SPEED DEVIATION AND MULTILAYER PERCEPTRON NEURAL NETWORK BASED TRANSIENT STABILITY STATUS PREDICTION SCHEME

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Abstract: In this paper, a rotor speed deviation and multilayer perceptron neural network (MPLNN) based transient stability prediction scheme is presented. The scheme uses the sum of the maximum rotor speed deviations (MSDs) of the individual generators in a power system as inputs to an MPLNN. The proposed scheme predicts transient stability one cycle after the tripping of a bus or line following a disturbance. The trained MLPNN responded to 56 transient unstable cases with 100% accuracy. The response to 41 transient stable cases was also 100% accurate. The IEEE 39-bus test system was used for the study.

Key words: Power system stability, Stability prediction, Transient stability, Artificial Neural networks

1. Introduction

Industrialization, population growth, and modernisation have led to a huge demand for electric power. This huge demand coupled with inadequate generation capacity has resulted in most power systems operating their generators with reduced stability margins**,** thus making such systems weak [1]. Consequently, the occurrence of a disturbance endangers the stability of such systems.

Under normal operating conditions, an electrical power system is near equilibrium, with only minor deviations from true steady-state conditions caused by small, nearly continuous, changes in load. When a large disturbance such as a three-phase short circuit occurs in a power network, there are significant, nearly instantaneous rise in power requirement from some generators. Instead of the power system returning to a steady-state condition after the disturbance, one or more generators may encounter sufficient variations in rotational speed and may lose synchronism. Generators losing synchronism must be taken off line to avoid catastrophic problems. Whenever generators are taken off line, capacity decreases, thus introducing another large disturbance leading to cascading system failures. This could cause equipment damage, pose safety hazards to personnel, contribute to cascading outages, and the shutdown of large areas of a power system or the entire system [2, 3]. Control measures such as out-of-step blocking and tripping, fast-valve control of turbines, dynamic braking, superconducting magnetic energy storage systems, system switching, modulation of high voltage direct current (HVDC) link power flow, and load shedding are employed to mitigate the effect of cascading system failures [4].

The effectiveness of the aforementioned control measures are improved with the prediction of transient instability [4]. To this end, researchers have come up with a number of transient instability prediction schemes [4-21]. These schemes employ decision trees [5], neural networks [4, 6-9], neural networks and fuzzy logic [10-14], support vector machines [15], wavelet analysis [16], apparent impedance [17], numerical routines or state space techniques [18-20] and autoregression [21].

The methods [18-20] are computationally demanding for on-line application. Also, the Decision tree based technique has limited forecast accuracy. Additionally, the proposed techniques have delayed prediction times

In this paper, a generator speed deviation and multilayer perceptron neural network based transient stability status prediction scheme is proposed. The scheme predicts transient stability status 20ms (1 cycle for a 50Hz) after the tripping of a bus or line in response to a disturbance. The scheme can be easily realized with the aid of phasor measurement units (PMUs) which can communicate time-tagged phasor measurements such as rotor speed deviations to a central location. This enables the tracking of the dynamic state of a system in real time. The proposed scheme uses the sum of the individual maximum rotor speed deviation of each generator as input to a trained MLPNN which does the prediction.

2. Used power system configuration

The transient stability status prediction scheme was developed using the IEEE 39-bus test system which is also known as the New England test system. The IEEE 39-bus test system is a standard test system that is widely used for small and large signal stability studies [4]. The test system consists of 10 generators, one of which is a generator representing a large system. Data for the modeling of the test system was obtained from [22]. The test system is shown below as Fig. 1.

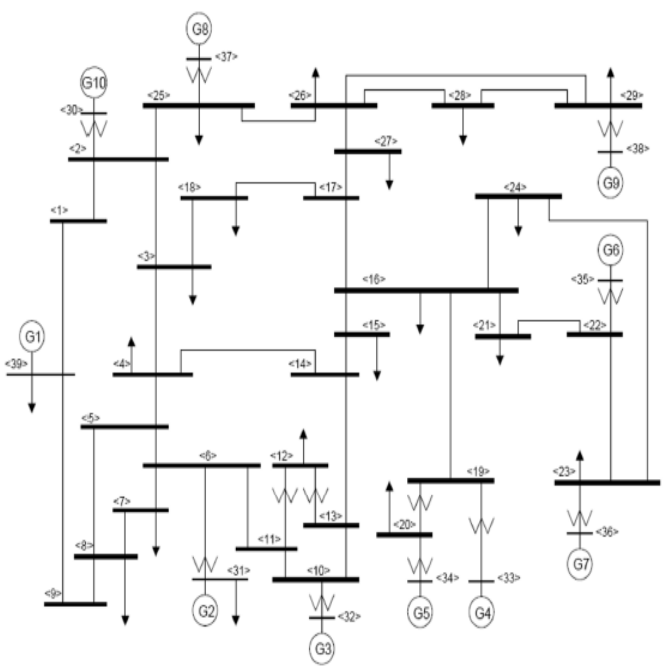

Fig. 1 IEEE 39-bus Test System

3. Rotor speed deviation

Equation 1 shows the fundamental equation governing rotor dynamics. This equation is commonly referred to as the swing equation [23 and 24].

$$M\frac{d^2\delta}{dt^2} = P_m - P_e(\delta) \tag{1}$$

where δ is the rotor angle, P_m is mechanical power, $P_e(\delta)$ is electrical power and M is the inertia coefficient.

Rotor angles have been extensively used for transient stability studies. Rotor angles need to be expressed relative to a common reference. This reference cannot be based on a single generator, since any instability in the reference generator makes the relative angles meaningless. In order to overcome this difficulty, the concept of system center of inertia (COI) angle, δ_{co} defined in equation 2 is used to obtain a reference angle.

$$\delta_{co} = \frac{\sum_{i=1}^{n} H_i \delta_i}{\sum_{i=1}^{n} H_i} \tag{2}$$

where δ_i and H_i are the rotor angle and inertia constant of the *ith* generator, respectively. The angle, δ_i is usually approximated by the phase angle of the respective generator bus voltage [25 and 26]. Many researches however discourage the use of rotor angles in algorithms. This is because the COI values, in practice require continuous updates using real time measurements. This requires extra pre-processing and has significant errors [25]. Rotor angles, thus best serve as the reference parameter for telling stability status of a system in a simulation. Other electrical parameters whose use in algorithms, do not have practical constraints may then be employed for algorithm development.

The time derivative of rotor angle is the rotor speed deviation in electrical radians per second [23, and 26]. Mathematically,

$$\frac{d\delta}{dt} = \Delta\omega = \omega - \omega_s \tag{3}$$

where $\Delta\omega$ is the rotor speed deviation, ω is the rotor speed at a particular time, and ω_s is the synchronous speed. It follows from equations (1) and (3) that the swing equation can be written as

$$M\frac{d\Delta\omega}{dt} = P_m - P_e \tag{4}$$

It can also be shown that

$$\frac{d\delta}{dt} = \left[\frac{\omega_0}{H} \int_{\delta_0}^{\delta} P_a d\delta \right]^{\frac{1}{2}} \qquad (5)$$

where H is the inertia constant and P_a is the difference between input mechanical power and output electromagnetic power. For stability to be attained after a disturbance, it is expected that $\frac{d\delta}{dt} = 0$ in the first swing. This equation gives rise to the equal area criterion which is a well-known classical transient stability criterion. From equations (3) and (5), it can be written that

$$\Delta\omega = \left[\frac{\omega_0}{H} \int_{\delta_0}^{\delta} P_a d\delta \right]^{\frac{1}{2}} \qquad (6)$$

Equation (6) then suggests speed deviation as a good input parameter for the prediction of transient stability status. The maximum speed deviation at some time during a disturbance can be used to predict transient instability or otherwise. The best time is within the first swing, like the equal area criterion.

This paper demonstrates the validity of rotor speed deviations for transient stability prediction. Fig. 2 and Fig. 3 show waveforms of rotor speed deviations for transient stable and transient unstable cases. It is noted from Fig. 2 and Fig. 3 that unstable swings are characterised by higher rotor speed deviations compared with stable swings. Consequently, the sum of the maximum speed deviations of the generators for an unstable swing is greater than the sum of the maximum speed deviations of the generators for a stable swing.

Thus, the sum of the maximum speed deviation of the individual generators of a system following a disturbance can be a suitable input data for the prediction of transient stability status. The input data used for the proposed scheme is given as follows:

$$x = \sum_{i=1}^{N} Max(\Delta\omega_i), \; i = 1, 2, 3, \ldots, N \qquad (7)$$

Where x is the input data, $\Delta\omega_i$ is rotor speed deviation, $Max(\Delta\omega_1)$ is the maximum rotor speed deviation, and N is the number of generators.

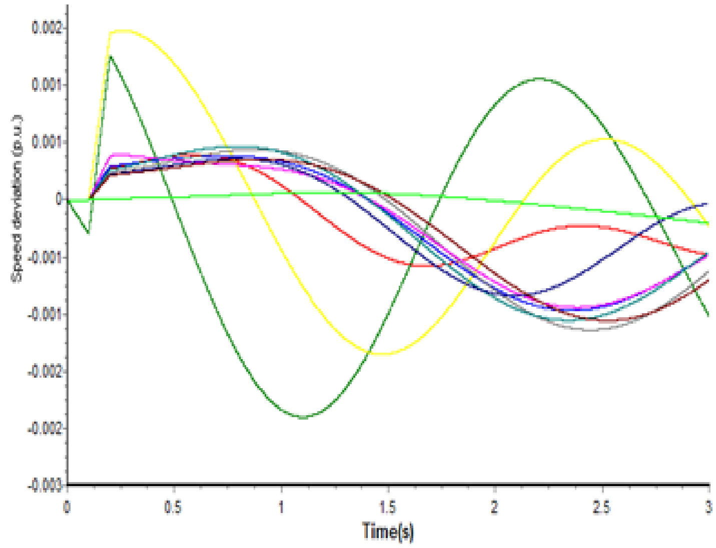

Fig. 2 Speed deviations for a stable swing for a three-phase fault between buses 11 and 6

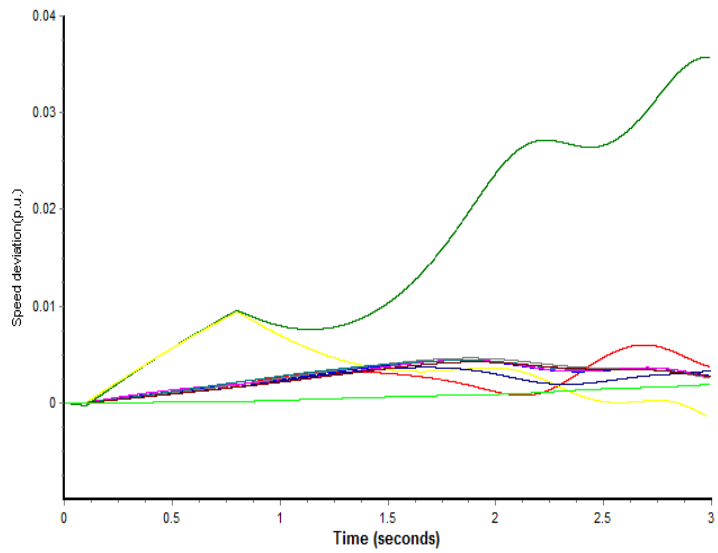

Fig. 3 Speed deviations for an unstable swing for a three-phase fault between buses 11 and 6

4. Multilayer perceptron neural network

Artificial Neural networks (ANNs) are constructed to make use of some organizational principles resembling those of the human brain [27]. They represent a promising new generation of information processing systems. Neural networks are good at tasks such as pattern-matching and classification, function approximation, optimization and data clustering [27]. ANNs can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [28]. ANNs are made up of a number of simple and highly interconnected processing elements called neurons, as shown in Fig. 4.

The mathematical model of a neuron is expressed as [28]:

$$O_j = f_j \sum_{k}^{N} w_{jk} x_k \ , \qquad j = k = 1, 2, 3, \dots, N \qquad (8)$$

where, O_j is the output of a neuron, f_j is a transfer function, which is differentiable and non-decreasing, usually represented using a sigmoid function, w_{jk} is an adjustable weight that represents the connection strength, and x_k is the input of a neuron.

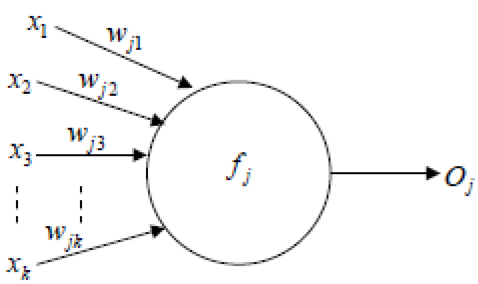

Fig. 4 Mathematical model of a neuron

A three-layer feed forward multilayer perceptron neural network (MLPNN) with no bias was used for this study. Fig. 5 shows the architecture of the MLPNN used. The choice was informed by the fast decision making capability of MLPs [29].

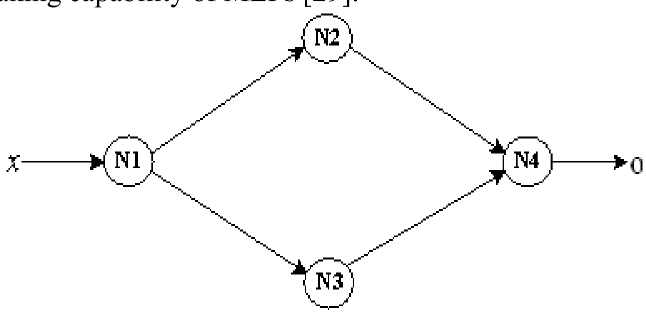

Fig. 5 A three-layered MLPNN

The input layer had one neuron with a transfer function, which is *purelin*. The input data x, was the sum of the maximum speed deviations of the 10 generators, in one cycle after the tripping of a bus or line.

The output, y of a purelin transfer function for a given input x is given as:

$$y = x \qquad (9)$$

The hidden layer had two neurons with *tangent sigmoid* transfer functions. The output, y of a tangent sigmoid transfer function for a given input x is given as:

$$y = \frac{1}{1 + e^{-x}} \qquad (10)$$

The output had one neuron with a transfer function which is *purelin*. The MLPNN was trained to give an output, O, of "0" for a swing that will be transient stable and an output of "1" for a swing that will be transient unstable. The MLPNN was trained using the Levenberg-Marquardt back-propagation technique. The Levenberg-Marquardt algorithm trains a neural network 10 to 100 times faster than the usual gradient descent back propagation method. This algorithm is an approximation of Newton's method and it computes the approximate Hessian matrix [30]

5. **Simulations**

The modeling and simulation of the test system were carried out using the Power System Simulator for Engineers (PSSE) software [31]. Three-phase faults were created at various buses and on various lines. The simulations were carried out for four different loading levels. The levels are base load, base load increased by 5%, base load increased by 7%, and base load increased by 10% [25].

A total of 107 fault cases were simulated out of which 61 resulted in transient instability while 46 were transient stable cases. A system was seen as being transient unstable if the rotor angle difference between any two generators exceeds 180 degrees 1 second after fault clearing time [4]. The output data (for analysis) from the simulations were generator speed deviations sampled using a sampling frequency of 6kHz. All transient stable cases had fault durations of 0.1s while transient unstable cases were realized for faults lasting between 0.7s and 0.9s. These times are similar to that reported in [4].

6. ***Data analysis***

The analysis of the output data (rotor speed deviations) was done using the MATLAB software

[32]. In MATLAB, the speed deviations of each generator after the tripping of a line or bus were further sampled using a time window of 20ms. For each cycle (sample window), the maximum speed deviation (MSD) was obtained for each generator. The obtained maximum speed deviations of each generator were then added. Table 1 shows sum of MSDs for unstable conditions within one cycle after the tripping of various lines following three-phase faults. Table 2 shows sum of MSDs for stable conditions within one cycle after the tripping of various lines following three-phase faults. Table 3 shows sum of MSDs for unstable conditions after the disconnection of a bus following a bus fault. Table 4 shows sum of MSDs for stable conditions after the disconnection of a bus following a bus fault. A study of the sum of MSDs for the various cases show that cases which led to transient instability had a much higher value compared to cases which did not result in transient instability. Thus the sum of the maximum speed deviations of the individual generators one cycle after the tripping of a line or bus can be used as an input data for the prediction of transient stability status.

Table 1: Sum of maximum speed deviations for various line faults (unstable cases)

Bus – Bus	11 – 6	10 – 13	13 – 10	13 – 14	22 – 21	22 – 23	26 – 25	29 – 26	28 – 26
Sum of MSDs	0.0324	0.0326	0.0313	0.0312	0.0283	0.035	0.0283	0.0165	0.0155

Table 2: Sum of maximum speed deviations for various line faults (stable cases)

Bus – Bus	11 – 6	10 – 13	13 – 10	13 – 14	22 – 21	22 – 23	26 – 25	29 – 26	28 – 26
Sum of MSDs	0.0047	0.0047	0.0045	0.0045	0.0041	0.0041	0.0036	0.0036	0.0019

Table 3: Sum of maximum speed deviations for various bus faults (unstable cases)

Bus	11	13	28
Sum MSD	0.0324	0.0312	0.0137

Table 4: Sum of maximum speed deviations for various bus faults (stable cases)

Bus	11	13	28
Sum of MSD	0.0047	0.0045	0.0019

7. Transient stability status prediction scheme

The proposed transient stability status prediction scheme uses a feedfoward multilayer perceptron artificial neural network with 1 input neuron, two hidden layer neurons and 1 output neuron [33]. The input to the neural network is the sum of the maximum speed deviation (SMSD) of the individual generators of the power system one cycle after the tripping of a line or bus following a disturbance. The network was trained with sum of maximum speed deviation (SMSD) data obtained from five transient unstable cases and SMSD data obtained from five transient stable cases. The clear distinction between the transient stable data as against the transient unstable data permitted the use of a small volume of training data set. The output pair of each of the five transient unstable case data was '1' while that of the transient stable data was '0'.

The output of the MLPNN like any other neural network in the testing phase usually has an error with respect to its actual binary value. A similar situation is observed in digital communication networks, where the received bits have some deviation with respect to the sent bits. In these networks, the TTL standard is usually used in the receiving equipment to detect the received bits. This standard is also used to determine the output status of the MLPNN [4].

$$O_j \geq 0.8 \rightarrow O_j = 1 \text{ (Transient unstable)} \quad (3)$$

$$O_j \leq 0.2 \rightarrow O_j = 0 \text{ (Transient stable)} \quad (4)$$

where O_j is the output of a MLPNN.

In the digital communication networks, if the value of a received bit is in the range of 0.2 to 0.8, it is considered as a missing bit. Besides, if a "1" bit is received in the range of 0 to 0.2 or a "0" bit is received in the range of 0.8 to 1 it is considered an error bit, which is a worse incorrect case than the missing bit. This interpretation for the error and missing bits is also used for the output of the MLPNN.

A flowchart of the proposed transient stability status prediction scheme is shown below as Fig. 6.

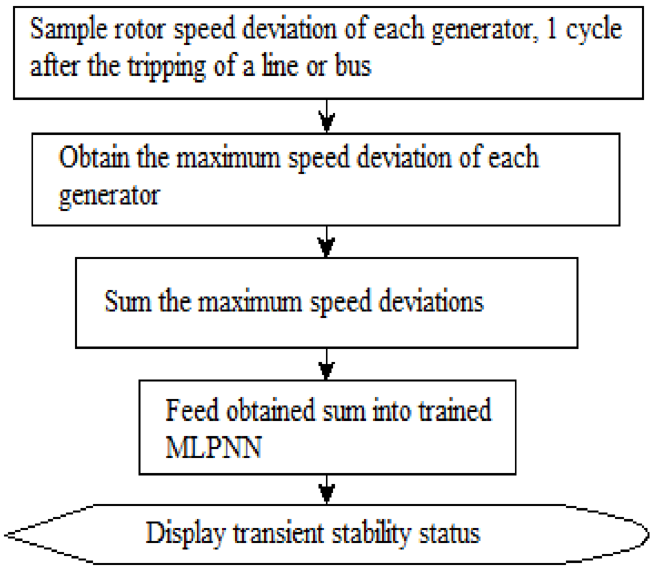

Fig. 6 Flowchart of transient stability status prediction scheme

The trained MLPNN, responded to the 56 transient unstable cases with 100% accuracy. The responses to the 41 transient stable cases were also 100% accurate.

8. Conclusion

A transient stability status prediction scheme has been proposed in this paper. The proposed scheme is based on the rotor speed deviations of generators in a power system 1 cycle after the tripping of a bus or line following a disturbance, and multilayer perceptron artificial neural network. The scheme sums the maximum rotor speed deviations of the individual generators of a system 1 cycle after the tripping of a bus or line and uses this sum as input to a trained multilayer perceptron neural network which predicts the transient stability status. The proposed scheme predicts transient stability status with 0% error.

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