WAVELET ANALYSIS AND NEURAL NETWORK TECHNIQUE FOR PREDICTING TRANSIENT STABILITY STATUS

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Abstract*: This paper presents a method based on wavelet analysis (WA) and Multilayer perceptron neural network (MLPNN) to predict transient stability status (TSS) after a disturbance. It uses as input data, generator terminal frequency deviations extracted at a rate of thirty-two samples per cycle. Only the first eight frequency deviation samples per machine are needed. The eight samples are sub-divided into two sets, one set consisting of the first four samples and the other set consisting of the last four samples. Each set of samples is decomposed into 2 levels using the Daubechies 8 mother wavelet and the absolute peak value of detail coefficients obtained. The absolute peaks of detail coefficients of the first sample sets of all generators are added and so are the absolute peaks of detail coefficients of the second sample sets. The two summed values are then used as inputs to a trained MLPNN which predicts the TSS. The method was evaluated using dynamic simulations carried out on the New England test system. The method was found to be accurate and can be implemented in real-world systems to provide system operators advance information on system stability, following disturbances, to aid the deployment of needed emergency control measures.*

1. INTRODUCTION

Power grids are subjected to a wide range of abnormal conditions due to faults. Severe abnormal conditions can cause rotor angle separations that may also lead to out-of-step (OS) conditions between generators (groups or individual) or interlinked systems. OS conditions can cause torsional resonance and pulsating torques that are destructive to machine shafts [1]. When OS conditions arise, generator or system separation is needed to avoid flashovers, damage to system equipment and wide-scale outages [2]. For example, in 2003, there were several major outages in USA, Canada and some European countries due to OS conditions [3]. Furthermore, in 2006, disturbances that occurred in the Union for the Co-ordination of Transmission of Electricity system caused it to uncontrollably separate into three islands [3]. A possible solution to OS problems is the use of schemes that analyse transient disturbances to determine critical clearing times, predict possible transient instability, and offer techniques for improvement of transient stability [4]. To this end, there is on-going research and a number of schemes for determining critical clearing times [5], detecting transient instability [2,6], predicting transient stability or otherwise [4], [7-12], and improving transient stability [13,14] have been put forth. These techniques have tackled the problem using various input parameters, signal processing and decision-making tools, with varying degrees of accuracy and easy of practical implementation.

An OS scheme must operate on-line, act speedily and accurately. It must also be robust and simple to implement. All these desired features are yet to be completely addressed in a single scheme. For example, the technique in [8] needs samples from ten to twelve different data types for each generator leading to a huge volume of required data for large systems which delays the technique's response. That in [9] takes close to two and half seconds after fault clearance to decide on the stability or otherwise of a system. The methods in [10] and [11] employ templates that are pre-determined. Thus, system conditions other than those used to develop the templates will cause the techniques to maloperate. Furthermore, the method in [12] uses pre-determined stability boundaries for each machine and its application in a practical system with a large number of generators will require extensive simulation to realize those boundaries.

To address the deficiencies in TSS prediction, this paper proposes a wavelet analysis and multilayer perceptron-based method. The scheme uses as input data, generator bus frequency deviations obtained after fault clearance. The frequency deviation samples are taken at a rate of thirty-two samples per cycle. Only the first eight samples of each machine bus frequency deviation are required. The eight samples are sub-divided into two sets, one set consisting of the first four samples and the other set consisting of the last four samples. Each set of samples is decomposed into 2 levels using the Daubechies 8 mother wavelet and the absolute peak value of detail coefficients obtained. The absolute peaks of detail coefficients of the first sample sets of all generators are added and so are the absolute peaks of detail coefficients of the second sample sets. The two summed values are then used as inputs to a trained MLPNN which predicts the stability status. The strengths of the proposed method are highlighted as follows:

(a) The technique makes use of data sampled in a very short time window.
(b) Minimal data is needed to train the MLPNN decision tool used.
(c) No predetermined templates are used.
(d) The working of the technique does not require complex computations.

(e) It can detect instability status early to aid the maintainance of synchronism.

The remaining sections of the paper are organized as follows: Section 2 explains the input parameter used while Section 3 describes the signal processing tool employed. In Section 4, the decision tool used is explained. Section 5 highlights the proposed technique. The study system used is described in Section 6. Results obtained and analysis done are captured in Section 7. Finally, conclusions drawn are elucidated in Section 8.

2. FREQUENCY DEVIATION AS INPUT PARAMETER

Like rotor angles, machine bus frequencies swing during disturbances [8,15]. For a system that becomes stable, although the bus frequencies of all machines may initially increase or decrease, they will ultimately settle at a synchronous value. The rates of change of the bus frequencies are all reduced. Conversely, for a system that becomes unstable, frequency of one or more machines will rise or decay with higher amplitudes [15].

Figures 1 and *2* show plots of frequency deviations of the ten machines of the New England test system (described in section 6) obtained through dynamic simulation of a three-phase line fault between buses sixteen and twenty-one. The simulation was done by means of the Power System Simulator for Engineers (PSS®E) software [16]. In *fig. 1*, the fault duration was 100 ms and the system was stable.

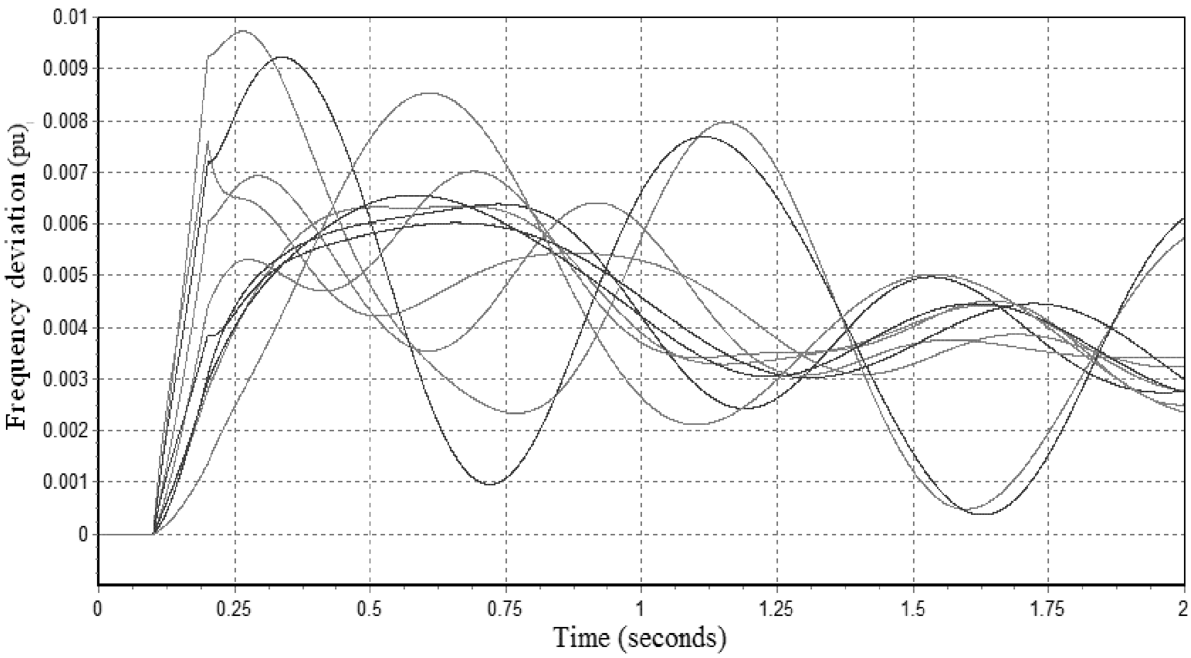

Fig. 1. Frequency deviations for a stable system.

On the other hand, when the fault duration was increased to 400 ms, the system became unstable as depictured in *fig. 2*. It is noted that in *fig. 1*, the bus frequencies initially increased but later stabilized. On the other hand, the bus frequencies of some of the generators in *fig. 2* grew progressively. The clear variations in the curves in the two figures illustrate the possibility of using the trajectories of bus frequencies to predict TSS [15]. However, the success or otherwise depends on the effectiveness of the methodology used for data processing.

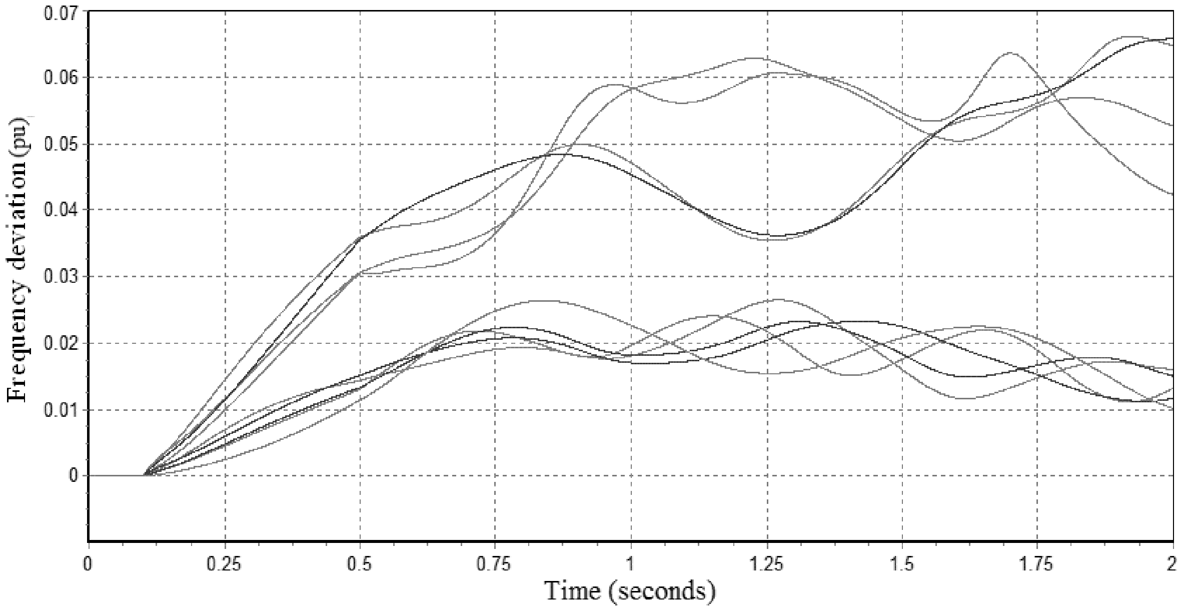

Fig. 2. Frequency deviations for an unstable system.

3. WAVELET TRANSFORM

Wavelet transform (WT) is a commonly used tool for analyzing localized variations of variables. It decomposes a time series into time–frequency space, allowing the realization of the pronounced modes of variability and how they vary in time. In power system studies, the widely used form of wavelet transform is discrete wavelet transform (DWT). This is so because the time series in power systems are discrete [17-19]. DWT is done using mother wavelets. Daubechies 4 and Daubechies 8 mother wavelets are commonly used to analyze transients in power systems [17, 18]. This work used Daubechies 8 wavelet. The choice was informed by the superiority of Daubechies 8 wavelet. Daubechies 8 wavelet has the following advantages over Daubechies 4 [18, 19]: (a) It closely matches a signal to be processed, which is of utmost importance in wavelet applications. (b) Daubechies 8 wavelet is more localized, that is, it is compactly supported in time and is better suited for short and fast transient analysis compared to Daubechies 4 wavelet. (c) It provides almost perfect reconstruction. (d) Daubechies 8 wavelet is found to be more suitable in representing transient signals because it is smoother and more oscillatory in nature which is also the nature of transient signals.

A *l*-level transformation of an input parameter like frequency deviations, $f(x)$, can be done using (1) [17]:

$$f\left(x\right)=\sum_{k} a_{l+1,k}\varphi_{l+1,k}\left(x\right)+\sum_{l=0}^{l} d_{l+1,k}\psi_{l+1,k}\left(x\right) \quad (1)$$

where $l=0,1,2,...,N$, $\varphi(x)$, is a scaling function, and $\psi(x)$ is the mother wavelet.

Approximate coefficients, $a_{l+1,n}$, and detail coefficients, $d_{l+1,n}$ at scale $l+1$ can be obtained if coefficients at scale *l* are available using (2) and (3):

$$a_{l+1,n}=\sum a_{l,k}h\left(k-2n\right) \quad (2)$$

$$d_{l+1,n}=\sum a_{l,k}g\left(k-2n\right) \quad (3)$$

where *h* and *g* are seen as filter coefficients of half band low-pass and high-pass filters respectively.

Wavelet transformation of a variable gives rise to one approximate coefficient (this is constant) and two or more detail coefficients (this equals the levels decomposed). Valuable information is contained only in the detail coefficients. One such valuable information is the absolute peak value [17]. It is expected that, the absolute peak values of detail coefficients of machine terminal frequency deviations for stable swings will be much lower than those for unstable swings. This forms the basis of the proposed scheme.

4. MULTILAYER PERCEPTRON NEURAL NETWORK

Multilayer perceptron neural network (MLPNN) is a commonly used form of artificial neural networks which imitate the human brain. Other types of neural networks include radial basis function networks, Kohonen networks and recurrent networks [20]. Two commonly used neural networks are radial basis function neural network (RBFNN) and multilayer perceptron neural network (MLPNN) [20]. A comparative study of the performances of RBFNN and MLPNN in stability prediction shows that MLPNN performance better than RBFNN [21].

MLPNNs can extract meaning from intricate or vague data and detect complicated trends [22, 23]. MLPNNs are composed of highly interconnected processing elements named neurons. A neuron may or may not have a bias. A bias has a fixed input value of 1. The output, O_j, of a neuron, *j*, with a bias, can be mathematical expressed as [15]:

$$O_j = f_j\left[\sum_{n=1}^{N} x_n w_{nj} + w_{0j}\right] \quad n=1,2,3,...,N \quad (4)$$

where, *j* is the neuron number, x_n is input signal, w_{nj} is connection weight between x_n and neuron *j*, w_{0j} is the bias weight, and f_j is the activation (transfer) function of neuron *j*.

Linear (*purelin*), log-sigmoid (*logsig*), and hyperbolic tangent sigmoid (t*ansig*) are widely used neuron activation functions [24]. The values of connecting weights are determined in the training phase using a training algorithm. MLPNNs are generally trained using the Levenberg-Marquardt back-propagation algorithm. The MLPNN is optimized by varying the number of layers as well as the number of neurons in the hidden layer(s) through a trial and error approach.

The architecture of the MLPNN used, which is optimal, is shown in Fig. 3. It had two neurons in the input layer because the input data set has two distinct values. Also, one neuron was used in the output layer since only one state (that is stable or unstable) has to be determined. The hidden layer had three neurons. In Fig. 3, s^1 and s^2 are the required inputs (explained in section 5). The neurons in the input and output layers had *purelin* transfer functions while those in the hidden layer had *tansig* transfer functions. *Purelin* and tansig functions are expressed as (5) and (6) respectively,

$$f(x) = x \tag{5}$$

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{6}$$

Letting y_n be the output of neuron *n*, the final output 'O' of the MLPNN is mathematically determined as follows:

$$y_1 = f\left(s^1 w_{11} + s^2 w_{21} + w_{01}\right) = s^1 w_{11} + s^2 w_{21} + w_{01} \tag{7}$$

$$y_2 = f\left(s^2 w_{22} + s^1 w_{12} + w_{02}\right) = s^2 w_{22} + s^1 w_{12} + w_{02} \tag{8}$$

$$y_3 = f\left(y_1 w_{13} + y_2 w_{23} + w_{03}\right) = \frac{e^{2(y_1 w_{13} + y_2 w_{23} + w_{03})} - 1}{e^{2(y_1 w_{13} + y_2 w_{23} + w_{03})} + 1} \tag{9}$$

$$y_4 = f\left(y_1 w_{14} + y_2 w_{24} + w_{04}\right) = \frac{e^{2(y_1 w_{14} + y_2 w_{24} + w_{04})} - 1}{e^{2(y_1 w_{14} + y_2 w_{24} + w_{04})} + 1} \tag{10}$$

$$y_5 = f\left(y_1 w_{15} + y_2 w_{25} + w_{05}\right) = \frac{e^{2(y_1 w_{15} + y_2 w_{25} + w_{05})} - 1}{e^{2(y_1 w_{15} + y_2 w_{25} + w_{05})} + 1} \tag{11}$$

$$O = y_6 = f\left(y_3 w_{36} + y_4 w_{46} + y_5 w_{56} + w_{06}\right) = \frac{e^{2\left(y_3 w_{36} + y_4 w_{46} + y_5 w_{56} + w_{06}\right)} - 1}{e^{2\left(y_3 w_{36} + y_4 w_{46} + y_5 w_{56} + w_{06}\right)} + 1} \tag{12}$$

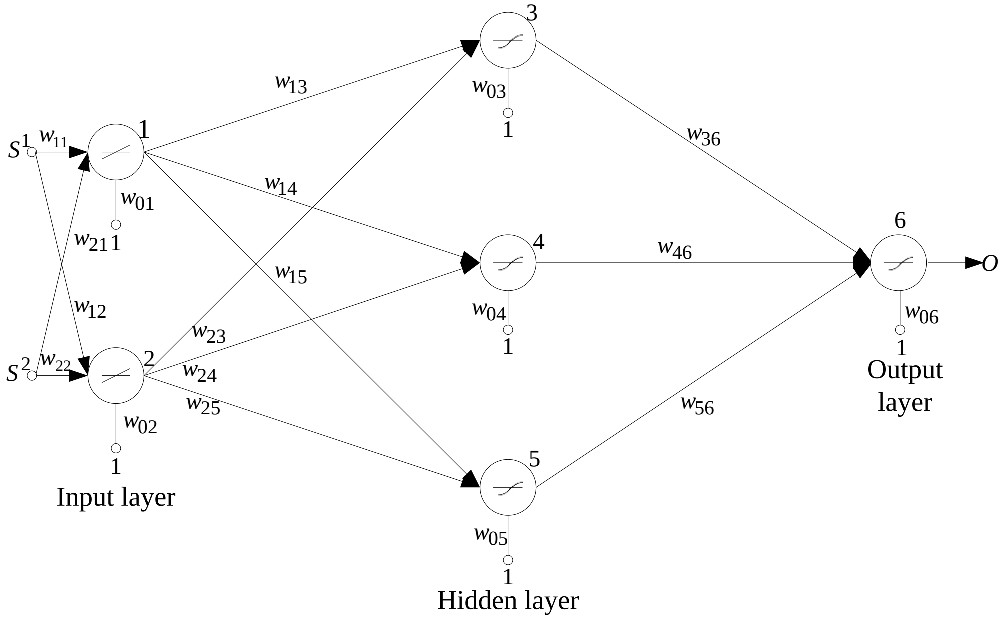

Fig. 3. Architecture of used MLPNN

5. PROPOSED METHOD

Figure 4 depicts a flowchart of the method proposed. It is triggered when a line, bus, generator, or transformer is tripped. The method is outlined as follows:

1. Capture the first eight samples of each generator's bus frequency deviation at a rate of thirty-two samples each cycle and divide each eight samples equally into two sets $f_n^{\,1}$ and $f_n^{\,2}$ as follows:

$$f_n^{\,1} = \left\{ f_{1n}, f_{2n}, f_{3n}, f_{4n} \right\}, \; n = 1, 2, 3, ..., N \tag{13}$$

$$f_n^{\,2} = \left\{ f_{5n}, f_{6n}, f_{7n}, f_{8n} \right\}, \; n = 1, 2, 3, ..., N \tag{14}$$

where N is the number of system machines and superscripts 1 and 2 indicate first sample and second sample respectively.

2. Decompose each set ($f_n^{\,1}$and $f_n^{\,2}$) into one approximate coefficient (a) and two detail coefficients (d_1 and d_2) using the Daubechies 8 (db8) mother wavelet. The useful outputs of $f_n^{\,1}$and $f_n^{\,2}$ after the transformation are mathematically represented as follows:

$$dwt\left(f_n^{\,1}\right)=\left\{d_{1n}^{\,1},d_{2n}^{\,1}\right\} \tag{15}$$

$$dwt\left(f_n^{\,2}\right)=\left\{d_{1n}^{\,2},d_{2n}^{\,2}\right\} \tag{16}$$

where d_{1n}, d_{2n} are detail 1 and 2 coefficients respectively of machine *n*. It must be noted that each detail coefficient d_{1n} or d_{2n} is a set of numerical values.

3. Extract the absolute peak value of each detail coefficient:

$$d_{1n\ \max}^{\,1}=\left|Max\left(d_{1n}^{\,1}\right)\right| \tag{17}$$

$$d_{2n\ \max}^{\,1}=\left|Max\left(d_{2n}^{\,1}\right)\right| \tag{18}$$

$$d_{1n\ \max}^{\,2}=\left|Max\left(d_{1n}^{\,2}\right)\right| \tag{19}$$

$$d_{2n\ \max}^{\,2}=\left|Max\left(d_{2n}^{\,2}\right)\right| \tag{20}$$

4. Obtain the sum of absolute peaks of detail coefficients of each sample namely D_n^1 and D_n^2 D_n^1 and D_n^2 are given by:

$$D_n^{\,1}=d_{1n\ \max}^{\,1}+d_{2n\ \max}^{\,1} \tag{21}$$

$$D_n^{\,2}=d_{1n\ \max}^{\,2}+d_{2n\ \max}^{\,2} \tag{22}$$

5. Sum D_n^1 values of all generators and D_n^2 values of all generators separately to obtain two composite values, S^1 and S^2 respectively:

$$S^1=\sum_{n=1}^{N}D_n^{\,1} \tag{23}$$

$$S^2=\sum_{n=1}^{N}D_n^{\,2} \tag{24}$$

6. Feed S^1 and S^2 values as inputs to the trained MLPNN to predict the TSS.

The MLPNN was trained to output ‘0’ and ‘1’ for conditions leading to stability and instability respectively. The training was done using input-output data pairs.

MLPNNs like other networks rarely give outputs that are precisely '0' or '1'. Consequently, in this method, (23) and (24) are utilized to achieve the desired output of '0' or '1'.

$$O \geq 0.5 \quad \Rightarrow \quad O = 1 \tag{25}$$

$$O < 0.5 \quad \Rightarrow \quad O = 0 \tag{26}$$

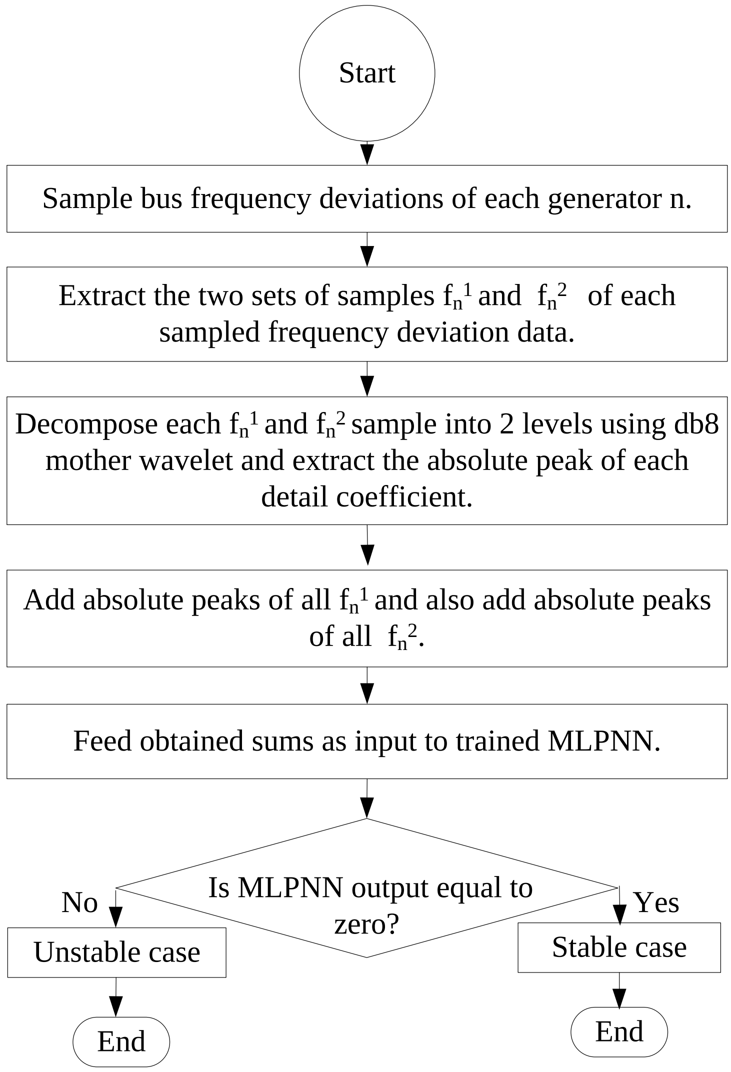

Fig. 4. Flowchart of method

The performance of the proposed technique was evaluated using a mean absolute percentage error (MAPE) index. The index is given as follows:

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|T(k) - O(k)\right| \times 100 \tag{27}$$

where $T(k)$ is the target value of the MLPNN for test case number k, $O(k)$ is the obtained output of the MLPNN and N is the total number of test cases.

6. STUDY SYSTEM

Testing of the method was done using the New England test system (also known as IEEE 39-bus system). It is a standard test system universally used for steady state and transient stability studies [4,10,11]. It is shown as *fig. 5*. It comprises ten generators, with one (G1) representing a large system.

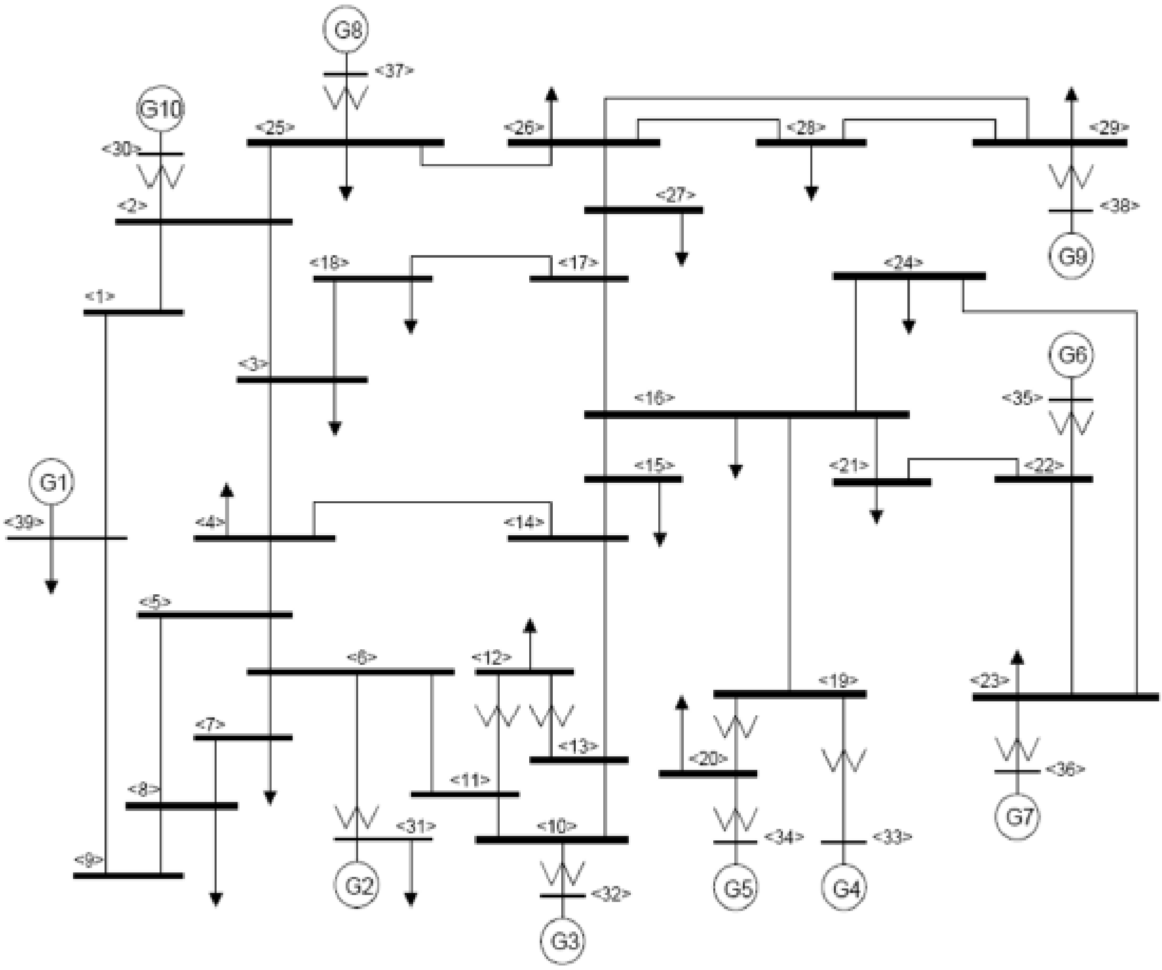

Fig. 5. IEEE 39-bus test system

Simulations of the study system was done using the PSS®E software. A comprehensive model capturing the dynamics of prime mover and excitation system was employed. Numerous fault conditions were simulated by changing fault location, fault duration, system loading, network topology and generator availability. In all, one hundred and sixty faults were simulated. The simulations were done such that stability was maintained for fifty percent of the cases while transient instability occurred for fifty percent of the cases. This was achieved by varying the fault duration. Frequency deviation data was obtained from the simulations for the development and testing of the proposed scheme. The percentages of data used for training and testing are 5% and 95% respectively.

7. RESULTS AND ANALYSIS

Figure 6 shows the architecture of the MLPNN after training. Results for two test cases (one stable case and one unstable case) are presented to demonstrate the scheme's operation. The fault for both cases is a three-phase line fault between bus sixteen and bus twenty-one at base load. Waveforms for this condition have been shown in *figures 1* and *2*. The fault duration for which stability was maintained was 100 *ms* whiles that for which stability was lost was 400 *ms*. The inputs S^1 and S^2 to the MLPNN are obtained as shown in Table 1 using (21), (22), (23) and (24).

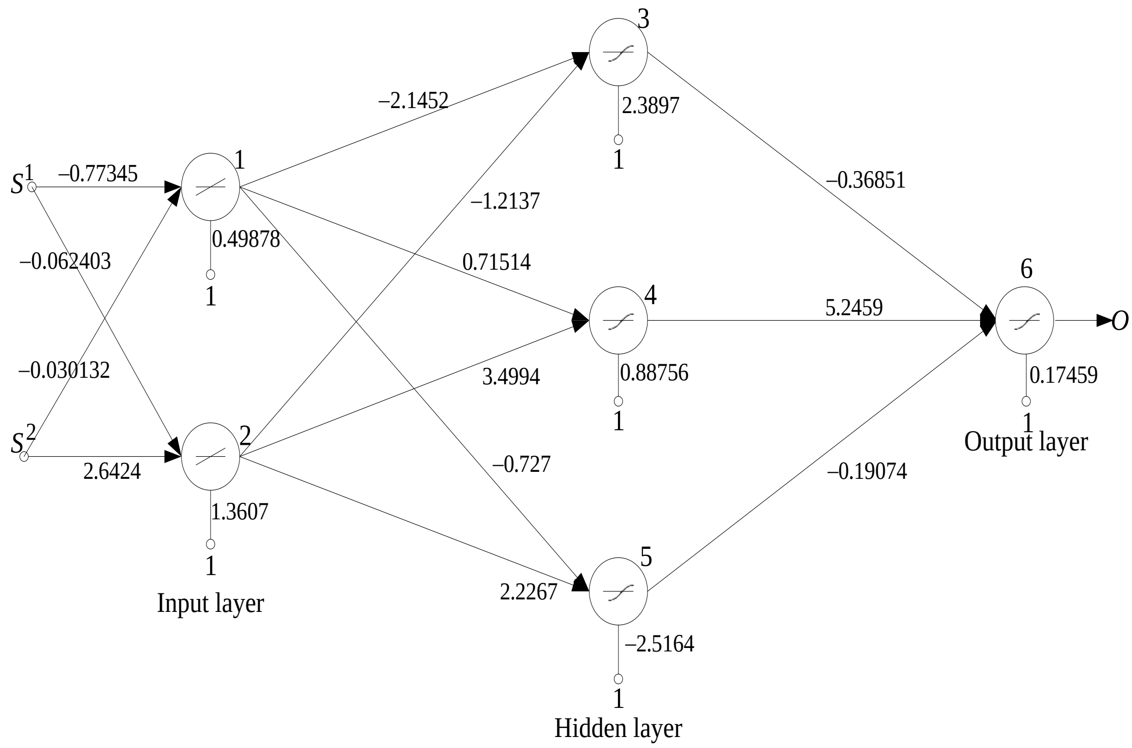

Fig. 6. Architecture of trained MLPNN.

Table 1. Sum of absolute peak values of detail coefficients

Machine no.	Stable		Unstable	
	$D_n^1 \times 10^{-3}$	$D_n^2 \times 10^{-3}$	$D_n^1 \times 10^{-3}$	$D_n^2 \times 10^{-3}$
1	0.02017	0.00630	0.03639	0.03633

Machine no.	Stable		Unstable	
	$D_n^1 \times 10^{-3}$	$D_n^2 \times 10^{-3}$	$D_n^1 \times 10^{-3}$	$D_n^2 \times 10^{-3}$
2	0.03098	0.02607	0.07401	0.07335
3	0.04181	0.03947	0.03945	0.03935
4	0.04243	0.02744	0.03130	0.03055
5	0.05960	0.07440	0.06423	0.04372
6	0.04490	0.00764	0.03245	0.03348
7	0.05897	0.00176	0.03508	0.03402
8	0.04542	0.00145	0.05325	0.05514
9	0.03219	0.02529	0.04886	0.04880
10	0.01669	0.01706	0.09134	0.08944
	$S^1 = 0.39316 \cdot 10^{-3}$	$S^2 = 0.22688 \cdot 10^{-3}$	$S^1 = 0.50636 \cdot 10^{-3}$	$S^2 = 0.48418 \cdot 10^{-3}$

Applying the above inputs to the MLPNN using (7)-(12), (25) and (26) yields the following results:

Stable case:

$O(s^1 = 0.39316 \times 10^{-3}, s^2 = 0.22688 \times 10^{-3}) = 0$, implying transient stable.

Unstable case:

$O(s^1 = 0.50636 \times 10^{-3}, s^2 = 0.48418 \times 10^{-3}) = 1$, implying transient unstable.

A summary of results for other fault cases are shown in Table 2. Overall, the method accurately predicted the TSS of 143 out of the 152 test cases. The MAPE, after testing, was 5.9%, which is low. The prediction accuracy of the scheme is thus 94.1%.

Table 2. Test results for some fault cases

Fault	Stable			Unstable		
	S^1	S^2	O	S^1	S^2	O
Bus11	0.2828	0.1047	0	1.0194	1.0007	1
Bus14	0.2646	0.1048	0	0.9741	0.9356	1
Bus28	0.1283	0.1297	0	0.4809	0.4800	1
Bus11-Bus12	0.2634	0.1664	0	0.6569	0.6493	1
Bus13-Bus14	0.2634	0.1664	0	0.4954	0.4736	1
Bus16-Bus21	0.39316	0.22688	0	0.50636	0.48418	1

The MLPNN produced these results having been trained with only 5% of total simulation data. This percentage of training data set is extremely low compared with the 85% training data set used in [25]. The low percentage of training data set was realised because the used input data and the data processing approach employed, resulted in the processed data for transient stable cases being distinct from processed data relating to transient unstable cases.

Such distinctiveness of processed data makes is easy for the decision tool used (MLPNN) to distinguish between conditions that will lead to transient instabilty and those for which a system will remain stable. On the contrary, the use of large volumes of training data, such as was the case in [25], depict a difficulty of the decision tool to make out differences in data sets for stable and unstable conditions. The advantage of realisng a low volume of training data set in a technique is that, it becomes easy to deploy such a scheme in large real world systems.

The proposed technique uses only one data variable (or component feature), which is generator frequency deviation. The data set required for processing and final decision making is also minimal. These avoid potential processing delays associated with large data variables and datasets. The lower the volume of data to be processed, the faster the processing. Furthermore, the approach to data processing and final decision is simple and will not present any computational delays. Consequently, the proposed technique will offer a quick response to provide system operators or emergency control softwares ample time to deploy the needed control measures.

Frequency deviation data can be captured by phasor measurement units which have seen increasing deployment in power systems, in recent times. Phasor measurement units are capable of capturing frequency data in real-time. Aided by phasor data concentrators (PDCs) and super phasor data concentrators (super PDCs), which are all integral parts of Wide Area Monitoring Systems (WAMS), frequency deviation data from generator buses can be collected at a control center for processing by the proposed technique, for utilization by system operators and the activation of emergency control softwares.

8. CONCLUSION

A method for predicting TSS has been presented. It employs bus frequency deviations as input data, wavelet analysis for signal processing and MLPNN for final decision making. The input data can be obtained from phasor measurement units (PMUs) which have seen active deployment in power systems. A low volume of input data, captured in a short time window, is required. Minimal training data is needed to train the decision tool. This will allow for easy application in large real-world systems. The method does not use any predetermined templates or stability boundaries that could adversely affect its application in real world systems. It can be easily implemented on-line aided by phasor measurement units capable of capturing real-time frequency data and transmitting them to a centralized point. The analytical and decision-making tools employed are also simple, reliable, and easy to implement. Also, the short time window (1/4 of a cycle) of input data capture will make the scheme respond speedily.

Consequently, systems operators will have ample notice to deploy the needed emergency control measures. The simulation results indicate that the proposed method has high accuracy.

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