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Research Article

On-line Transient Stability Assessment through Generator Rotor Angles Prediction Using Radial Basis Function Neural Network

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Abstract: On-line Transient Stability Assessment (TSA) is challenging task due to the large number of variables involved and continuously varying operating conditions. This study proposes an on-line transient stability assessment methodology based on the predicted values of generator rotor angles under varying operating conditions for predefined contingency set through Radial Basis Function Neural Network (RBFNN). The real and reactive power loads are taken as input features for training of the neural network. Principal Component Analysis (PCA) is used for dimensionality reduction of the input data set to select informative features. The proposed method is tested on IEEE-39 bus test system and the results obtained for transient stability assessment through predicted rotor angles are promising.

Keywords: Artificial neural network, feature selection, on-line power system transient stability, principal component analysis, radial basis function

INTRODUCTION

Modern power systems operating close to their stability limits due to economic and operational constraints are more vulnerable to transient instability under severe credible contingency. To monitor and control transient stability, the rotor angle of the synchronous generators is very important reference quantity. On-line Transient Stability Assessment (TSA) involves generation of off-line data for varying operating conditions under probable contingencies and then predicting the future state on-line for given operating scenarios under predefined set of contingencies so that preventive actions can be taken to enhance the transient stability (Morison, 2006). Normally preventive actions are derived based on the predicted state of the system for particular operating scenarios. Thus it becomes imperative to find the correct post-fault scenarios so that suitable preventive actions can be taken accordingly (Vega and Pavella, 2003). Time Domain Simulation (TDS) is the established and accurate method for TSA but due to heavy computational burden it is suitable only for off-line purposes (Sobajic and Pao, 1989). Transient Energy Function (TEF) and extended equal area criterion based TSA has been proposed (Chiang *et al*., 1994; Vittal *et al*., 1988; Xue *et al*., 1989) for fast on-line TSA. The challenging task in implementation of energy based methods for on-line TSA is to find the function that defines the transient energy of the large and complex power system and simultaneously finding the critical transient energy of the system under given disturbance.

In the past few years Artificial Intelligence (AI) based techniques such as Artificial Neural Network (ANN), Support Vector Machines (SVM) and decision tress have been proposed for on-line TSA (Krishna and Padiyar, 2000; Moulin *et al*., 2004; Sawhney and Jeyasurya, 2006; Voumvoulakis *et al*., 2006). Normally these AI techniques are used to learn from off-line data and then can be utilized for on-line transient stability evaluation. Various neural network based techniques has been proposed for on-line TSA in recent years due to their ability to synthesize complex mappings very accurately and rapidly for practical applications. A backpropagation neural network is used for on-line TSA with 2 hidden layers (Krishna and Padiyar, 2000). A feed-forward ANN based method was proposed for TSA with two feature selection techniques (Sawhney and Jeyasurya, 2006), fuzzy neural network based transient stability prediction method with transient swings as input was proposed in Liu *et al*. (1999). Fisher discrimination feature selection technique based ANN was proposed for dynamic security analysis (Jensen *et al*., 2001).

Majority of ANN based methods available in literature determines security state of type stable/ unstable (0 or 1) (Moulin *et al*., 2004; Krishna and Padiyar, 2000; Liu *et al*., 1999), i.e., able to classify the system stability successfully but fails to determine the degree of stability/instability in the postfault state of the system. The energy function based method using neural

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network techniques for TSA proposed in Mansour *et al*. (1997), is able to determine the severity of contingency and can find the stability margins for the contingency. However majority of the methods require heavy computational time for training, as well it is difficult to construct the energy function for multi-machine system. Thus it is desirable to have a method which can predict the future transient stability state based on the present operating conditions for the set of contingencies and as well able to evaluate the severity. In the simple classification based methods accuracy is the major issue, as insecure scenarios predicted to be secure can make the entire system to collapse.

Most of the authors have used feed forward neural network (Krishna and Padiyar, 2000; Sawhney and Jeyasurya, 2006; Jensen *et al*., 2001) with sigmoidal nonlinearities using back propagation algorithm, which usually suffers from the problem of local minima and over fitting. Another shortcoming of this network is that it takes long time for training. Radial Basis Function Neural Network (RBFNN), which has nonlinear mapping capability, has become increasingly popular in recent years due to its structural simplicity and training efficiency. Therefore, in this paper RBFNN based approach for TSA is proposed by predicting the rotor angles of all the machines for given operating conditions and then evaluating the transient stability state by Transient Stability Index (TSI) using the values of these predicted rotor angles under predefined contingency set. The severity of contingency can be determined based on the predicted values of rotor angles for these operating conditions. The input features of neural network are real and reactive power demands, whereas the output is the rotor angles of all the generators. The dimensionality of the input features is reduced by Principal Component Analysis (PCA) which enhances the speed of training. The effectiveness of the proposed scheme is investigated on IEEE-39 New England test system. The results shows that the predicted values of generator rotor angles are very close to the values obtain through dynamic simulation.

Power system dynamics and rotor angle prediction: One of the main objectives of the dynamic simulation is to observe the transient stability state of the system following contingency. This is accomplished by determining the rotor trajectories of all the generators in post disturbance scenario. If the rotor trajectories increases/decreases monotonously without bounds the system is termed as unstable, however if rotor trajectories swings within specified limits the system is termed as stable. The rotor angle of all the generators is obtained by solving the set of following equations given by Hiyama (1981) as:

$$\frac{d\delta_g}{dt} = \Delta\omega_g \text{ for } g = 1, 2 \ldots\ldots N_G \tag{1}$$

$$\frac{d\omega_g}{dt} = \frac{1}{M_g}\left(P_{mg} - P_{eg} - D_g\Delta\omega_g\right) \text{ for } g = 1, 2 \ldots\ldots N_G \tag{2}$$

$$P_{eg} = G_{gg}E_g^2 + \sum_{\substack{h=1 \\ h\neq g}}^{n}\left\{E_g E_h G_{gh}\cos\left(\delta_g - \delta_h\right) + B_{gh}\sin\left(\delta_g - \delta_h\right)\right\} \tag{3}$$

where, N_G is the total number of generators, δ_g and $\Delta\omega_g$ are the rotor angle and speed deviation of the g^{th} generator, respectively, P_{mg} and P_{eg} are the input mechanical and output electrical power respectively of the generator g, E_g is the internal voltages of the g^{th} generator, M_g is the moment of inertia of machine g, D_g is the damping coefficients of g^{th} machine, $G_{gh} + jB_{gh}$ is the transfer admittance between the g^{th} and h^{th} machine, n is the total generating buses except g. These rotor angles can be utilized to assess transient stability state of the system by Transient Stability Index (TSI) as follows:

$$TSI = \left|\delta_g(t) - \delta_{COA}\right| = \delta_g^{COA}(t) \leq \delta_{max} \tag{4}$$

where,

$\delta_g(t)$ = The rotor angle of the generator g

δ_{COA} = The centre of angles

$\delta_g^{COA}(t)$ = The relative rotor angle of the g^{th} generator with respect to Centre of Angles (COA)

t = The time step during dynamic simulation. The COA is determined as given by (Kundur, 1994):

$$\delta_{COA} = \frac{\sum_{g=1}^{NG}\delta_g H_g}{\sum_{g=1}^{NG} H_g} \tag{5}$$

where, H_g is the inertia constant of the generator g, if the rotor trajectories of all the generators with respect to COA remains below the predefined value during the entire simulation the system is transiently stable (1) else it is unstable (0). In this study, δ_{max} is taken as 120°. For each contingency, with varying operating conditions, a class label of 0 or 1 is assigned based on (4) as transiently stable or unstable, respectively. The rotor angles obtained through these simulations can be utilized for training the network and can be used for online applications for the unseen operating scenarios through trained ANN to predict the values of rotor angles for defined contingency set.

Ann based on-line transient stability assessment: For on-line TSA, the offline data is generated for the given set of credible contingencies by randomly varying the real and reactive loads, the real and reactive power generations of all the generators are set to optimal point of the base case. In this study, the initial input features considered are real and reactive power load demands (P_{D_m} and Q_{D_m}) of all the buses. The initial input feature set for ANN training is defined as:

$$[x_j] = [P_{D_m}, Q_{D_m}] = F_i \text{ where, } m = 1 \ldots N_D \quad (6)$$

The target for ANN output is the rotor angle in degrees of all the generators at given time instant defined as:

$$[x_t] = [\delta_g], \text{ for } g = 1 \ldots\ldots N_G \quad (7)$$

Contingency selection: The selection of critical contingencies depends upon the knowledge of the operator about the probability of their occurrence and severity. In this paper, two credible contingencies (three phase fault) are selected for testing the proposed scheme based upon their severity for different given operating conditions. After simulating different contingencies it is found that these two faults are more sensitive to the load variation with large excursions in the rotor angles. The purpose of RBFNN in this study is to map the pre-fault operating conditions to the post-fault rotor angles of all the generators for the specific contingency.

Data generation: The offline database of operating points is required to train the neural network. The database consists of large number of randomly varied load patterns covering wide range of scenarios. The dynamic simulation is performed by numerical integration technique such as trapezoidal method. The real and reactive load demands are considered as input features to neural network and the rotor angle of all the machines at the end of simulation are taken as output targets, each contingent case is assigned a class label of stable (1) or unstable (0) based on the *TSI* as (4).

Data normalization: The input features P_{D_m} and Q_{D_m} in this study is normalized in the range of 0 and 1 for each pattern and shuffled several times for enhancing the randomness and minimizing the sequential effect. Normalization is done to make the Euclidean length of the vector equal to 1 by dividing vector by norm of the vector. Each input is normalized to x_n for training and testing of neural network as:

$$x_n = \frac{(x_i - x_{i,min})}{(x_{i,max} - x_{i,min})} \quad (8)$$

where,

x_i = The actual value of the input
$x_{i,min}$ = The minimum value in the input data set
$x_{i,max}$ = The maximum value in the input data set

Feature selection using PCA: The purpose of feature selection is to reduce the dimension of the input features. With large-scale power systems, the number of input variables increases sharply and therefore, it is necessary to discard the redundant features, having no additional information, from the original feature set. A neural network with less inputs have less adaptive parameters to be determined and thus better generalization and reducing training time drastically (Haykin, 1999). In this study, Principal Component Analysis (PCA) is investigated to reduce the dimensions of the input features. The dimension reduction of the input variables can be achieved by transforming to a new set of uncorrelated variables known as Principal Components (*PCs*), which are ordered with first few hold most of the variation present in the original input variables. PCA is orthogonal linear transformation which transforms the original data to new coordinate system such that data which have large variations comes to lie in the first coordinate (termed as first *PC*) and so on in the decreasing order of their variance. Normally most of the original information is retained by the first *PCs*, reducing the dimensions of input features drastically.

RBFNN for TSA: RBFNN is the class of single nonlinear hidden layer feed forward neural networks (Devaraj *et al*., 2002), which have nonlinear mapping capability and uses radial basis function as activation functions. The input nodes pass the input to the hidden layer directly without any connection weights.
The transfer function in the hidden nodes is given as:

$$\emptyset_j(x) = exp\left(-\frac{\|x-\mu_j\|^2}{2\sigma_j^2}\right) \quad (9)$$

which is similar to the multivariate Gaussian density function, where x is the d-dimensional input vector with elements x_i, μ_j is the vector which determines the centre of the basis function $\emptyset_j$, σ_j is their widths. Thus each RBF correspond to a unique local neighbourhood in the input space. The generalised RBFNN architecture is shown in Fig. 1.
The k^{th} output node value given by y_k is determined by:

$$y_k(x) = \sum_{j=1}^{p} w_{kj}\emptyset_j(x) + w_{k0} \quad (10)$$

where,

w_{kj} = The connection weight between the output and the j^{th} hidden node
w_{k0} = The bias term and p is the number of the basis function

PROPOSED METHODOLOGY

The flowchart of the proposed scheme for transient stability assessment through rotor angle prediction is shown in Fig. 2.
The algorithm steps are as follows:

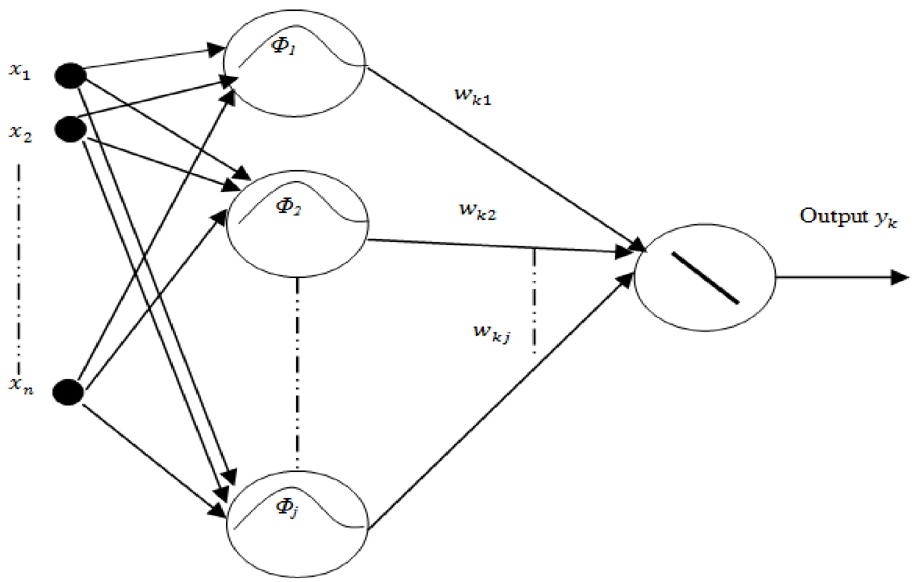

Fig. 1: RBFNN architecture

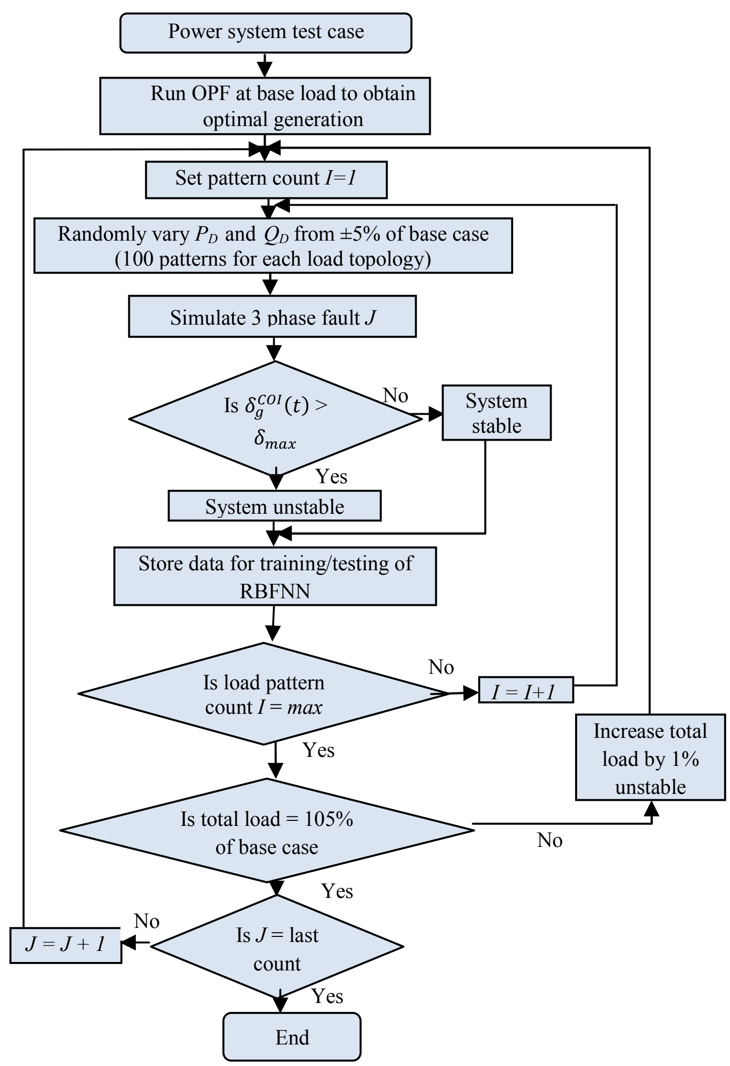

Fig. 2: Flowchart of data generation for on-line TSA

- Run Optimal Power Flow (OPF) on the given test system at base case and obtain the optimal generation schedules, Set contingency count $J = 1$.
- Set total load of the system to 95% of the base case.
- Set pattern count $I = 1$.
- Randomly vary the real and reactive load of each bus of the system.
- For credible contingency J (three phase fault), perform dynamic simulation for given load pattern.
- Record the rotor angles with respect to *COI*, $\delta_g^{COI}(t)$ (g = 1, 2........, N_G) at each time step during simulation.
- Is $\delta_g^{COI}(t)$ >120°, the system for the given operating conditions for contingency J is transient unstable (0) otherwise transient stable (1).
- Is pattern count = max? Yes, go to step 9 else $I = I+1$ and go to step 4.
- All load scenarios simulated for the contingency J? Yes, go to step 10, otherwise, increase the total load by 1% and go to step 3.
- All contingencies simulated? Yes, divide the total patterns into train set and test set for ANN, otherwise, take next contingency J, i.e., increment $J = J+1$ and go to step 2.
- The normalized and shuffled values of P_D and Q_D are taken as input variables for training RBFNN and $\delta_g^{COI}(t)$ as targets for the network.
- With the predicted values of rotor angles evaluate the stability state of the system for the unseen cases.

RESULTS AND DISCUSSION

The proposed RBFNN based TSA approach is tested on IEEE-39 bus New England test system (Pai, 1989), the system consists of 10 generators, 12 transformers and 46 transmission lines. The slack bus is taken as bus 39. Classical generator models are used having turbines, governors, exciters and stabilizers. All the simulations are carried out using MatPower 4.1 (Zimmerman, 2011), PSAT (Milano, 2005) and MATLAB 7.7 2008.

Training and testing data generation: The real and reactive loads are varied from 95 to 105% of the base case in steps of 1% and for each load topology 100 patterns are generated by randomly varying all loads, which covers a wide range of scenarios, the two contingency are simulated for each load pattern as mentioned in Table 1: three phase fault at bus-28 cleared by opening the line 28-26 (contingency-A) and three phase fault at the midpoint of line 21-22 cleared by opening the line (contingency-B). Both faults are applied at 1 sec and are cleared after 0.2 sec.

The dynamic simulation is performed for 3 sec and rotor angle value of all the generators at the end of simulation is observed. Thus total 2200 patterns are generated, 1100 patterns for each contingency. The on-line TSA is done by pre-contingent data. The RBFNN is used for mapping the nonlinear relationship of pre-fault operating conditions to the post-fault rotor angle of the generators. One RBFNN is trained for each contingency.

Table 1: Applied credible contingencies

Contingency #	Location of fault	Tripped line	Duration
A	Bus-28	26-28	12 cycles
B	Line 21-22	21-22	12 cycles

Table 2: Features reduced using PCA

Contingency #	Initial features (F_i)	Selected features (F_s)	Dimensionality reduction (%)
A	42	20	52.24
B	42	16	61.90

Feature selection using PCA: The features are selected for training and testing of network using PCA to reduce the dimensionality and increasing the speed of the network. Since most of the contingency are localized in nature thus remote power system variables do not affect the transient stability of the system, as these variables not only complicate the network but also degrade the performance of the network. The real and reactive loads are considered as input features for ANN, as post fault rotor angle excursions largely depends upon these load demands, hence these features can predict transient stability status for the given contingency. In the IEEE-39 bus system total dispatchable loads considered are 21, therefore, initial feature set; F_i consists of total 42 input features. The features selected from F_i after applying feature selection using PCA are 20 and 16, respectively shown in Table 2 for the two contingencies applied. The data set with reduced features F_s is shuffled several times and divided into training set and test set. Out of 1100 cases of each contingency 700 cases are used to train the network and remaining 400 cases for testing the network.

Test results: The two contingencies defined in Table 1 are simulated for IEEE-39 test system; the sample results obtained for the two contingencies for stable and unstable operating scenarios are shown in Table 3 and 4.

Table 3 indicates an unstable case, where the actual relative rotor angle of generator of G9 is above the threshold value of 120° and goes out of step with respect to COA. The predicted value of all the rotor angles obtained from RBFNN are nearly the same as the actual values obtained from time domain simulations. The proposed methodology using RBFNN is able to classify correctly this operating condition as transiently unstable. Figure 3 shows the relative rotor angles of all machines for contingency-A for unstable operation. It can be observed from the figure that for contingency-A (fault at bus-28) generator G9 is most sensitive to load variations, since this generator is near to the faulted bus-28. For all the unstable cases for contingency-A it is found that rotor angle of G9 is above the threshold value and the RBFNN is able to predict these cases correctly

Table 3: Actual and predicted relative rotor angles for contingency-A (unstable case)*

Generator No.	Actual rotor angle (deg)	Predicted rotor angle (deg)	Actual state	Predicted state
1	-2.08	-4.32	Instep	Instep
2	15.15	14.41	Instep	Instep
3	23.93	23.06	Instep	Instep
4	24.87	21.98	Instep	Instep
5	28.35	21.34	Instep	Instep
6	21.60	20.50	Instep	Instep
7	25.02	25.30	Instep	Instep
8	31.19	29.77	Instep	Instep
9	717.17	755.81	Outstep	Outstep
10	-15.49	-23.27	Instep	Instep

*: Pattern number:754

Table 4: Actual and predicted relative rotor angles for contingency-B (stable case)*

Generator No.	Actual rotor angle (deg)	Predicted rotor angle (deg)	Actual state	Predicted state
1	20.75	22.54	Instep	Instep
2	51.39	52.51	Instep	Instep
3	60.78	61.95	Instep	Instep
4	65.84	66.82	Instep	Instep
5	71.15	72.45	Instep	Instep
6	76.86	78.71	Instep	Instep
7	77.41	79.19	Instep	Instep
8	69.28	69.94	Instep	Instep
9	81.78	80.19	Instep	Instep
10	7.53	7.16	Instep	Instep

*: Pattern number: 625

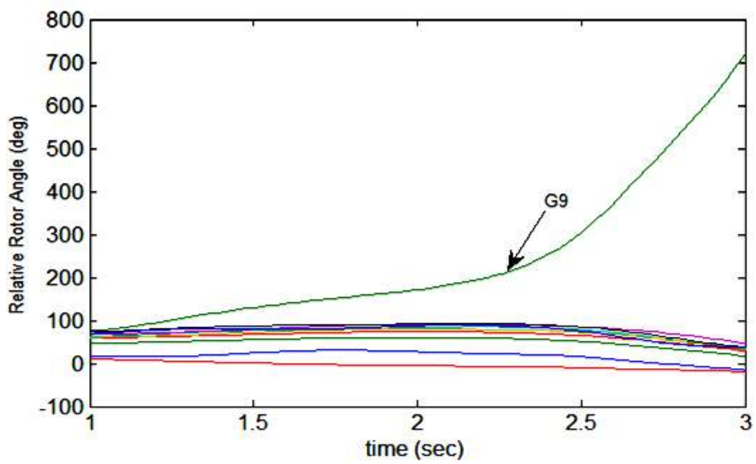

Fig. 3: Relative rotor angle of sample unstable case for contingency-A (pattern number-754)

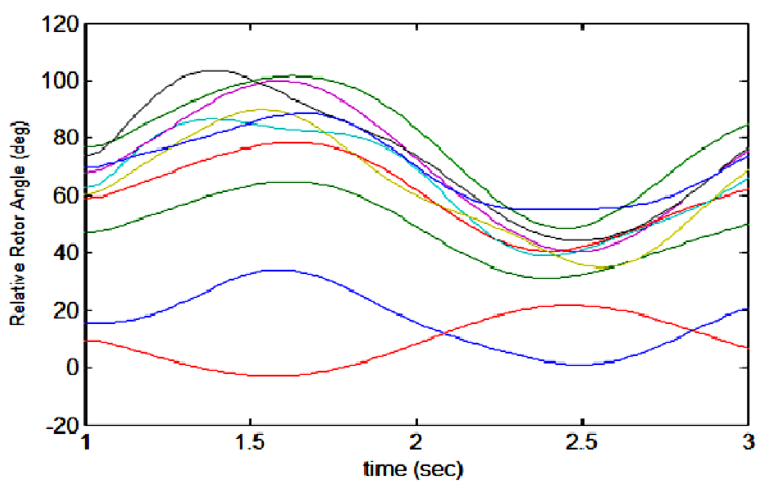

Fig. 4: Relative rotor angle of sample stable case for contingency-B (pattern number-625)

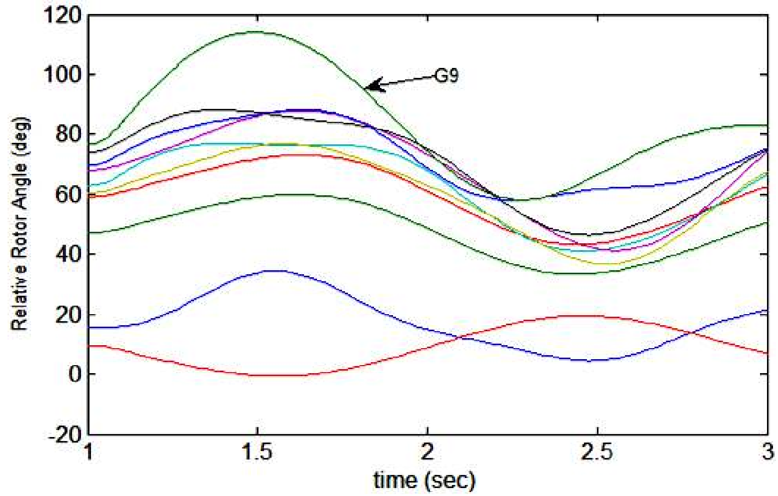

Fig. 5: Relative rotor angle of sample marginal stable case for contingency-A (pattern number-454)

as unstable with an average error of 5% in predicting the rotor angles.

From Table 4, it can be observed that the excursions of rotor angles are small from their pre-fault value indicating that it is stable case. The predicted values obtained from RBFNN are very close to their actual values obtained using time domain simulations. The RBFNN is able to classify correctly this operating condition as transiently stable for contingency-B. Figure 4 shows the relative rotor angles for stable case of all the generators for contingency-B. However, it is found for this contingency, the generators G6 and G7 are the most sensitive to load variations, as faulted line 21-22 is close to these two generators and therefore the rotor angle excursions of these generators is maximum for an unstable case.

For all other transiently unstable operating conditions simulated for contingency-B, it is found that the rotor angles of G6 and G7 are always above threshold values and for all these cases the RBFNN can able to predict these angles correctly with an average error of 5% and all these cases are correctly classified as unstable.

Figure 5 is another marginally stable case where the relative rotor angle of G9 is very close to threshold value of 120°. For this case also, the proposed methodology is able to predict correctly the rotor angles and the stability status of the system.

CONCLUSION

This paper presents fast and effective neural network based approach for on-line transient stability assessment of power systems for varied operating conditions. The transient stability of the system depends upon the trajectories of the rotor angles of the generators and thus in post-fault scenario they indicates the stability state of the system. The proposed method is based on predicting the rotor angles of the generators using RBFNN for a given contingency to assess the transient stability of the system. The input features for ANN are reduced using PCA. For all the unseen operating cases the average error in predicting the rotor angles using RBFNN is about 5% and the network is able to predict instability/stability state correctly. With these predicted values the severity of the contingency can be determined on-line and they can be ranked for the current operating conditions from the set of credible contingencies. The proposed approach is tested on IEEE-39 bus system and the test results obtained for proposed RBFNN in predicting the rotor angles highlights the effectiveness of the proposed methodology.

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