NEURAL NETWORK AND SPEED DEVIATION BASED GENERATOR OUT-OF-STEP PREDICTION SCHEME

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Abstract: A multi-layer perceptron neutral network (MLPNN) has been used as a decision tool to predict out-of-step conditions. Rotor speed deviations are sampled and the maximum speed deviation in 1 cycle is obtained, and used as input to the MLPNN. Each generator has one trained MLPNN assigned to it to predict whether or not that generator will go out of step following a disturbance. The trained neural network responded to the 88 individual generator out-of-step (OOS) cases with 100% accuracy while the responses to 512 synchronism cases were 98.05% accurate. The 340 predictions for 34 simulations with all 10 generators in synchronism were 100% accurate. The study used the IEEE 39-bus as the test system.

1. Introduction

To ensure a high level of reliability of power supply, today's power systems are largely interconnected networks of transmission lines linking generators and loads into large integrated systems. A critical prerequisite for the reliable operation of power systems is to keep the synchronous generators running in parallel [1]. Power system faults, which are largely unpredictable, present the greatest threat to the maintenance of synchronism among generators.

Severe power system disturbances could cause large separation of the rotor angles between individual generators and groups of generators leading to eventual loss of synchronism between generators and groups of generators or between neighboring utility systems. When two areas of interconnected power systems lose synchronism, the areas must be separated from each other quickly and automatically to avoid equipment damage and power blackouts [2]. Over the years, several power systems have suffered wide scale blackouts because of generator OOS conditions [2-4]. OOS conditions are usually characterized by large separation of generator rotor angles, large swings of power flows, and large fluctuations of voltage and current [5]-[9]. These OOS conditions may cause equipment damage, pose safety hazards to personnel, contribute to cascading outages, and the shutdown of larger areas of the power system if uncontrolled. Therefore, controlled tripping is necessary to prevent equipment damage and widespread power outages [2].

A number of techniques have been proposed for the detection of OOS conditions [9-18]. The schemes used inputs such as generator angles, angular velocities and their rates of change [10], active power and reactive power [11], critical velocities of generators relative to a center of inertia [12], generator pre-fault loading, and generator kinetic energy deviation and average acceleration during fault [13]. Signal processing and decision making tools such as K-means clustering [18], discrete Fourier transform [14], wavelet transforms [17], and neural networks [13] have been used. Other methodologies have been proposed for OOS predictions [5, 19 – 21], including autoregressive model [20] and three-impedance element principle that uses the least square method [21]. Transient stability is better enhanced with OOS prediction rather than detection [2]. Even though the above-mentioned schemes predict OOS conditions, they fail to tell the specific machine(s) which will go out of step.

This paper proposes a generator speed deviation and MLPNN-based OOS prediction method that can predict OOS conditions 1 cycle (20 ms in a 50 Hz

system) after the tripping of a bus or line following a disturbance. For each generator, the speed deviation is sampled at a frequency of 6 kHz and the maximum deviation within one cycle is used as an input to a trained MLPNN. Each MLPNN gives an output of "1" if the generator will go out of step and an output of "0" if the generator will be stable.

2. Speed deviation as input parameter

Rotor angles are the most widely used power system data for transient stability studies. Rotor angle is a key parameter in the fundamental equation governing generator rotor dynamics. Equation 1 shows the fundamental equation governing rotor dynamics. This equation is commonly referred to as the swing equation [22].

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

where M is the inertia coefficient, δ is the rotor angle, P_m is the mechanical power and P_e is the electrical power.

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 centre of inertia (COI) angle, δ_{co} defined in equation 2 is used to obtain a reference angle.

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

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 [5 and 23]. 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 [5]. 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 [22, 24]. Mathematically,

$$\frac{d\delta}{dt} = \Delta\omega = \omega - \omega_s \qquad (3)$$

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

$$M\frac{d\Delta\omega}{dt} = P_m - P_e \qquad (4)$$

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 higher the rotor speed deviation following a disturbance, the more unstable the system becomes [25]. Thus, the maximum speed deviation at some time during a disturbance can be used to predict transient stability or otherwise. The best time is within the first swing, like the equal area criterion. This work proposes an algorithm for transient stability prediction using rotor speed deviation as power system input data.

Unlike rotor angles, rotor speed and for that matter rotor speed deviation of a particular generator need not be referenced to any particular machine. Hence rotor speed deviation has the potential to assist in determining transient stability conditions following a large disturbance.

Generator speeds, just like their rotor angles, swing

following a power system disturbance. For a stable generator, the speed will settle at a new value or the value before the disturbance; there is a reduced amplitude speed deviation. For an unstable generator, the speed will increase progressively; there is higher amplitude of speed deviation. Figure 1 shows speed deviations of generators following a three-phase short-circuit on a line which lasted for 0.9 s, after which the line was tripped. At time $t = 1s$ the generator (GEN 1) which went out of step had a higher speed deviation compared to the stable ones.
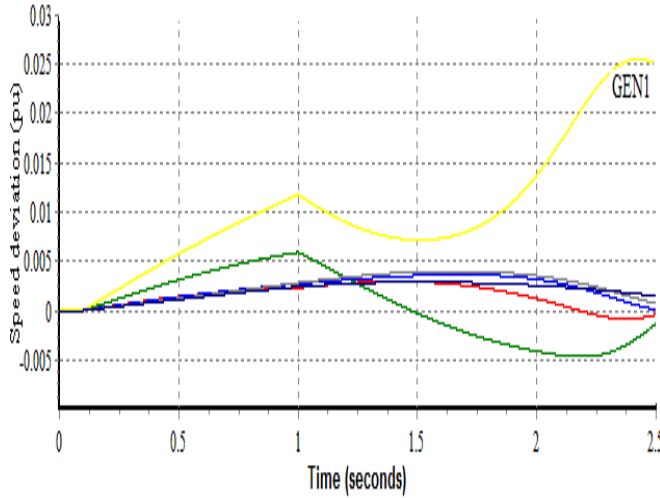

Fig. 1 Generator speed deviations

3. Multilayer perceptron neural network

Artificial Neural Networks (ANNs) represent a modern and sophisticated approach to problem solving widely explored also for power system protection and control applications. ANNs perform actions similar to human reasoning, which relies upon experience gathered during a training process [26]. ANNs can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [27]. Advantages of ANN computing methodologies over conventional approaches include faster computation, learning ability, adaptive features, robustness and noise rejection [26].

ANNs are made up of a number of simple and highly interconnected processing elements called neurons, as shown in Fig. 2.
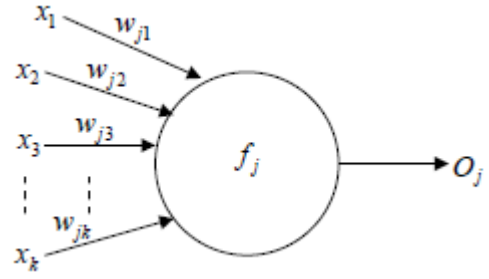

Fig. 2 Mathematical model of a neuron

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.

The mathematical model of a neuron is expressed as [27]:

$$O_j = f_j \sum_k^N w_{jk} x_k \qquad j = k = 1, 2, 3, ..., N \qquad (7)$$

A three-layer feed forward multilayer perceptron neural network with no bias was used for this study. The choice was informed by the fast decision making capability of MLPs [28]. The input had one neuron with a *purelin* transfer function. The input data, x_k, was the maximum speed deviation in one cycle after the tripping of a bus or line. The hidden layer had two neurons with *tangent sigmoid* transfer functions. The output had one neuron with a *purelin* transfer function.

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

$$y = x \qquad (8)$$

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

$$y = \frac{1}{1 + e^{-x}} \qquad (9)$$

The neural network gives an output, O_j, of '1' for a generator which will go out of step and '0' for a stable generator. The neural network was trained using the Levenberg-Marquardt back-propagation technique with 10 input and output pairs (5 OOS maximum speed deviation data and 5 stable data). The maximum speed deviation data for OOS conditions were distinct from that of stable conditions. This permitted the use of such

minimal training data set. The input data used for the proposed scheme is given as follows:

$$x_k = Max(\Delta\omega_k) \qquad (10)$$

where x_k is the input data of the neural network assigned to generator k and $\Delta\omega_k$ is the rotor speed deviation of generator k.

4. Used power system configuration

The OOS 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 [12]. 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 [29]. The test system is shown below as Fig. 3.
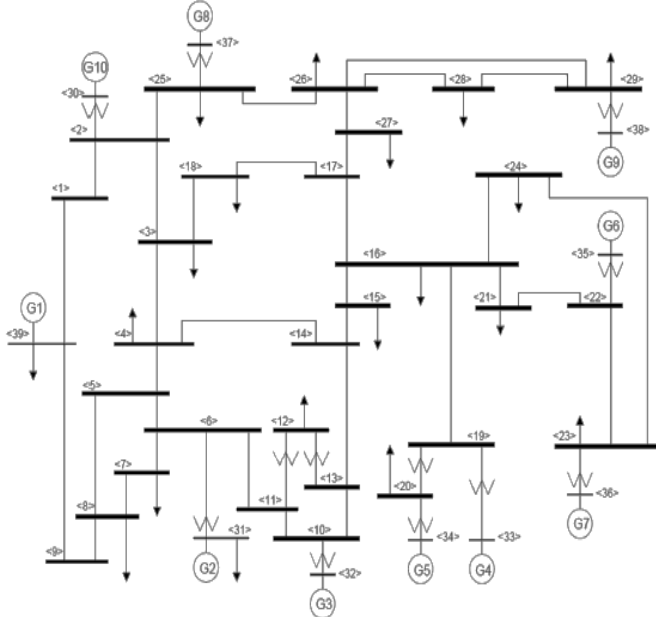

Fig. 3 IEEE 39-bus Test System

5. Simulations

Modeling and simulation of the test system were carried out using the Power System Simulator for Engineers (PSSE) software [30]. Three-phase faults were created at various buses and on various lines. Simulations were carried out for four different loading levels; base load, base load increased by 5%, base load increased by 7%, and base load increased by 10% [5]. In total, 95 three-phase fault cases were simulated. The number of OOS cases was 61 while the remaining 34 had all generators remaining stable. A generator was seen as going out of step with respect to the other generators when the angle difference between that generator and other generators exceeds 180 degrees 1 second after fault clearing time [31]. The output data (for analysis) from the simulations were generator speed deviations sampled using a sampling frequency of 6 kHz. All stable cases had fault durations of 0.1 s while OOS conditions were obtained for faults lasting between 0.7 seconds and 0.9 s. These times are similar to those reported in [31]. The 61 OOS cases had different combinations of generators going out of step. For example, in some OOS cases, one, two, and a maximum of four generators went out of step. Table 1 shows the number of generators which went out of step for the OOS cases.

Table 1: Number of generators involved in OOS cases

Number of generators which went out of step	Number of system OOS cases
1	38
2	21
4	2
Total	61

The outputs of the simulations (for OOS scheme development) were the speed deviations of the generators. For example, Fig. 4 shows generator speed deviations for fault at bus 28 for 107% of base load condition. The fault was applied at 0.1 s and lasted for 0.7s after which the bus was disconnected resulting in generator 9 going out of step. All other machines remained in synchronism for the aforementioned fault condition. Also, Fig. 5 shows the speed deviations of generators for a line fault between buses 6 and 11 for 107% of base load conditions. The fault was applied at 0.1 s and lasted for 0.8 s. This resulted in generators 2 and 3 going out of step. All other generators remained in synchronism.
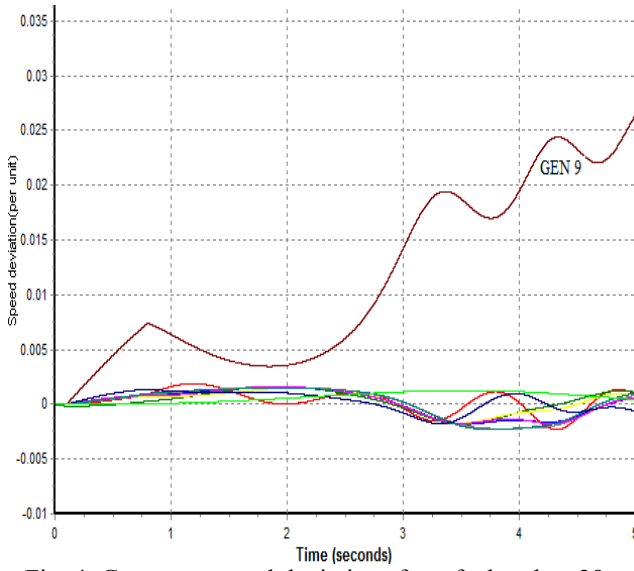
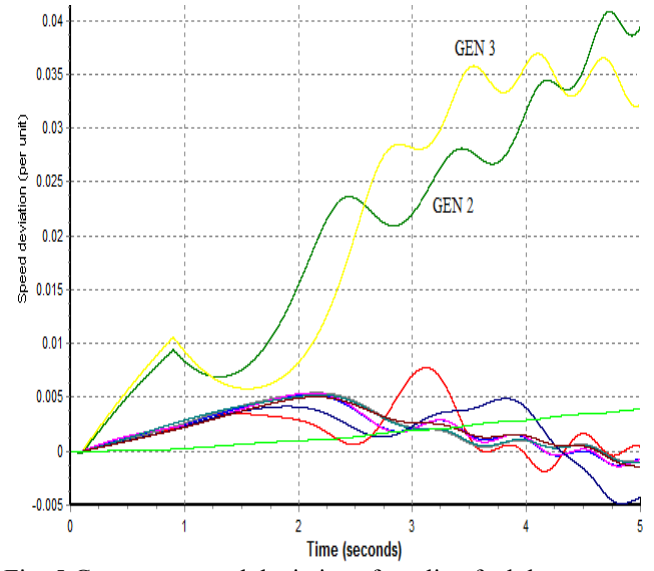Fig. 4 Generator speed deviations for a fault at bus 28

Fig. 5 Generator speed deviations for a line fault between bus 6 and 11

6. Data Analysis

The analysis of the output data was done using the MATLAB software [32]. In MATLAB, the speed deviations were further sampled 20 ms after the tripping of a line or bus. The maximum speed deviation (MSD) within each cycle was then obtained. Table 2 shows MSDs within one cycle after the

disconnection of bus 28 following a three-phase fault at bus 28. Table 3 shows MSDs within one cycle after the tripping of the line between bus 6 and 11 following a three-phase fault on that line.

A study of the MSDs revealed that generators which went OOS had higher speed deviations than the stable generators.

TABLE 2: MAXIMUM SPEED DEVIATIONS FOR A FAULT ON BUS 28

Gen.	1	2	3	4	5	6	7	8	9	10
MSD	0.0001	0.0003	0.0007	0.0009	0.0009	0.0008	0.001	0.0014	0.0074	0.001

TABLE 3: MAXIMUM SPEED DEVIATIONS FOR A LINE FAULT BETWEEN BUSES 6 AND 11

Gen.	1	2	3	4	5	6	7	8	9	10
MSD	0.0002	0.0094	0.0106	0.0023	0.0023	0.0022	0.0026	0.002	0.002	0.0022

A. Out-of-Step Scheme

The proposed OOS prediction scheme uses a feedfoward multilayer perceptron artificial neural network with one input neuron, two hidden layer neurons and one output neuron. Each generator has one trained MLPNN assigned to it to predict whether or not that generator will go out of step following a disturbance. The input to each neural network is the maximum speed deviation of the rotor of the generator in one cycle after the tripping of a line or bus.

Five MSDs of generators which went out of step and 5 MSDs of stable generators were used to

train the neural network. Each MLPNN assigned to each generator gives an output of "1" if the generator will go out of step and "0" if the same generator will remain in synchronism.

The study system has 10 generators, so the proposed scheme employs 10 trained MLPNNs, one assigned to each generator. Hence for every fault condition, there will be 10 MLPNN predictions. Each of the 10 MLPNNs will make a prediction for each fault scenario. Thus for the 61 simulations which resulted in OOS conditions, there were a total of 610 (61 × 10) MLPNN predictions. A total of 88 individual generator

out of step predictions were expected out of the 610 predictions. The remaining 512 predictions were expected to be predictions indicating stable generators.

The input data set (P) and the target data set (T) used for the training are given below.

P=[0.0118 0.0141 0.0072 0.0072 0.0059 0.0055
0.0035 -0.0001 0.0030 0.004]

T=[1 1 1 1 1 0 0 0 0 0]

The settings used in MATLAB [28] for training the MLPNN are given below.

     net.trainParam.epochs=600;
     net.trainParam.goal=1e-5;
     net.trainParam.min_grad=0;
     net.trainParam.max_fail=10;
     net.trainParam.mu=0.001;
     net.trainParam.mu_max=1e10;

The training progress was obtained as follows:

     Epochs = 82 iterations
     Training time = 3 seconds
     Performance = 8.04e-06
     Gradient = 0.00448

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 the 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 [31].

$$O_j \geq 0.8 \rightarrow O_j = 1 \text{ (Out of step)} \quad (11)$$

$$O_j \leq 0.2 \rightarrow O_j = 0 \text{(Stable)} \quad (12)$$

where O_j is the output of a neuron and $j = 1,...,n$.

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.

The trained MLPNN responded to the 88 OOS cases with 100% accuracy while the response to the 512 synchronism cases was 98.05% accurate. The 340 predictions for the 34 simulations which had all 10 generators being in synchronism were 100% accurate.

V. CONCLUSION

A rotor speed deviation and MLPNN based out-of-step prediction scheme for improving power system transient stability has been presented. The scheme predicts out-of-step conditions of individual generators 1 cycle after the tripping of a bus or line after a disturbance. The scheme uses maximum speed deviation of rotor as input signal and a multilayer perceptron neural network as a decision making tool. The proposed out-of- step prediction scheme has a 1.05% prediction error for 950 (610 predictions involving OOS cases plus 340 predictions of synchronism cases) individual generator predictions.

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