: Iteration = iteration + 1.
Step 6: Integration of the faulted system between ta and $t_c$.
Step 7: Integration of the post-fault system between $t_c$ and $t_f$.
Step 8: Visualization of the rotor angle curves.
Step 9: Decision about the stability of the system from the rotor angle curves.
Step 10: If the system is stable, increase $t_c$ and got to step 5. Otherwise, go to step 10.
Step 11: If iteration > 1, CCT = $t_c$. Otherwise, decrease $t_c$ and go to step 12.
Step 12: iteration = 0 and go to step 5.

Numerical integration based on the Runge-Kutta method is the most accurate approach for determining the CCT [6]. Unfortunately, it presents many difficulties for the on-line applications due to its excessive computation time.

### Implementation of the ANFIS based approach

ANFIS was originally suggested in [22], where the ANFIS architecture was presented to model nonlinear functions, identify nonlinear components on-linely in a control system and predict a chaotic time series. As in [22], this ANFIS has five layers. A description of each layer is presented in [23].

Selection of initial number of membership functions is an important step in the ANFIS application. In [23], the authors have determined this number by trial and error. They demonstrated that this method was not effective because it is based on a grid partition and it causes an explosion of the number of rules when the inputs number is large. So, they have proposed another method based on a clustering algorithm. The objective of clustering is to generate a concise representation of a system's behaviour by dividing the data space into clusters. Several clustering methods are used in literature [23]. In this paper, a procedure based on subtractive clustering algorithm is used to generate the initial fuzzy inference system (FIS) structure. This non-iterative algorithm is based on a density measure at data point in the feature space, as follows.

Step 1: Consider a set of *n* data points $\{X_1, X_2, \cdots, X_n\}$. The density measure at point $X_i$ is described by the following equation.

$$D_i = \sum_{j=1}^{n} \exp\left( -\frac{\left\| X_i - X_j \right\|^2}{\left( r_a/2 \right)^2} \right) \tag{9}$$

$r_a$ is a positive constant representing a neighborhood radius.

Step 2: Select the data point $X_{C1}$ having the highest density $D_{C1}$ as the first cluster center. Then, update the density measure of each data point $X_i$ using the following equation. $r_b$ is a positive constant.

$$D_i = D_i - D_{C1} \exp\left( -\frac{\left\| X_i - X_j \right\|^2}{\left( r_a/2 \right)^2} \right) \tag{10}$$

Step 3: Select the next cluster center and revise the density measure of data points. Repeat this process until a sufficient number of clusters is reached.
In this study, the ANFIS block is employed to establish the relationship between operating conditions and the corresponding CCT. ANFIS block input are load real ($P_{Li}$) and reactive ($Q_{Li}$) powers.

## RESULTS

To evaluate the effectiveness and robustness of the proposed ANFIS-based DSA, its performance has been examined on the 3-machine 9-bus WSCC (western system coordinating council). The system data and its single line diagram can be found in [1, 24]. The system operating condition for the base case is depicted in Table I.

**Table 1:** System operating condition for the base case

| | | *P* [pu] | *Q* [pu] |
|---|---|---|---|
| Gen | G1 | 0.72 | 0.27 |
| | G2 | 1.63 | 0.07 |
| | G3 | 0.85 | -0.11 |
| Load | A | 1.25 | 0.50 |
| | B | 0.90 | 0.30 |
| | C | 1.00 | 0.35 |

### Data collection phase

A 6-cycle fault disturbance at bus 5 at the end of line 5–7 is considered. The fault is cleared by tripping the line 5–7 with successful reclosure after 1.0s. In this phase, the CCT is computed using Runge-Kutta method for several operating conditions defined by equations (11) and (12).

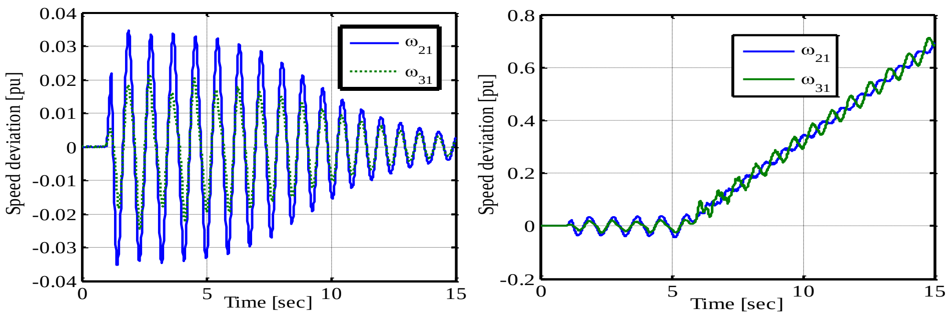
$$P_{Li} = \lambda_p P_{L0_i} \tag{11}$$

$$Q_{Li} = \lambda_q Q_{L0_i} \tag{12}$$

where, $P_{L0_i}$ and $Q_{L0_i}$ are the nominal active and reactive loads at the *i*-th bus given in Table I. Coefficients $\lambda_p$ and $\lambda_q$ are active and reactive loading factors, respectively. They will be ranged independently, from 0.2 to 1.5, in order to cover several values of the load power factors.

The collected input-output data pairs will be stocked in the training set. Inputs are described by the loading factors and outputs are the corresponding CCTs. In this case, the training set is composed of 200 input-output data pairs.

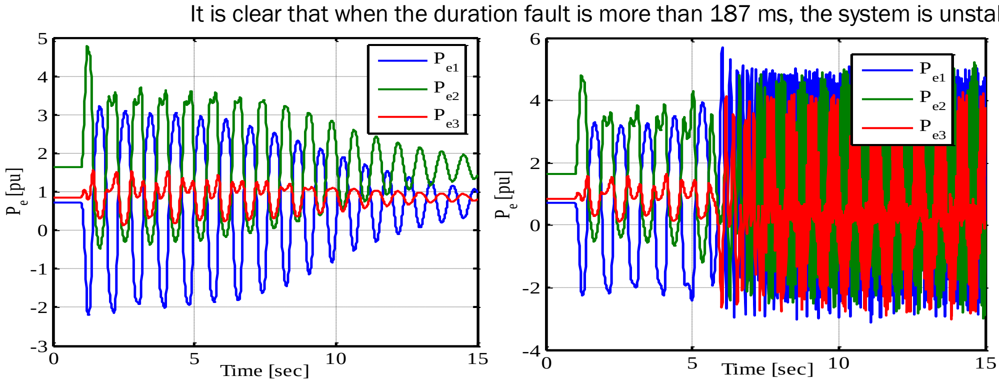
For example, the CCT is determined for the base case. Fig. 1 shows speed deviations of machines G2 and G3 using the nonlinear time domain simulations. G1 is the reference machine. From Fig. 1, it is clear that the system is stable for fault duration time $t_f$ = 187 ms and it is unstable for $t_f$ = 188 ms. Thus, the CCT is 187 ms.




(a) For $t_c$ = 187 ms (b) For $t_c$ = 188 ms

**Fig. 1:** Change in speed deviations for WSCC system

Fig. 2 shows the electrical power output of the three generators for the same duration faults as previously. It is clear that when the duration fault is more than 187 ms, the system is unstable.




(a) For $t_c$ = 187 ms (b) For $t_c$ = 188 ms

**Fig. 2:** Variation of the electrical power output for the WSCC system

### Training phase

The initial fuzzy inference system (FIS) is trained using ANFIS, to converge to the least possible error between the desired output and the FIS output through the training set. A combination of least-squares and back-propagation gradient descent methods are used. The cluster radius was $r_a = 0.25$.

Fig. 3 depicts a comparison between real training data and checking data obtained for various loading factors. It can be clearly seen that the ANFIS output provides good approximation of the variation of CCTs versus loading conditions.

## DISCUSSION

The performance of the proposed online DSA is also confirmed using the New England power system. All system data and the single line diagram are taken from [1,24]. A 6-cycle fault disturbance near bus 29 at the end of the line 26-29 with 20% step increase in mechanical power is applied. The disturbance is removed by tripping the line 26–29 with successful reclosure after 1.0 second. G8 and G9 are the nearest machines to the fault location. Thus, the system DSA can be summarized in studying the dynamic behaviour of these two generators.

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The NTDS depicted in Fig. 4 shows an example of computing of the CCT for a loading condition selected randomly from the input set. In this example, $\lambda_p = 1.0266$ and $\lambda_q = 1.2379$. From Fig. 4, it is evident that the corresponding CCT is 172 ms.

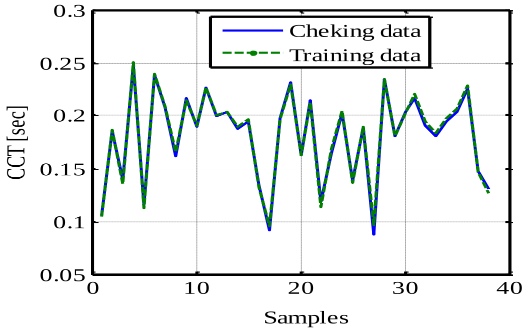
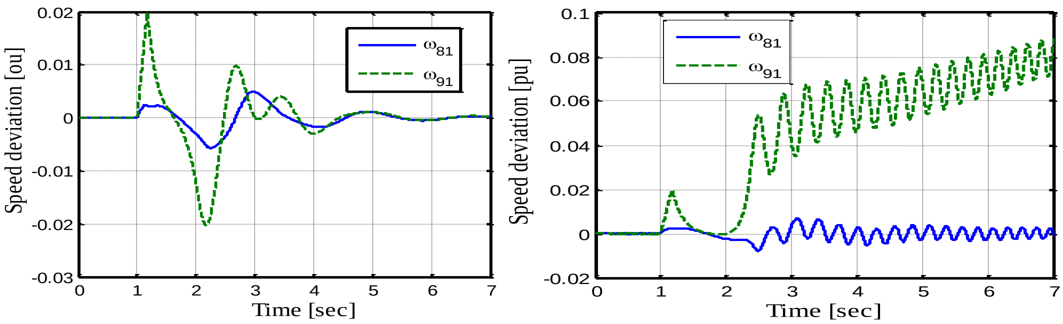



**Fig. 3:** Checking and training data for WSCC system




(a) For $t_c$ = 172 ms (b) For $t_c$ = 172 ms

**Fig. 4:** Variation of the electrical power output for the NE system

Fig. 5 demonstrates the real training data and checking data for various samples of loading conditions. As concluded for WSCC system, the proposed ANFIS-based approach provides accurate values of CCTs. Moreover, Table II shows that the proposed approach is convenient for on-line DSA because of its reduced computation time. In fact, the results presented in Table II show that the CPU time using the proposed method is reduced 8 to 10 times compared to the trajectory-based method presented in [14]. Therefore, it can be concluded that the proposed ANFIS-based method is an accurate technique that can be used for online dynamic security assessment over wide range of operating conditions.

The times reported here were computed using MATLAB R2013a with 64-bit operating system on a PC with an Intel i7-4510U CPU@2.00 GHz.


**Fig. 5:** Checking and training data for NE system

**Table. 2:** CPU time for the studied techniques

| Method | WSCC system | NE system |
|---|---|---|
| NTDS | (4 to 8)X0.375 sec | (4 to 8)X0.426 sec |
| Critical trajectory-based method [14] | 0.125-0.156 sec | - |
| ANFIS-based approach | 0.0121 sec | 0.0122 sec |

## CONCLUSION

In order to monitor the security of the power network and specifically to provide an extended visibility of the transmission system to the operator, the online prediction of the CCT is becoming a key issue for the DSA. This paper presents an intelligent technique for online DSA of power networks. This technique can provide an accurate CCT in a rapid and robust way. To do so, CCTs are firstly calculated using NTDS under various loading conditions and severe faults. Then, collected input-output data pairs will be stocked in training set whose inputs are the loading conditions and outputs are the corresponding CCTs. In order to provide real time estimation of CCTs for any loading condition, a neuro-fuzzy based approach is used to establish the relationship between inputs and outputs. Simulation results demonstrated that the proposed method can be applicable for online DSA since it is more than 142 times faster compared to the NTDS method.

### CONFLICT OF INTEREST

There is no conflict of interest

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### FINANCIAL DISCLOSURE

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