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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR POWER SYSTEM OSCILLATION PREDICTION

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Abstract. *Some of the outage caused by power system oscillation could not be avoided and the data of the resulted fault recorded by phasor measurement unit (PMU) or digital fault recorder (DFR) could only be used for post-fault analysis. This paper describes the process to predict the oscillation condition in power system as an alarm to the operator before the oscillation could cause power system outage. Using PMU, the phasor sifting data of power system could be observed and treated to achieve the quantitative measures. To process the phasor measurement data, Hilbert-Huang transform (HHT) is utilized to extract specific parameters such as instantaneous power of individual correspondent frequency. These parameters are fed to an artificial neural network (ANN) to distinguish between a stable and an oscillating condition. The ANN is trained with simulated data that represents the stable and oscillating conditions which might be taking place in power system. To increase the prediction precision, the majority vote algorithm is used for all results from the ANN. The speed of the prediction process is compared with the time of an actual event which causes an outage in the power system, in order to determine the effectiveness of the process model. These suggest that the model might be used, since the computation time of prediction model is faster than the time of the power system outage.*
Keywords: Artificial neural network, Hilbert-Huang transform, Power system oscillation, Instantaneous power, Majority vote algorithms

1. **Introduction.** Continuation of improvements in power system reliability is necessary for the increasing complexity of electrical power systems imposed by economic and demand growth. Since the testing of large-scale power systems in order to determine the power system response to various types of disturbances is practically impossible, a lot of researches have been conducted to model the system. However, a model that is suitable in terms of speed and accuracy for the prediction of the condition of the power system is still being studied [1-4]. One of the disturbances which could occur with the growth of power systems is caused by low frequency oscillation in the power system, as a result of an undamped rotor swing in generator. This study tried to predict the stability of power systems caused by the existence of low frequency oscillation in the system.

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A few researches have been conducted to derive and validate the power system model to simulate the low frequency oscillation using a very detailed representation of power systems such as transmission line impedance and generator control system [5-7]. The advantage of such a model is that the time responses of all the state variables are computed. However, this model has the shortcoming of being inherently slow, owing to the calculation process in order to solve the differential equations. Therefore, this model is unsuitable for online transient stability detection, in which the data has to be calculated in milliseconds. Moreover, since the configuration of power system changes all the time caused by operational reasons, the model should always comply with the changes which, for complex power systems, are not easy.

Another research by [8] tried to predict the oscillatory condition by calculating the synchronizing torque coefficient (K_s), and the damping torque coefficient (K_d) using artificial intelligence (AI) technology. [8] used particle swarm optimization (PSO), evolutionary programming (EP), artificial immune system (AIS) resulting in AIS being the fastest algorithm to calculate K_s and K_d. Both these parameters should be positive for the system to be called in a stable condition. However, the results from [8], require data of voltage and power from all buses in the simulation model of the power system network. To implement the algorithm using real-time data is very challenging, since it will take a long time to collect the data from all the buses in very complex power system network.

Several researches have used artificial neural networks (ANN) to determine the condition of power systems [9,10]. None of them have used real-time data with real restrictions, in terms of the computing time. Since the oscillatory condition has to be detected in order that the operator could be warned and do something to mitigate the situation, the computation time should be fast enough before the system collapses. This paper shows how ANN, along with the majority vote algorithms could be utilized to predict the oscillatory condition of power systems in a short time, using phasor measurement unit (PMU) data processed by Hilbert-Huang transform (HHT), as an input. Data to train the ANN is taken from simple simulations of the power system model to simulate the phase angle of the stable and unstable conditions and the trained ANN is tested using real data events.

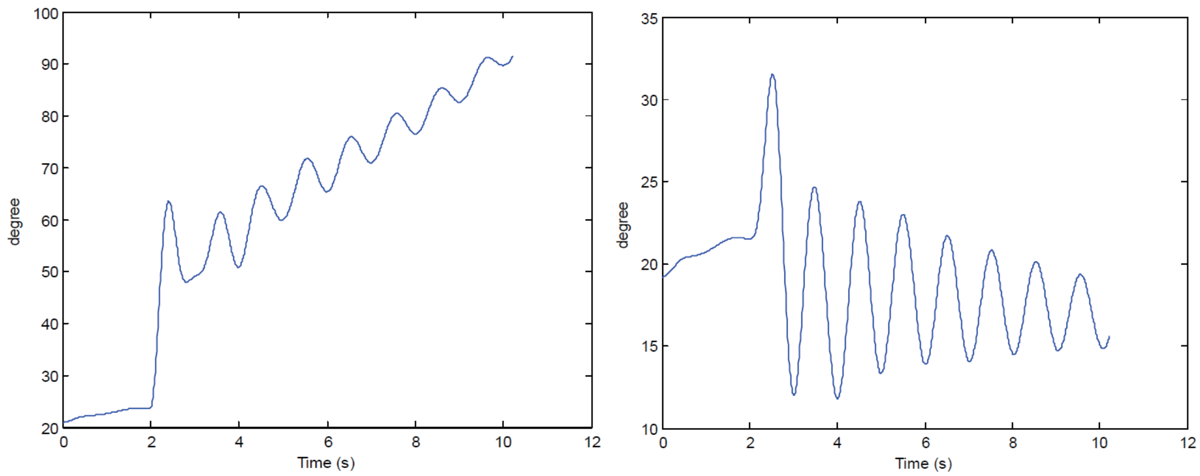
The remainder of this paper is organized into the following sections. Section 2 presents the materials taken from PMU data and the proposed method that has been used including the implementation of HHT and ANN in the method. Section 3 presents and discusses the obtained result and Section 4 concludes the paper by reaching an inference based on validation of the proposed method.

2. Materials and Methods.

The present paper uses data collected by the PMU, which has been developed recently to observe power system parameters. Due to limitation in time to collect all data from all PMUs to analyze the stability of the system and errors introduced by the accuracy of the measurement instruments, the data that is used is only the voltage phases' angle difference between two observed buses.

2.1. Phasor measurement units data.

With the technology development in measuring phasors in the form of PMUs, phasor as one of the power system parameters could be observed [11-13]. [14] indicates that the phases' angle difference of the voltage from two distinctive PMU recorded data taken from two different substations could be used for the analysis of the power system oscillation condition. Since unstable conditions in the power system have rarely occurred, in order to obtain enough data in this research, the power systems network was simulated. This simulation is processed in order to generate data similar to the PMU data which has intervals of 40 milliseconds between each data. The resulted data is the voltage phase angle signal between two observed substations in the network, which indicates the existence of the oscillation being in low frequency. An example of the oscillation signal and the stable signal could be observed in Figure 1.



(a) Low frequency oscillation signal

(b) Stable signal

FIGURE 1. Example of low frequency oscillation signal and stable signal

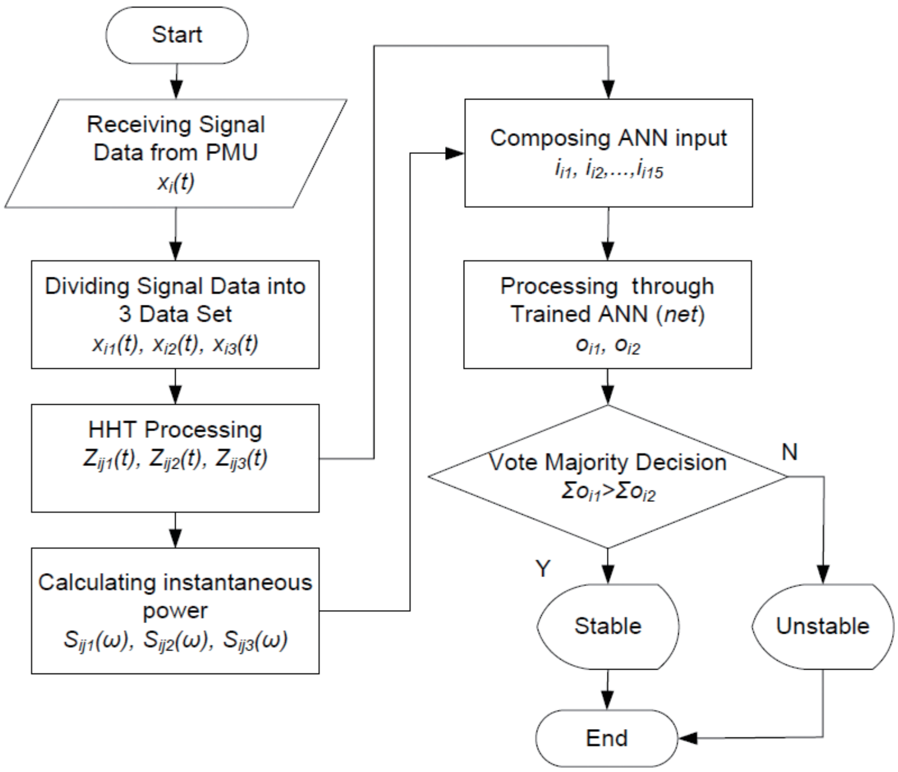


FIGURE 2. Flowchart of the proposed method

2.2. **Proposed method.** The flowchart of the proposed method to predict the power system oscillation condition is illustrated in Figure 2. The phasor of the voltage from two observed substations is compared ($x_i(t)$). The difference between the phasor magnitude from these two data is divided into three sets of data (Figure 3): $x_{i1}(t)$, $x_{i2}(t)$, $x_{i3}(t)$. The length of each set of data is 3.92 seconds and half the data from each dataset share the same data, with half the data from the next dataset. Each of these three datasets is processed using HHT ($Z_{ij1}(t)$, $Z_{ij2}(t)$, $Z_{ij3}(t)$). The combination of parameters taken from HHT results ($S_{ij1}(\omega)$, $S_{ij2}(\omega)$, $S_{ij3}(\omega)$) is accepted as an input for the ANN ($i_{i1}, i_{i2}, \ldots, i_{i15}$). The output of ANN is either an only stable (o_{i1}) or a not stable condition (o_{i2}). To

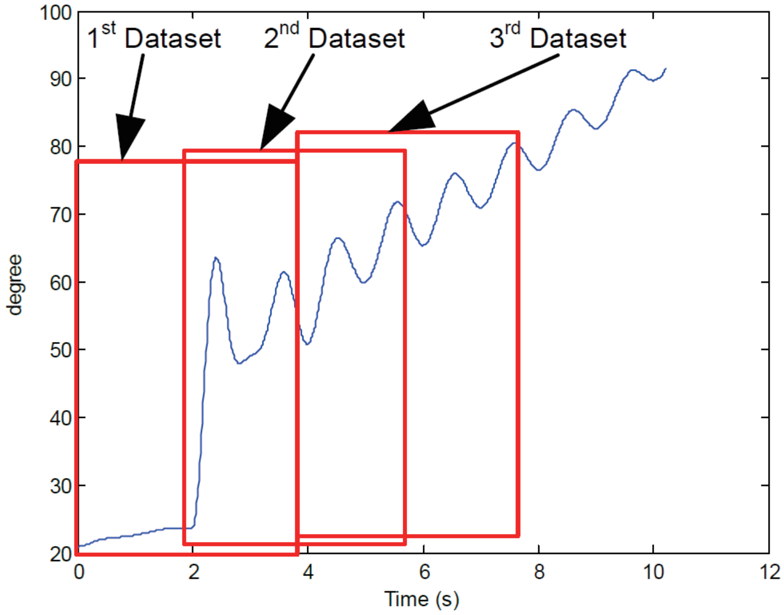


FIGURE 3. Dividing example data into three datasets

increase the accuracy of the ANN output, the majority vote algorithm is used, since a decision error is not accepted in the power system.

2.3. **Hilbert-Huang transform.** Hilbert-Huang transform (HHT) is the empirical mode decomposition (EMD) method which is a data-analysis method. In HHT, a complex signal data is elaborated to become a set of finite intrinsic mode functions (IMF) which is then processed through Hilbert transforms. EMD displays the original signal significant characteristics. IMF reveals each of the oscillatory modes with stipulation [15].

- The total number of zero-crossings and the total number of extremes must either differ at most by one or an equal number from the dataset.
- The envelope, which is outlined by the local minima, is zero at any point and the average value of the envelope is outlined by the local maxima.

The function, such as low-frequency signal $s(t)$, is decomposed from the identification of all local extremes. The upper envelope is formed by connecting all local maxima by a cubic spline line. The lower envelope is produced by repeating the procedure for the local minima. All the data should be covered by the lower and upper envelopes. The data difference is represented by $c(t)$. If $c(t)$ satisfies the definition of an IMF, then $c(t)$ is one of the components of IMF. Alternatively $c(t)$ should comply with the definition, by repeating the procedure. The sifting processes are conducted by subtracting the original signal with the decomposed component and is repeated to the remaining component. The initial signal becomes the sum of various components of the IMF ($c_i(t)$) and a residue (r), as shown in (1).

$$s(t) = \sum_{i=1}^{n} c_i(t) + r \tag{1}$$

Each analysis function of IMF low-frequency signal is produced using Hilbert transform as shown in (2).

$$Z_i(t) = c_i(t) + j\widetilde{c_i}(t) = a_i(t)e^{j\theta_i(t)} \tag{2}$$

Each of the three datasets that have been prepared is processed by utilizing HHT and an example of the resulting IMF of the first dataset of signal data, which represents low frequency oscillation shown in Figure 4.

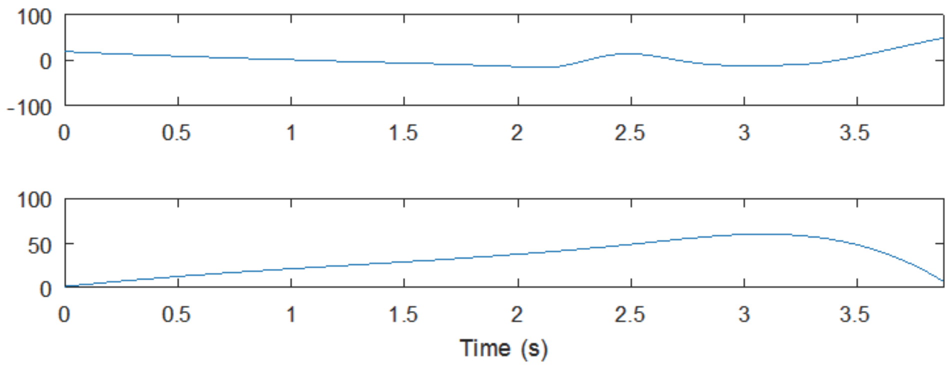


FIGURE 4. Example of IMF from the first dataset

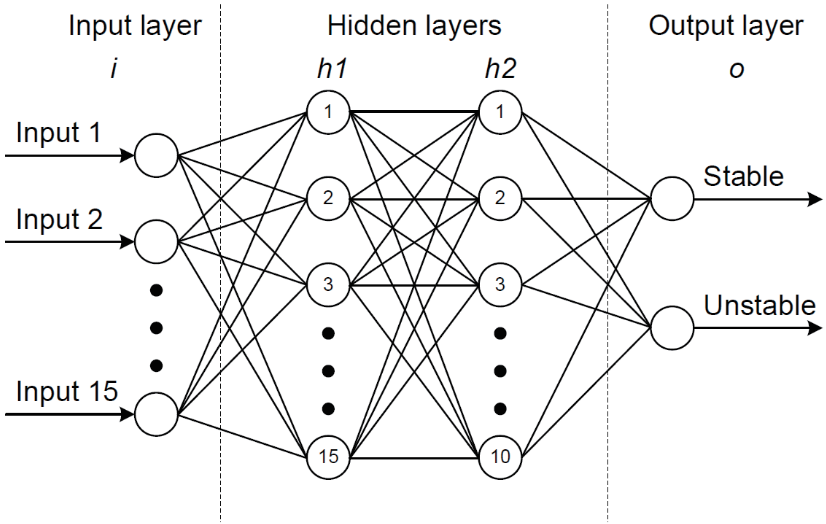


FIGURE 5. Proposed ANN model

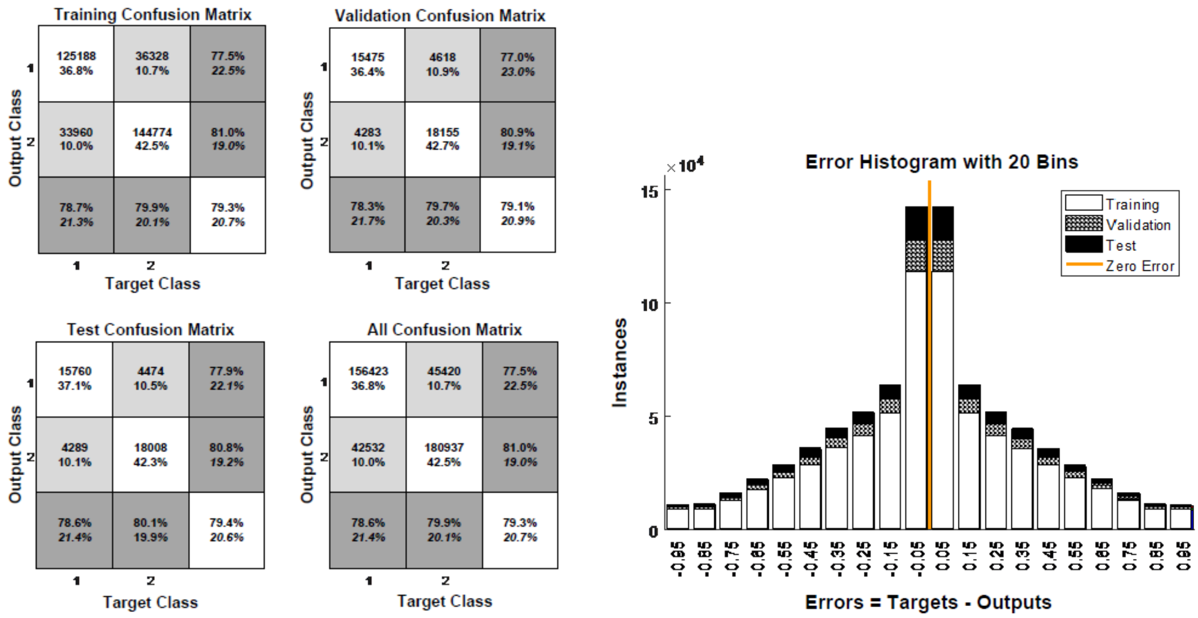
With the assumption that using only the power of a single measurement in Δt time, the instantaneous power of each instantaneous frequency of all IMFs could be proposed in (3) with n as the amount of data, with the same instantaneous frequency resulting from HHT.

$$\widetilde{S}_i(\omega) = \frac{2\pi\Delta t}{\Delta\omega(t)} \sum_{i=0}^{n} \left| a_i(t) e^{-j\theta_i(t)} \right|^2 \tag{3}$$

2.4. **Artificial neural network.** The ability to learn and generalize is one of important features of ANN that is suitable for determining the oscillatory condition of power systems in this proposed method, since the source of data is very limited. The ANN performance depends on the learning process, which, in this method, is supervised learning [16]. In supervised learning, the output of ANN is compared with a known or a real output. Therefore, the learning process in this method uses data from simulation, in which the output of the oscillation condition of a power system is known. The topology of the ANN used can be seen in Figure 5, which consists of one input layer, two hidden layers and one output layer. The input consists of 15 data which is formed by the data in Table 1. The 1st hidden layer consists of 15 neurons, and the 2nd hidden layer consists of 10 neurons. The output layer only consists of stable or unstable conditions. The learning process alters the weight vector inside the hidden neuron, using an activation function, in which the final result is matrix of the trained hidden layer. The confusion matrix and the graph of the error histogram with 20 bins, which describes the performance of the ANN classification model is shown in Figure 6.

Table 1. Structure of input data

Number	Description
1	Number of instantaneous frequencies whose instantaneous power is increased from the first to the third dataset
2	Minimum of instantaneous power which is increased from the first to the third dataset
3	Maximum of instantaneous power which is increased from the first to the third dataset
4	Number of instantaneous frequencies whose instantaneous power is increased only from the second to the third dataset
5	Minimum of instantaneous power which is increased only from the second to the third dataset
6	Maximum of instantaneous power which is increased only from the second to the third dataset
7	Number of instantaneous frequencies whose instantaneous power is increased only from the first to the second dataset
8	Minimum of instantaneous power which is increased only from the first to the second dataset
9	Maximum of instantaneous power which is increased only from the first to the second dataset
10	Gradient of last IMF of the first dataset
11	Gradient of last IMF of the second dataset
12	Gradient of last IMF of the third dataset
13	Maximum of absolute value of last IMF of the first dataset
14	Maximum of absolute value of last IMF of the second dataset
15	Maximum of absolute value of last IMF of the third dataset



(a) Confusion matrix (b) Error histogram

Figure 6. Confusion matrix and error histogram of the proposed ANN model

2.5. **Majority vote algorithms.** Majority vote algorithms are described by [17,18] which find a majority of a sequence of elements using linear time and constant space. If there is a value which exists for more than half of the element, then the decision is based on that value. This algorithm is fault-tolerant, since the computation will be performed multiple times to ensure that the majority of the results agree. The algorithm is perfectly suitable for the proposed model, since in the power system, any decision must be ensured in order to avoid any operation error. In the proposed model, for every 200 ms, the phasor signal is processed through HHT and ANN, and the result will be the classification between the stable or unstable conditions. Based on 40 data classifications, the majority of the classifications will decide the outcome of the power system oscillatory condition.

3. **Results and Discussion.** For the proposed model, the computation and prediction of the oscillatory condition of power systems take between 0.1 seconds to 0.2 seconds, which is quite fast, compared to the AIS method that has been conducted by [8]. However, to count the majority vote algorithm, the model needs 8 seconds of signal data to ensure that the power system is in a stable or an unstable condition. To validate the method, an example of an unstable occurrence in the power system is tested using the proposed method. The phasor difference between two substations taken by PMUs could be seen in Figure 7. The graph shows that the system collapses after 9 seconds. By applying the proposed method, the unstable condition could be detected after 3.32 seconds, which can be seen in Table 2. There is enough time for the operator or any equipment to take any necessary action to prevent the collapse of the power system.

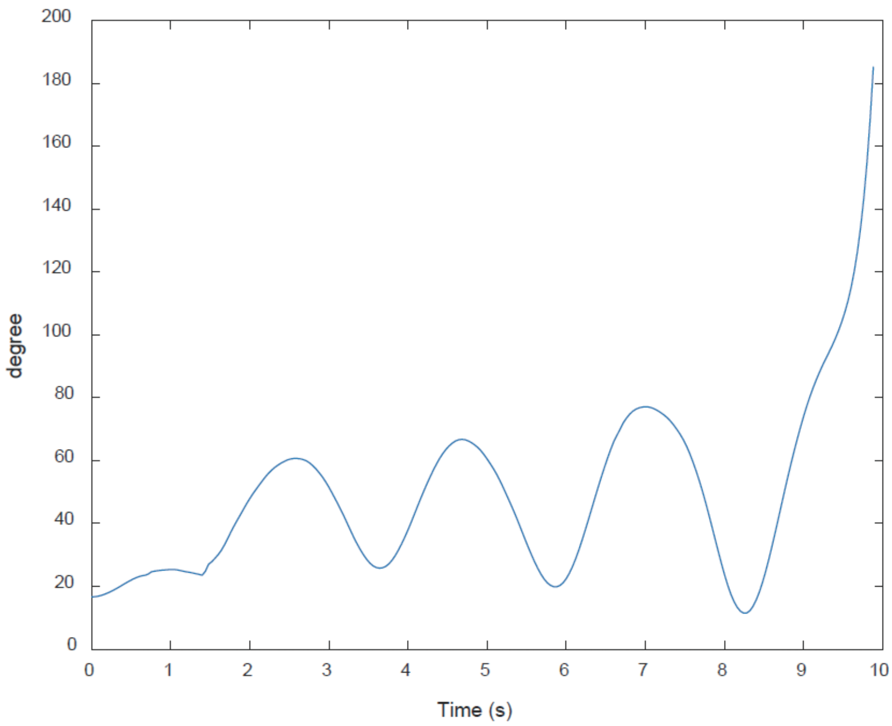


FIGURE 7. Phasor angle of unstable event

TABLE 2. The output of the proposed method for the unstable event

Time (s)	2.32	2.52	2.72	2.92	3.12	3.32	3.52	3.72	3.92
Stable	1	1	1	1	1	0	0	0	0
Unstable	0	0	0	0	0	1	1	1	1

4. **Conclusions.** In this paper, ANN is applied to predicting the oscillatory condition of the power system. The signal data of the phasor difference between two observed substations taken using the PMU is modified to be processed by HHT. The result of the HHT process is used as the input for ANN, which has been trained to distinguish between stable and unstable conditions of the power system. Using the majority vote algorithm in order to increase the confidence level, the output of the ANN is counted to decide whether the oscillatory condition exists or not. The experimental results using real events of the oscillatory condition in the power system indicate that the proposed method could predict the stability of the power system fast enough to warn the operator to take any action before the power system collapses. Future work intends to improve this method by differentiating the oscillatory condition, which leads to a total system failure and the temporary oscillatory condition, which could be a warning to the operator.

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