

Development of Back-Propagation Neural Network for Transient Stability Assessment of Power Systems



R. Anirudh, Sk. Janibasha, M. Naga Chaitanya, Sk. Moulali

Abstract: Transient Stability Assessment (TSA) is aspect of the power system dynamic stability assessment, which includes measuring the capacity of the system to stay synchronized under extreme disturbances. This research work shows the transient stability status of the power system following a major disturbance, such as a faults, line switchings, generator voltages. It can be predicted early based on response trajectories of rotor angle. This early prediction of transient stability is achieved by training a Back Propagation Neural Network (BPNN) taking trajectory of rotor angles as training features. Transient stability index (TSI) proposed in [4] is utilized as a target feature. The proposed methodology is tested with wide range of fault data collected from simulated IEEE 39-Benchmark system. The simulation results shows, utilization of BPNN for transient stability prediction resulted in better performance when compared to Radial Basis Neural Network (RBFNN) [4].

Keywords : Power system stability, rotor angle stability, back propagation neural networks (BPNN).

I. INTRODUCTION

Monitoring a power system's reliability status in real time was recognized as a primary task in avoiding blackouts. If there is a disruption that contributes to temporary instability, it is very important to quickly locate the fault and allow enough time for action. Many attempts have been reported to establish an active transient measure of stability in real time [1]. Measuring the necessary variables using phasor measuring units (PMUs) is a key feature for successfully predicting the transient stability in order to avoid the collapse of the system [2].

Even if best efforts are made in planning and operation, unforeseen events may occur leading to grid failure and

blackout. Based on the behaviour of the power system after the fault, response-based actions are expected under these conditions [3]. It is therefore important to find fast and precise methods to determine transient instability and also to estimate the severity of the disorder. To prevent cascaded blackouts, Control islanding is used [4]. Since this involves more significant detection of coherent devices after the occurrence of a fault in real time. The required results will be obtained in order to achieve fast and accurate real-time transient stability assessment (TSA) deploying phasor measuring units (PMUs) at required locations and fast processing algorithms [5]. TSA includes evaluating the rotor swings future behaviour after failure or significant disturbance to accurately predict transient stability [6]. The data received from PMUs at the control centre provides sufficient information about the present and future state of the system after disturbance from a stability point of view, it is possible to deal with the stability in real time [7, 8, 9]. A Multilayer Perceptron neural network with three layers consisting of one input layer, one hidden layer and one output layer is proposed in [10] and compared with radial basis neural networks (RBFNN) in [11]. In [12, 13, 14] authors presented method to detect and classify the power system transmission line faults using discrete wavelet transformation and artificial neural networks. It is reported that STATCOM is a better solution for preserving the voltage stability of a power system [15, 16]. Intelligent based Transient stability prediction are proposed in [17, 18]. The proposed electric spring methodology in [19] provides a better voltage, power stability. This can be monitored and controlled using cloud computing [20]. A computationally fast implementable methodology to predict the system's post-fault transient stability is proposed. The rotor angles predicted from BPNN are used to assess the transient stability status of each generator. Post-fault rotor angles data at high reporting rates are collected from simulated fault conditions which will be used for stability predictions Outline of the paper is as follows: Basics of transient stability problems and its related mathematical equations are represented in Section II. Section III discuss the basic implementation structure of Back propagation neural network (BPNN). Proposed methodology for assessment of transient stability status of generators is presented in Section IV. This proposed methodology is tested on IEEE 39 bus system and simulation results are discussed in Section V. Section VI concludes up with the key findings observed in the research work.

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II. TRANSIENT STABILITY PROBLEM

Transient state stability is the system's ability to be stable when the system state changes unexpectedly or significantly [21]. First swing stability is concerned with the rotor angles swing just after the disturbance. In this paper, the proposed methodology is concerned with the first swing stability of the system. A power system is in a stable state of operation, if all the physical parameters representing the state of the system are within the prescribed limits. After the sudden disturbances in the system such as faults, line switching, etc can either make the operating point of the system to settle in a new operating point or return to the same operating point based upon the intensity of the disturbance. The goal of a transient stability problem is to determine whether the system preceding a disturbance returns to a stable operating point or not. After the disruption, the rotor angle excursions of all machines reflect the power system's transient stability condition. The system's transient stability condition can be identified by finding the machine rotor angle values. Time Domain Simulation (TDS) approach is the classical approach to determining the post-disturbance rotor angles. All machines rotor angles are controlled by a series of equations called swing equations.

$$\frac{d\delta_g}{dt} = \Delta\omega_g \tag{1}$$

$$\frac{d\Delta\omega_g}{dt} = \frac{1}{M_g} (P_{mg} - P_{eg} - D_g \Delta\omega_g) \tag{2}$$

$$P_{eg} = G_{gg} E_g^2 + \sum_{h=0}^N E_g E_h [G_{gh} \cos(\delta_g - \delta_h) + B_{gh} \sin(\delta_g - \delta_h)] \tag{3}$$

Where $g = 1, 2, 3, 4, \dots, N$ [N = Total number of generators]

δ_g and ω_g are rotor angle and rotor speed deviations of the g th generator

P_{mg} and P_{eg} are Mechanical Power Input and Electrical Power Output, respectively.

M_g is the Moment of Inertia of the g th machine

D_g is the Damping Factor of the g th machine

There are many methods [4, 9] reported in the literature to solve the transient stability problem. Among them equal area criteria is extensively used single machine infinite bus (SMIB) or a two-machine systems. In [4] Padmore have used direct method to determine the system stability. Stability analysis is calculated by the lynapnov method in [9].

III. BACKPROPAGATION NEURAL NETWORK

A neural network is a linear, distributed data processing system consisting of local memory processing components and regional information. The processing operations that are interconnected with unidirectional signal channels called connections. Every processing component has a single output connection that connects to as many collateral connections as desired. The neural network architecture of backpropagation

is a hierarchical model consisting of entirely interconnected layers or unit lines [10]. Backpropagation involves activation function derivatives. Automatic differentiation is a technique that can transmit the derivatives to the learning algorithm automatically and analytically. It is widely used by the gradient descent optimization algorithm to adjust the weight of the neurons by measuring the loss function gradient; back propagation calculates the gradient(s), while gradient descent uses the gradients to train the system by optimization. It is possible to break down the Back propagation algorithm to four key stages. The back propagation algorithm is used to calculate the necessary corrections after randomly selecting the weights of the network. In the following four steps, the algorithm can be broken down:

1. Feed-Forward Computation
2. Back Propagation to the output layer
3. Back Propagation to the hidden layer
4. Weight Updates

The algorithm will be conversed when the error function value has become less the tolerance value.

The main aim of the Backpropagation algorithm aim is to refine weights such that the neural network can learn to map arbitrary inputs to outputs non-linearly.

A) Feed-Forward Computation

Let the neural network now predict randomly given its weights and biases. To do this, through the network, we must feed those inputs forward.

Provide total net input to each hidden layer of neuron, decrease the total net input using an activation function, then repeat the cycle with the neurons of the output layer.

Calculate the total net input for h_1, h_2, \dots, h_n .

$$h_{1net} = b_1 * 1 + w_1 * i_1 + w_2 * i_2 + \dots + w_n * i_n \tag{4}$$

$$h_{2net} = b_2 * 1 + w_3 * i_3 + w_3 * i_4 + \dots + w_n * i_n \tag{5}$$

until required hidden layers (as per inputs)

We will decrease it using logistic function to get the output of h_1, h_2, \dots, h_n .

$$O_{1out} = \frac{1}{1 + e^{-h_{1net}}} \tag{6}$$

$$O_{2out} = \frac{1}{1 + e^{-h_{2net}}} \tag{7}$$

Calculating the Total Error

Calculate the error of each output neuron using **mean square error** and sum them to get the total error

$$E_{Total} = \sum \frac{1}{2} (target - output)^2 \tag{8}$$

$$E_{Total} = E_{o1} + E_{o2} \tag{9}$$

B) Backwards Computation

Backwards computations are done to update the weights in the network to make the actual output closer to the targeted output.



This minimizes the error of the each output neuron.

$$\frac{\partial E_{total}}{\partial \omega_i} = \left(\frac{\sum \frac{\partial E_{total} \cdot \delta_{out}}{\partial net} \cdot \delta_{net}}{\delta h_{innet}} \right) * \delta \frac{h_{out}}{\delta h_{innet}} * \delta \frac{h_{innet}}{\delta w_i} \quad (10)$$

$$\frac{\partial E_{total}}{\partial w_i} = \delta_{hi} i_i \quad (11)$$

We can update weights by:

$$w_i = w_i - \frac{n * \partial E_{total}}{\partial w_i} \quad (12)$$

IV. PROPOSED METHODOLOGY

The main objective of the presented research work is to assess the system's future stability state within few cycles after the disturbance. In order to assess the transient stability of the system, a BPNN is trained with change in rotor angles of all generators as input features and Transient stability index (TSI) [4] as the output feature. BPNN is trained with a few cycles of post-disturbance simulated fault scenarios information to estimate the TSI values. The transient stability and synchronization state of the individual generator in the system is assessed by predicting the TSI value with the trained neural network. Eventually, the coherent groups of machines can also be identified.

A) Data Collection:

Data collection is aimed at collecting data covering a large number of operating conditions under all expected disruptions. The data collected at different operating conditions can be summarized as:

- 1) The real and reactive loads at all buses were raised by 1% from 95% to 105% of the base case.
- 2) A 3-phase fault is considered for each load pattern at different locations.

Rotor angles and the voltages of the each generator is collected from the simulated fault scenarios for consecutive cycles. Then the data is split into training data and testing data. The training data consists of the 65% of the data collected and the other 35% for testing the neural network.

B) Transient Stability Index:

The additional feature used for training the neural network is TSI values [4]. The synchronization state of the generating machines must be identified with less computational stress and time for each unstable condition possibly. TSI is calculated on the basis of time domain simulation (TDS) and is defined as:

$$TSI_j = 1 - \frac{\delta_{max} - \Delta \delta_{j,COI}(\tau)}{|\delta_{max} + \Delta \delta_{j,COI}(\tau)|} \quad (13)$$

Where $\Delta \delta_{j,COI}(\tau)$ is the final value of rotor angle deviations

δ_{max} is the maximum rotor angle allowable

TSI can be used to assess power system stability, rank generator criticality and individual stability status, and generator coherence.

$$GeneratorStabilityStatus = \begin{cases} Unstable & if TSI > 1 \\ Stable & if TSI < 1 \end{cases} \quad (14)$$

In the first step of the proposed methodology, the rotor angles are collected by simulating various fault scenarios described in Section III(a). These rotor angles collected from different scenarios will be used to compute change in rotor angles (input feature) and TSI values (output feature). In the second stage, the BPNN is trained with the above mentioned input and output features. After training, the BPNN is tested by different test data patterns with change in fault location and durations to increase accuracy. The performance of trained BPNN is determined by testing with the new fault scenarios. Thus, this methodology predicts the stability status of each generator.

V. SIMULATED RESULTS AND DISCUSSION

The effectiveness of the proposed methodology is tested on the IEEE 10-generator 39 bus benchmark system. The proposed methodology is developed in python 3.6 on AMD Ryzen 5 3200 CPU@2.1Hz personal computer. The data is collected at a frequency of 1000 Hz. The various parameters considered for BPNN are: 3-layer network consisting of one input layer, one hidden layer and one output layer. The hidden layer uses logistic activation function i.e. the sigmoidal function to calculate the outputs. The weights are changed to decrease the error between the actual output and the expected output. For all the cases, 3-phase fault is applied with different fault durations that varies between 5 to 13 cycles. The average load of the system ranges from 95% to 105% of the base case load. A wide range of fault scenarios are considered. Table I summarizes various contingencies that are simulated for the collection of test data. From the data collected the BPNN is able to predict the stability status of all generators.

Table I: Applied Contingencies

Contingency	Type of fault	Location of fault	Tripped line	Fault duration (freq. 60Hz)	System load (% of Base case)
Case I	3-phase fault	Bus 26	Line 26-29	5 Cycles	99%
Case II	3-phase fault	Bus 13	Line 13-14	10.37 Cycles	97.50%
Case III	3-phase fault	Bus 21	Line 21-22	12 Cycles	98%
Case IV	3-phase fault	Bus 26	Line 26-29	8.3 Cycles	Base Case

TABLE-II
Results

		Gen1	Gen2	Gen3	Gen4	Gen5	Gen6	Gen7	Gen8	Gen9	Gen10
Case I	TSI	0.0305	0.2457	0.3117	0.3273	0.4732	0.3565	0.3680	0.3874	1.0195	0.2789
	Stability Status	0	0	0	0	0	0	0	0	1	0
	BPNN	0.030	0.2448	0.3089	0.3222	0.4699	0.3487	0.3666	0.3777	0.9996	0.2668
Case II	TSI	1.8022	1.9225	1.9304	1.8050	1.8066	1.8055	1.8057	1.8056	1.8072	1.7699
	Stability Status	1	1	1	1	1	1	1	1	1	1
	BPNN	0.9999	0.9916	0.9024	0.9974	0.9987	0.9799	0.9999	0.9998	0.9996	0.9991
Case III	TSI	1.6819	1.6658	1.6723	1.6326	1.6373	1.8608	1.8616	1.6750	1.6696	1.5963
	Stability Status	1	1	1	1	1	1	1	1	1	1
	BPNN	0.9955	0.9996	0.9987	0.9861	0.9999	0.9949	0.9899	0.9988	0.9878	0.9895
Case IV	TSI	0.3005	0.3348	0.4111	0.4095	0.553	0.4156	0.4147	0.4827	1.0039	0.3367
	Stability Status	0	0	0	0	0	0	0	0	1	0
	BPNN	0.2997	0.3288	0.4045	0.4006	0.5496	0.4086	0.4067	0.4785	0.9987	0.3306

Case I: In Case I, the predicted values of TSI are shown in table II. It shows that the value of TSI for G9 is greater than 1 whereas for other generators it is less than 1. Hence, G9 is the only unstable generator. The actual rotor angles of all generators is shown in Figure 1.

Case II: In Case II, the predicted values of TSI are shown in table II. It shows that the value of TSI for all the generators is greater than 1. Hence, all generators are unstable. The actual rotor angles of all generators is shown in Figure 2.

Case III: In Case III, the predicted values of TSI are shown in table II. It shows that the value of TSI for all the generators is greater than 1. Hence, all generators are unstable. The actual rotor angles of all generators is shown in Figure 3.

Case IV: In Case IV, the predicted values of TSI are shown in table II. It shows that the value of TSI for G9 is greater than 1 whereas for other generators it is less than 1. Hence, G9 is the only unstable generator. The actual rotor angles of all generators are shown in Figure 4.

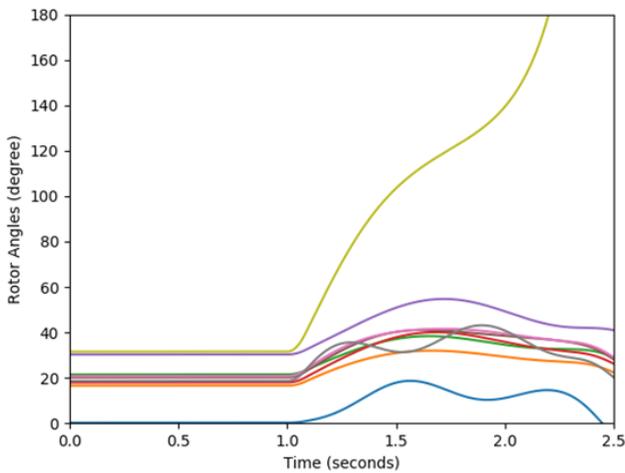


Fig. 1 Actual rotor angles of all the generators for Case I

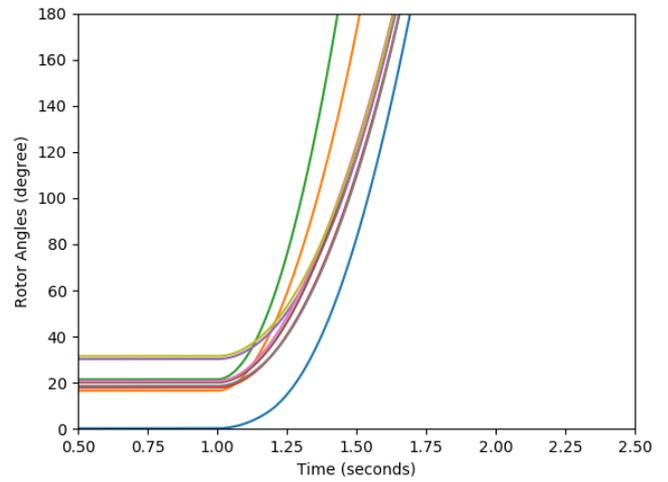


Fig. 2 Actual rotor angles of all the generators for Case II

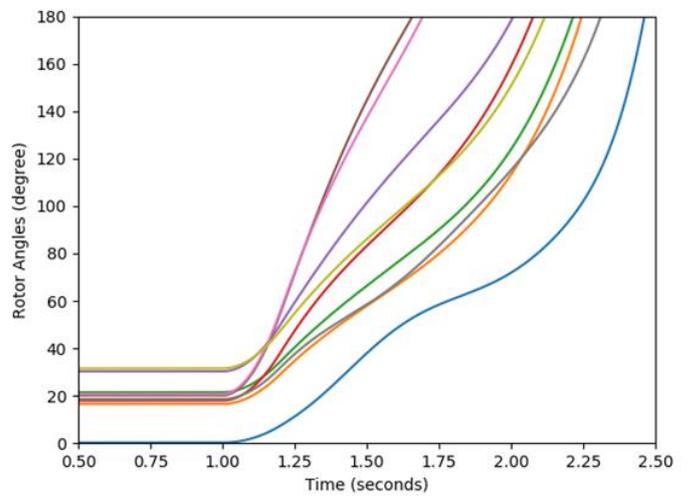


Fig. 3 Actual rotor angles of all the generators for Case III

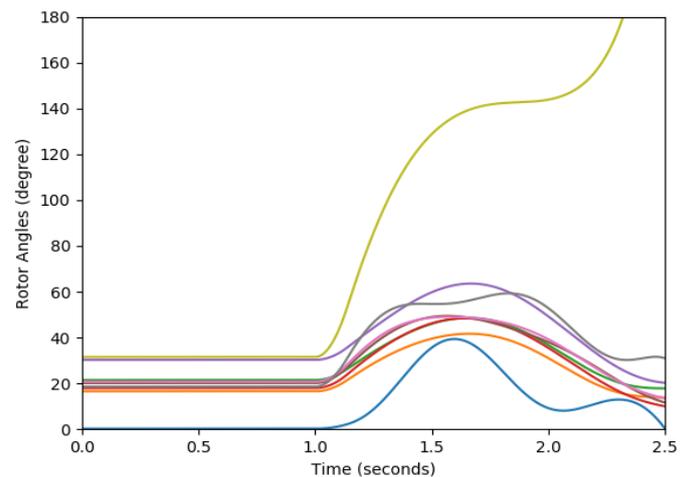


Fig. 4 Actual rotor angles of all the generators for Case IV

In all the simulated cases, the predicted TSI values are able to assess the stability status of the generators. In Table III, the proposed method is compared with the method using radial basis neural network (RBFNN) [1] for transient stability assessment.

Table III: Comparison of the proposed method with the method in [1]

Methodology	Test Case	Stable Generators	Unstable Generators
Proposed Method	Case I	G-1,2,3,4,5,6,7,8,10	G-9
	Case III	-	G-1,2,3,4,5,6,7,8,9,10
Method using RBFNN [1]	Case II	G-1,2,3,4,5,6,7,8,10	G-9
	Case III	-	G-1,2,3,4,5,6,7,8,9,10

VI. CONCLUSION

Estimation of post-fault stability in real time within few cycles is very significant for taking remedial actions. In this paper, transient stability status of all generators is assessed using Back propagation neural network (BPNN). Transient stability index (TSI) used in [4] is used as additional feature to train neural network. The computational burden of the BPNN is less when compared to radial basis neural network (RBFNN). The simulated results are compared with the method using RBFNN. Thus, the stability status identified by the proposed methodology is on par with the method using RBFNN. Further this research work can be extended to identify the coherency of the generators.

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