Walsh-Hadamard Transform and Support Vector Machine Based Rotor Angle Stability Status Prediction

Emmanuel Asuming Frimpong [1], Philip Yaw Okyere[2], Johnson Asumadu[3]

[1,2] Department of Electrical and Electronic Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

[3]Department of Electrical and Computer Engineering, Western Michigan University, Kalamazoo, USA

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Abstract - *A novel scheme is presented for real-time prediction of rotor angle stability status. The scheme is activated following a large disturbance and operates by obtaining a set of two rotor angles for each generator. Each set of two rotor angles sampled is decomposed using the fast Walsh-Hadamard transform resulting in two Walsh coefficients. The absolute value of each coefficient is obtained and the maximum of the two is selected. The selected absolute maximum values, one for each generator, are then summed and fed into a trained support vector machine which predicts the stability status. The scheme was tested using the IEEE 39-bus system. It successfully predicted the stability status of all two-hundred and four test cases.*

Key Words: **Power system transient stability, Rotor angle, Support vector machine, Transient analysis, Walsh-Hadamard transform**

1. INTRODUCTION

Although modern power systems have been designed to withstand various power system disturbances, there are instances that severe disturbances may lead to system instability. A severe disturbance may be a sudden loss or application of a large load, loss of generation, or a major fault on a system [1], [2]. During normal operations of a generator, the output electric power from the generator produces an electric torque that balances the mechanical torque applied to the generator rotor shaft. The generator rotor, therefore, runs at a constant speed. When a fault reduces the amount of power transmitted, the electric torque that counters the mechanical torque is also reduced. If the mechanical power is not reduced during the period of the fault, the generator rotor will accelerate with a net surplus of torque input. The situation can lead into an unstable condition, where one or more generators rotate at speeds different from the other generators of the system. Such an unstable condition is referred to as loss of synchronism or an out-of-step (OS) condition [1], [2]. OS conditions may result in torsional resonance and pulsating torques that are severely harmful to generator-turbine shaft. When OS conditions occur, it is imperative that all asynchronous generators are isolated to avoid widespread outages, flashovers, and equipment damage [3].

Emergency control strategies such as out-of-step blocking and tripping, fast-valve control of turbines, dynamic braking, use of superconducting magnetic energy storage system, 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 actions is improved with early detection or prediction of transient instability [5]. In view of that, researchers have come up with various techniques for transient instability detection and prediction.

Several of the transient instability detection and prediction schemes, which exist in the literature, use various power system input data that can be captured via phasor measurement units (PMUs) and global positioning system (GPS). They also employ various signal processing and decision-making tools [4]-[14]. For example, rotor angle and multilayer perceptron neural network have been used in [4], post-fault voltage and support vector machine have been combined in [13], [14]. Albeit significant successes have been chalked in transient instability detection and prediction, there is still room for improvement in the areas of simplicity, reliability, speed of operation and practical realization. For example, the work presented in [10] requires 10 -12 input data samples per generator which makes the volume of data required for large systems huge and consequently delays the response time of the scheme. The work in [11] also requires a relatively long period of up to 2.5 seconds after fault clearance to decide as to whether the system will be stable or not. The schemes proposed in [13], [14] use predetermined templates which make their performance prone to changes in system conditions. The technique presented in [6] also uses a predetermined stability boundary for each generator. To apply this scheme to a real system with many generators, extensive dynamic simulations to establish the stability boundaries are required.

A comprehensive review of some existing schemes carried out in [15] suggested bus voltage trajectories and generator rotor angle trajectories as the most appropriate inputs for transient instability detection. Rotor angle is a key parameter in the fundamental equation governing rotor dynamics. However, the use of rotor angle as input parameter was not encouraged in the past owing to practical

difficulties associated with its measurement and utilization [5], [13]. However, in recent work, researchers comprising engineers from Schweitzer Engineering Laboratories, Inc. and San Diego Gas & Electric successfully installed and commissioned a rotor angle measurement system on the generators of a 740 MVA combined cycle plant [16]. This breakthrough in capturing rotor angle data has offered a tremendous boost to the use of rotor angles as input parameter for power system studies.

In this paper, a novel scheme for predicting transient stability status is presented. The proposed scheme has one or more of the following advantages over several existing rotor angle stability prediction schemes [4], [6], [13], [14]:

(i). It uses data captured in a very short time window.

(ii). It requires minimal training data.

(iii).It does not require predetermined templates.

(iv).Its implementation does not require complex computations.

The scheme uses generator rotor angles captured at the rate of 60 samples per second as input parameter. This sampling rate is the same as that used in [16]. It is also a typical reporting rate of phasor measurement units [17].

For each generator, a set of two rotor angles, all captured within the first 36ms (i.e. 2ms trigger delay time + sampling time of first two samples at 60 samples per second) following a fault clearance, are required. The fast Walsh-Hadamard transform (FWHT), a signal processing tool, is applied to decompose each set of rotor angles. This results in a set of two Walsh coefficients for each generator. The absolute value of each coefficient is obtained and the maximum of the two extracted. These extracted maximum absolute Walsh coefficient values, one for each generator, are then summed and fed into a trained support vector machine which predicts the stability status of the system. The SVM produces an output of +1 if a disturbance will lead to transient stability and an output of -1 if transient instability will arise.

Some researchers perceive machine learning techniques including SVM as black-box type decision making tools [6]. This perception is erroneous. SVMs like other machine learning techniques are based on sound mathematical principles. Their outputs can be mathematically determined from given inputs. This has been demonstrated in this paper.

The rest of the paper is organized as follows: Section 2 discusses the use of rotor angle as input parameter; Section 3 explains the fast Walsh-Hadamard transform. In Section 4, the use of support vector machine as decision making tool is explained. Section 5 presents the proposed scheme while Section 6 presents the test system used and simulations

done. Test results of the proposed scheme are presented in Section 7. Conclusions drawn are highlighted in Section 8.

2. ROTOR ANGLE AS INPUT PARAMETER

The transient stability of a power system following a severe disturbance depends on the deviations in angular positions of the rotors of the synchronous machines. The time responses of rotor angles to a severe disturbance obtained over a period, typically 3 to 5 seconds, following the disturbance enable us to infer the transient stability status. Hence, the rotor angle becomes a natural input parameter for transient instability detection and prediction [18].

One drawback that hinders the use of rotor angles as an input parameter is that in a multi-machine system, the 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. To overcome this difficulty, the concept of system centre of inertia (COI) angle, δ_{co} is used to obtain a reference angle [13]. Many researchers would not encourage the use of rotor angles in algorithms in the past because the COI values, in practice, need to be continuously updated using real time measurements [13]. These updates require extra pre-processing, which gives rise to significant errors.

In the rotor angle measurement system installed and commissioned by engineers of Schweitzer Engineering Laboratories, Inc. and San Diego Gas & Electric on the generators of a 740 MVA combined cycle plant, no reference angle value is required [16]. This project, accomplished by these engineers, has been the chief motivation behind the use of rotor angles as input parameter in this work.

3. FAST WALSH-HADAMARD TRANSFORM

The Walsh-Hadamard transform (WHT) is used in a wide variety of scientific and engineering applications [19]. It is employed in image processing, speech processing, filtering, and power spectrum analysis. It is very useful for reducing bandwidth storage requirements and spread-spectrum analysis [20]. However, WHT has limited application in power system studies and has hardly been used for power system transient stability studies.

WHT is a real orthogonal transform. Its implementation starts from the Hadamard matrix, **H** which is real and symmetric. **H** is defined recursively as [21]:

$$\mathbf{H}_1 = \frac{1}{k}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \qquad (1)$$

where k is a scaling factor which may be chosen to be √2 so that **H₁** becomes orthogonal.

$$\mathbf{H_n} = \mathbf{H_1} \otimes \mathbf{H_{n-1}} = \begin{bmatrix} \mathbf{H_{n-1}} & \mathbf{H_{n-1}} \\ \mathbf{H_{n-1}} & -\mathbf{H_{n-1}} \end{bmatrix} \qquad (2)$$

where $\otimes$ indicates the Kronecker product. The dimension of matrix $\mathbf{H}_n$ is $2^n \times 2^n$. The integer n is obtained from the length, N of the signal vector being processed as follows:

$$n = log_2 N \qquad (3)$$

For example, for a signal vector of length $N = 4$, $n = 2$ and if k is omitted or k = 1, the Hadamard matrix will be given as [21]:

$$\mathbf{H_2} = \mathbf{H_1} \otimes \mathbf{H_1} = \begin{bmatrix} \mathbf{H_1} & \mathbf{H_1} \\ \mathbf{H_1} & -\mathbf{H_1} \end{bmatrix} \text{ or }$$

$$H_2 = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \qquad (4)$$

If the length, N of the signal vector is less than a power of 2, its length is padded with zeros to the next greater power of two before processing [20]. The Hadamard matrix **H** can be used to define an orthogonal transform, called Hadamard ordered Walsh-Hadamard transform (WHT). The WHT of signal vector **x** is given as [21]:

$$\mathbf{w} = \mathbf{Hx} \qquad (5)$$

where $\mathbf{x} = [x_1, x_2, \ldots\ldots, x_n]^T$ is the N-point signal vector to be transformed and $\mathbf{w} = [w_1, w_2, \ldots\ldots, w_n]^T$ is its WHT spectrum vector. The elements of the spectrum vector **w** are commonly referred to as Walsh coefficients.

It is important to note that WHT can be carried out by additions and subtractions alone. For an array of size N, where N is an integer power of two, the total number of arithmetic operations to compute WHT is N^2 [21]. To reduce the number of computations and hence improve the speed of computing Walsh coefficients, a fast algorithm known as Fast Walsh-Hadamard transform (FWHT) is employed [21]. The FWHT reduces the number of computations from N^2 to $N log_2 N$. The FWHT is a divide and conquer algorithm that recursively breaks down a WHT of size N into two smaller WHTs of size $N/2$. It is based on matrix factoring or matrix partitioning technique [22].

4. SUPPORT VECTOR MACHINE

Support vector machine (SVM) is an extremely powerful machine learning algorithm that focuses on classifying data [20], [23]. SVMs are inherently two-class classifiers. The main idea of a support vector machine is to construct a hyperplane as the decision surface in such a way that the margin of separation between two data categories is maximized. SVMs can be used when the data to be classified has two classes. They separate the data into two categories, namely positive (+1) and negative (-1). Figure 1 illustrates these definitions, with + indicating data points of type 1, and – indicating data points of type –1 [24].
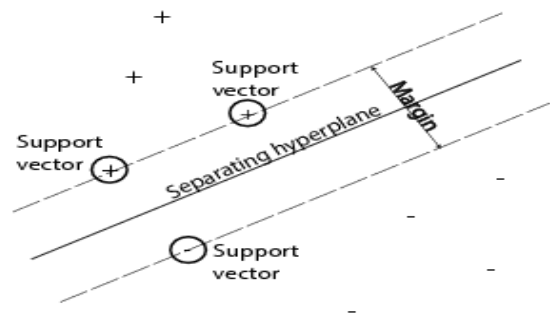

Fig -1: Data points of SVM

SVMs can provide good generalization performance on pattern classification problems even though they do not incorporate problem-domain knowledge. This attribute is unique to SVMs [23].

In addition to using separating hyperplanes, SVMs use support vectors to aid in data classification. Support vectors are points that are closest to the separating hyperplane; these points are on the boundary of the slab separating the two classes of data [20]. The building of a support vector machine hinges on the following two mathematical operations: (a) nonlinear mapping of an input vector into a high-dimensional feature space that is hidden from both the input and the output, and (b) construction of an optimal hyperplane for separating the features discovered in (a) [23].

Figure 2 shows the general architecture of a SVM [23]. The input layer consists of the input signal vector. In the hidden layer, an inner-product kernel is computed between the input signal vector (**x**) and support vector (**s**i). The linear outputs of the hidden layer neurons are summed in the output neuron. The output neuron has a bias.

The interim output, O of a support vector machine can be computed as [24]:

$$O = \sum_i \mathbf{w}_i \, k(\mathbf{x}, \mathbf{s}_i) + b \qquad (6)$$

where **x** is the input vector, **s**i is the support vector, b is the bias, and **w**i is the weight vector. The function k(**x**, **s**i) is a

kernel of **x** and **s**$_i$. The weight and bias values are obtained in the training phase. A linear kernel, meaning dot product, was used in this work because the data appeared to be linearly separable after preprocessing. Other possible kernel functions are quadratic, polynomial, Gaussian or radial basis function, and multilayer perceptron [24].

SVMs are trained with input-output pairs to give targets of either +1 or -1. An output of $+1$ is given when $O \geq 0$ while -1 is recorded when $O < 0$. In this work, the SVM was trained to produce a target of +1 for a condition that will lead to transient stability and -1 for a condition that will lead to transient instability. The training was done using the sequential minimal optimisation method [20]. The training data used is given in section 7.
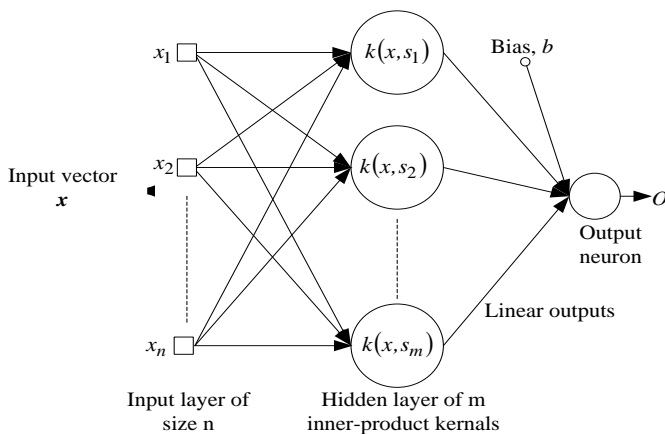

Fig -2: General architecture of support vector machine

5. PROPOSED TRANSIENT STABILITY STATUS PREDICTION SCHEME

Figure 3 shows a flowchart of the proposed technique. The scheme is activated upon the tripping of a line or bus following a disturbance. For each generator, a set of two rotor angles are captured at a sampling rate of 60 samples per second. The two rotor angles were enough to give accurate prediction results. The fast Walsh-Hadamard transform (FWHT) is employed to decompose this set of two rotor angles for every generator. Each set of two rotor angles when decomposed yields a Walsh coefficients vector that has two elements w_1 and w_2 called the Walsh Coefficients. The absolute value of each Walsh coefficient is obtained and the maximum of the two is then extracted. All the extracted maximum absolute Walsh coefficient values, one for each generator, are summed and used as input to a trained support vector machine which predicts the stability status of the system. The scheme ends its operation after a final decision has been made and resets for the next operation.

The procedure of operation is outlined as follows:

(i). For every generator i, form the rotor angle vector, δ_i:

$$\boldsymbol{\delta}_i = \left[\delta_{i,1}, \delta_{i,2}\right]^T \quad i = 1,2,\ldots,N \qquad (7)$$

where N is the number of generators of the system and $\delta_{i,1}$ and $\delta_{i,2}$ are the two rotor angles of generator i sampled.

(ii). Obtain the Walsh coefficients vector $\mathbf{w}_i$ for every generator rotor angle vector as follows:

$$\mathbf{w}_i = \mathbf{H}\boldsymbol{\delta}_i \quad i = 1,2,\ldots,N \qquad (8)$$

(iii). For each vector $\mathbf{w}_i$ having elements $w_{i,1}$ and $w_{i,2}$ obtain absolute values of the elements and extract the maximum of the two:

$$w_{ai,max} = \text{max. of}\left[\left|w_{i,1}\right|,\left|w_{i,2}\right|\right] \quad i = 1,2,\ldots,N \qquad (9)$$

(iv). Obtain the input to the support vector machine, x by summing the maximum absolute Walsh coefficient of all generators as follows:

$$x = \sum_{i=1}^{N} w_{ai,max} \qquad (10)$$

(v). Feed input signal x into trained SVM and determine the stability status, t from SVM output, O as follows:

$$O \geq 0 \implies t = +1 \implies system\ is\ stable \qquad (11)$$

$$O < 0 \implies t = -1 \implies system\ is\ unstable \qquad (12)$$
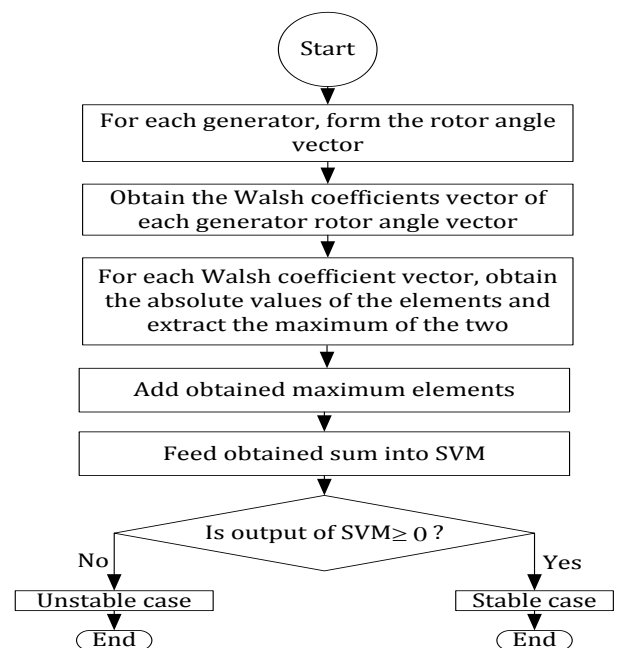

Fig - 3: Flowchart of proposed scheme

6. TEST SYSTEM AND SIMULATIONS

The IEEE 39-bus test system was used to test the proposed scheme. This test system, also known as the New England test system, is a very popular test system for transient stability studies. Several researchers have used it for their work [4], [6], [13], [25] for these main reasons: it is a model of a practical system; and it can be modeled and simulated using several non-commercial versions of simulation tools. The system consists of 10 generators, one of which is a generator representing a large system. Data for its model were obtained from [26]. The system is shown in Figure 4.

Transient stability analysis of the test system was performed using the PSS®E software. A detailed dynamic model which includes prime mover and excitation system dynamics was used. Several fault simulations were obtained by varying the following:

(i) Fault location,

(ii) Fault duration,

(iii) System loading,

(iv) Network topology, and

(v) Generator availability.

As regards fault location, bus and line faults at different locations were simulated. Fault durations were also varied by starting with short durations which resulted in transient stability and extending them gradually until instability occurred. The loading conditions simulated were base load, 80% of base load, 90% of base load, 110% of base load and 120% of base load. The effect of shutting down a generator due to low loading conditions or for purposes of maintenance was also considered. For example, for a loading level of 80% base load, generator 10 (G10) was removed from circuit before disturbances were applied. Additionally, the effect of changes in network topology was investigated by considering N-1 contingency. For example, for some of the simulations, the line between bus 18 and bus 17 was removed before the application of faults.

A total of 208 fault simulations were done to obtain 104 cases of transient stability and 104 cases of transient instability. Rotor angle data from two cases of transient stability, and two cases of transient instability, representing 1.92% of data generated, were used to train the SVM. The remaining 98.08% of the data generated (102 cases of instability and another 102 cases of stability) were then used to test the proposed scheme. The training data of 1.92% is very low when compared with the training data of 75% used for some stability status prediction schemes existing in literature [13], [14]. The large volume of test data, generated under varying system conditions, was necessary to ascertain the robustness of the proposed scheme.

The following criterion was used to determine the stability status of the system following a simulated disturbance: A system was seen as being transiently unstable if the rotor angle difference between any two generators exceeded 180 degrees within a typical study period of 3 seconds following fault clearance, otherwise, the system was seen to be stable [18].

The rotor angle data used for training and testing the SVM were sampled allowing for a trigger delay time of 2 ms after fault clearance. The sampling and analysis of data were done using the MATLAB software.
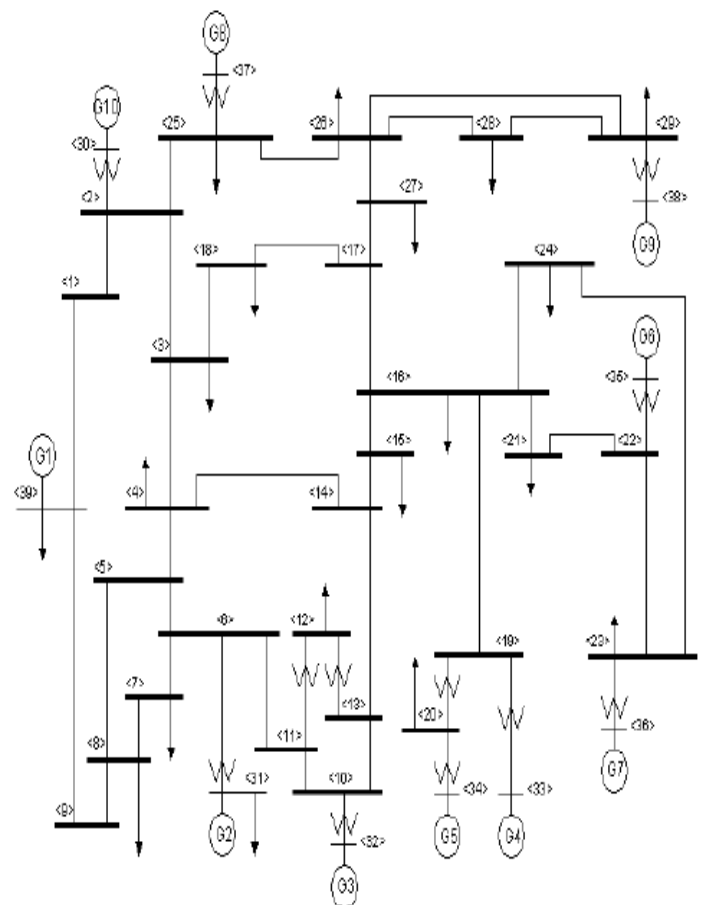

Fig - 4: IEEE 39-bus Test System

7. RESULTS AND ANALYSIS

7.1 Structure of support vector machine

Table 1 shows the data used to train the SVM. The structure of of the SVM after training is presented in Table 2.

Table -1: Training data for S VM

Input(x)	114.7374	145.2864	275.8693	281.6902
Target(t)	1	1	-1	-1

Table -2: SVM structure after training

s	α or **w**	b	Shift	Scale factor (k)
$s_1 = -0.6808$	$w_1 = -0.88418$	-0.0947	-204.3958	0.0115
$s_2 = -0.8232$	$w_2 = -0.88418$			

For the above SVM which has a scalar input data, two support vectors, and has its input data shifted and scaled, the interim output, O given by (6) becomes

$$O(x) = k(s_1 \times w_1 + s_2 \times w_2)(x + \text{shift}) + b \qquad (13)$$

The constants in the equation are as defined in the above table. Substituting in values results in the following classifying equation for the test system:

$$O(x) = -0.01529(x - 204.3985) - 0.0947 \qquad (14)$$

The stability status of all the 102 cases of instability and the 102 cases of stability when tested on the trained SVM were all correctly predicted. Thus, the overall prediction accuracy of the scheme proved to be 100%.

To further illustrate the performance the scheme, four representative cases are presented. The cases are: (i) a stable case (Case 1) and an unstable case (Case 2) for a pre-fault condition with all generators in service at base loading, and (ii) a stable case (Case 3) and an unstable case (Case 4) for a pre-fault condition with only nine generators in service at 80% base loading.

7.2 Performance of scheme with all generators in service at base load

(a) Rotor angle trajectories for Cases 1 and 2

Figure 5 shows time responses of rotor angles for the case of transient stability (Case 1). The fault was applied on the line between buses 6 and 7 of the test system at base loading. The fault was applied at $t = 0.1s$ and the line tripped at $t = 0.2s$. Figure 6 shows time responses of rotor angles for the unstable case (Case 2). The system and fault conditions were the same as those for Case 1 except that the fault duration was extended by 0.3 seconds to make the system transiently unstable.
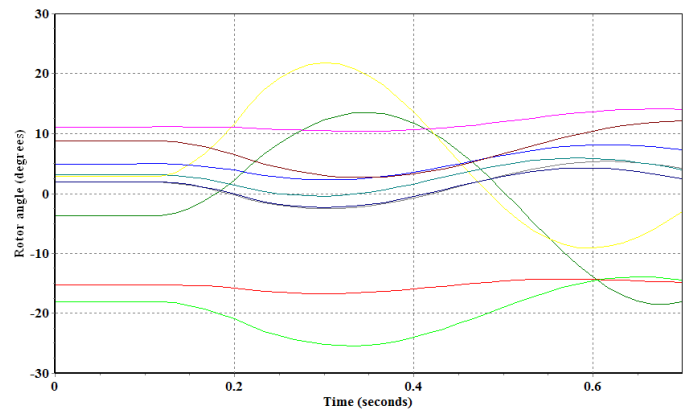
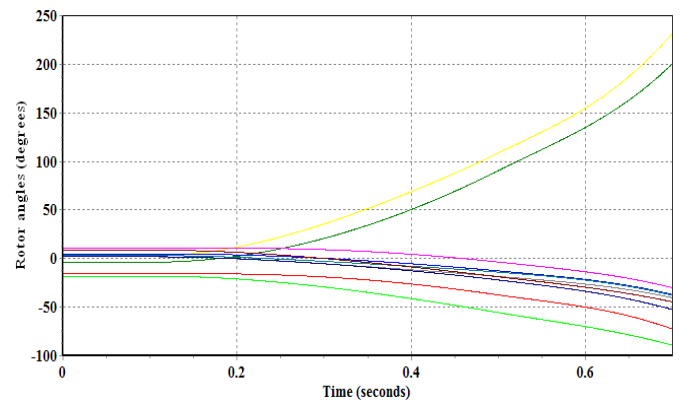**Fig -5**: Rotor angle trajectories for a stable condition(Case 1)

Fig -6: Rotor angle trajectories for an unstable condition (Case 2)

(b) Walsh coefficients for Cases 1 and 2

For each rotor angle input vector $\boldsymbol{\delta}_i$ of machine i, the vector length N equals 2. From (3), $n = 1$. Thus, the appropriate Hadamard matrix is $\mathbf{H}_1$, which is given by (1). In this work, a scaling factor of 2 was used, in accordance with Walsh-Hadamard transformation in Matlab. In Matlab, the fast Walsh-Hadamard transform (FWHT) includes a scaling factor that is equal to the length of the input vector [24]. Using (8) with a scaling factor of 2, the Walsh coefficients $w_{i,1}$ and $w_{i,2}$ are given as:

$$\begin{bmatrix} w_{i,1} & w_{i,2} \end{bmatrix} = \frac{1}{2}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} \delta_{i,1} \\ \delta_{i,2} \end{bmatrix} \qquad (15)$$

From (15), $w_{i,1}$ and $w_{i,2}$ are given as:

$$w_{i,1} = \frac{1}{2}(\delta_{i,1} + \delta_{i,2}) \qquad (16)$$

$$w_{i,2} = \frac{1}{2}(\delta_{i,1} - \delta_{i,2}) \qquad (17)$$

The scaling factor does not have any effect on the performance of the proposed scheme since the sum of the maximum absolute Walsh coefficients is scaled by the SVM.

Table 3 shows Walsh coefficients w_1 and w_2 obtained for each of the 10 generators using the rotor angle data sampled from Case 1 (Stable case) and Case 2 (Unstable case). The coefficients were obtained using (16) and (17). Table 4 shows the maximum of their absolute values for each generator, for both the stable and unstable cases.

Table -3: Walsh coefficients for Cases1 and 2

Gen.	Stable Case		Unstable Case	
	w_1	w_2	w_1	w_2
1	-22.4732	0.4814	-40.6929	0.9920
2	5.5511	-1.0540	101.4233	-3.6118
3	16.0449	-1.3508	119.8042	-3.5702
4	3.2671	0.2039	-14.6161	0.6786
5	-1.239	0.2985	-20.1306	0.6022
6	10.8573	0.0501	-5.7712	0.7862
7	0.5745	0.2569	-15.6203	0.6019
8	-1.0525	0.2984	-24.7674	0.9058
9	5.2993	0.3786	-21.4627	0.8696
10	-16.1433	0.1300	-59.4304	1.2003

Table -4: Maximum of the absolute values of Walsh coefficients for Cases 1 and 2

Gen.	Maximum Walsh coefficients, $w_{i,max}$	
	Stable case	Unstable case
1	22.4732	40.6929
2	5.5511	101.4233
3	16.0449	119.8042
4	3.2671	14.6161
5	1.2390	20.1306
6	10.8573	5.7712
7	0.5745	15.6203
8	1.0525	24.7674
9	5.2993	21.4627
10	16.1433	59.4304

From Table 4, the sums of the maximums of the absolute values of Walsh coefficients using (10) are:

$$x_{stable} = 82.5002 ; \quad x_{unstable} = 423.7191$$

(c) SVM responses for Cases 1 and 2

From the classifying equation (14), the outputs of the SVM are obtained as follows:

Case 1 (Stable case)

$$O(x = 82.5002) = 1.7691 > 0$$

Hence the stability status $t = +1$, which implies system is stable.

Case 2 (Unstable case)

$$O(x = 423.7191) = -3.4482 < 0$$

Therefore, the stability status $t = -1$, which implies system is unstable.

7.2 Performance of scheme with nine generators in service at 80% base load condition

(a) Rotor angle trajectories for Cases 3 and 4

Here, generator 10 (G10) was taken out of service at 80% base loading. Figure 7 shows time responses of rotor angles for the case of transient stability (Case 3). The fault was applied on the line between buses 26 and 27 of the test system. The fault was applied at $t = 0.1s$ and the line tripped at $t = 0.2s$.

Figure 8 shows time responses of rotor angles for the unstable case (Case 4). The system and fault conditions were the same as those for Case 3 except that the fault duration was extended by 0.2 seconds to make the system transiently unstable.
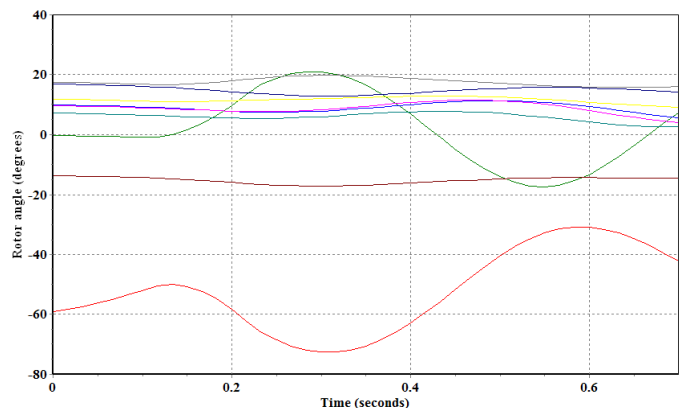

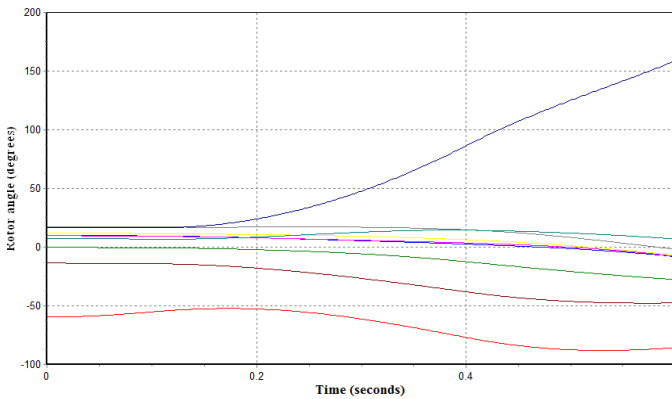**Fig -7**: Rotor angle trajectories for a stable condition (Case 3)

Fig -8: Rotor angle trajectories for an unstable condition (Case 4)

Walsh coefficients for Cases 3 and 4

Table 5 shows Walsh coefficients w_1 and w_2 obtained for each of the remaining 9 generators using the rotor angle data sampled from Case 3 (Stable case) and Case 4 (Unstable case). The coefficients were obtained using (16) and (17). Table 6 shows the maximum of their absolute values for each generator, for both the stable and unstable cases. From Table 6, the sums of the maximums of the absolute values of Walsh coefficients using (10) are:

$$x_{stable} = 160.5291; \; x_{unstable} = 273.9834$$

Table -5: Walsh coefficients for Cases 3 and 4

Gen.	Stable Case		Unstable Case	
	w_1	w_2	w_1	w_2
1	-16.4775	0.1556	-40.4046	0.8601
2	-64.1608	1.8391	-83.6551	1.328
3	15.1759	-1.6204	-13.9991	0.8236
4	11.5232	-0.0665	5.5941	0.3362
5	7.5406	0.0592	1.8693	0.2417
6	18.6903	-0.229	14.0645	0.3992
7	7.7743	0.0228	3.1314	0.2044
8	5.432	0.0111	14.6127	0.1422
9	13.7545	0.174	96.6526	-3.6045

Table 6: Maximum of the absolute values of Walsh coefficients for Cases 3 and 4

Gen.	Maximum Walsh coefficients, $w_{ai,max}$	
	Stable case	Unstable case
1	16.4775	40.4046
2	64.1608	83.6551
3	15.1759	13.9991
4	11.5232	5.5941
5	7.5406	1.8693
6	18.6903	14.0645
7	7.7743	3.1314
8	5.4320	14.6127
9	13.7545	96.6526

(b)SVM responses for Cases 3 and 4

From the classifying equation (14), the outputs of the SVM are obtained as follows:

Case 3 (Stable case)

$$O(x = 160.5291) = 0.5761 > 0$$

Hence the stability status $t = +1$, which implies system is stable.

Case 4 (Unstable case)

$$O(x = 273.9834) = -1.15865 < 0$$

Therefore, the stability status $t = -1$, which implies system is unstable

The two rotor angles captured for each generator may all be greater than zero, may all be less zero, or one will be positive and the other negative. For any of these three cases, the maximum absolute Walsh coefficient for the i*th* generator, according to (16) and (17), will be given by:

$$w_{ai,max} = \frac{1}{2}\left(\left|\delta_{i,1}\right| + \left|\delta_{i,2}\right|\right) \tag{18}$$

Using (18) to compute the maximum absolute Walsh coefficients may reduce further the signal pre-processing time.

8 CONCLUSION

A rotor angle transient stability status prediction scheme has been presented. The input data consists of generator rotor angles which can be easily captured and quickly transmitted

to a centralized location via PMUs and GPS. The input data is captured in a very short time window. The signal processing approach is fast, simple and easy to implement. The above features facilitate its implementation in real time. Again, the volume of training data is low, thus making it practical for large systems. Last but not least, its prediction accuracy proved to be 100% for the test system used in the study.

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