Predicting loss of synchronism and instability in generators using wide area measurements

[1]Soheil Naderi, [2]Mojtaba Azimifar, [3]Saeed Afsharnia, [4]Ali Safiabadi

[1,2,3,4] School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran

s.naderi69@ut.ac.ir , m.azimifar@ut.ac.ir , Safshar@ut.ac.ir , asafitali@gmail.com

Abstract- In this paper, a new comprehensive framework is proposed to diagnose stability status of power systems and generators. The proposed method predicts rotor angles of generators using an online algorithm in the first place. Since it compensates for the delay in PMUs, rotor angles of generators will be available online with an acceptable accuracy. The proposed approach properly recognizes the power system stability status by calculating the difference between rotor angles of mutually coupled generators using the online data. Obtained value compare with threshold value and when this value exceeds threshold value, warning is given. Accordingly, it identifies the most critical generator using the fault occurrence and fault clearing time data. Moreover, the proposed method predicts the generator stability status using the boundary decision and the previously collected data, 150ms after clearing the fault. Decision boundaries are an inherent characteristic of each generator which can predict the generator stability status with minimum errors. As a result, the proposed method determines critical and unstable generators for generator shedding to prevent blackout in the system. The potential of this approach is tested using IEEE 39-bus (New England system) system.

Keywords: Generator status prediction, Online monitoring, PMU, Protection Scheme, Stability status prediction, Transient stability assessment.

1. Introduction

Stability status of power systems is an essential part of their operation and planning.

Nowadays, because of the restricting and economic constraints to develop power grids, power systems operate within their stability border. Accordingly, the online monitoring of power system stability status has been recognized as an important and initial task specially for preventing blackouts. Fast recognition of transient instability situation is very important to buy enough time for determining proper remedial control action. Numerous attempts have been made to develop an approach for quick predicting of stability status [1] and prediction of transient stability status [2-7].

Presence of phase or measurement units in power systems with modern communication facilities can change many traditional methods of monitoring, controlling and protecting the power systems [8]. Available online data is a key feature for exact prediction of power systems transient stability status, and accordingly, to avoid blackouts. Phasor measurement units (PMU) [9] make the data of different elements of power system available and thus make the online monitoring almost possible. Yet, for exact online monitoring of data, delay of PMU's and communication links should be compensated. In the literature [10]-[11], decision tree (DT) method is proposed for processing data collected by PMU. DT method uses voltage magnitude and voltage angle of each bus as the input data for the algorithm. Artificial Neural Network (ANN) method is also a powerful tool which is used for classifying various types of data into pre-defined classes. This method has been used in several studies for transient stability prediction of power systems [12]-[13]. In [14], support vector machine (SVM) is used to define stability boundaries in power networks. In [6] a modern machine learning based on lasso algorithm, the transient stability boundary is estimated. The references for transient stability prediction are a subset of machine learning methods. The main Problems of these methods include load changing, configuration of network, and etc. In addition, efficiency of these methods completely depends on the training process. Therefore, training should be comprehensive and consist of different types of contingencies [15].

Other categories which identify transient stability status use generator energy [1]. In reference [16], a special protection scheme is proposed in which after the fault occurrence and transient stability is predicted. These methods are accurate because they solve the generator equations to predict its stability status. However, their speed is low.

Moreover, the presence of micro grids in the power system provides new situation for the analysis of transient stability. In [17], transient stability is assessed in the presence of Doubly Fed Induction

Generator (DFIG), and a wind power controller for improvement of transient stability is designed.

The above mentioned methods have a common problem; none of them can predict the rotor angles. Therefore, they have a limited time for prediction and finding the remedial control action. The proposed method in this paper presents a new algorithm for prediction of transient stability status of power systems. This algorithm provides capability of online monitoring of rotor angles with high precision and compensates delays of transferring data to control center. Using the definition of system transient stability and trial and error method, the proposed algorithm predicts the system transient stability status. Besides, it determines the most critical generator using data of rotor angle for different generators. Thus, based on the collected data by PMU and decision boundary, the algorithm recognizes the most critical and unstable generators which need to be shed.

The rest of this paper is organized follows; Online monitoring of rotor angle of generators is explained and simulated in section II. The proposed method is explained in Section III. In section IV, the proposed method is used for prediction of transient stability status of IEEE 39- bus system. The obtained results by the proposed methods are analyzed in this section. Section V concludes the paper.

2. Online Monitoring

In order to enable the system to make control actions in real time, the rotor angles of generators should be known at the time of operation. However, the inevitable transfer time of the data provided by the PMUs, imposes a certain delay on the arrival of rotor angles data

[18], [19]. Hence, it is necessary to compensate this delay for the proper operation of the system.

We consider the rotor angle of a generator as the time series $\delta(t)$. Then, the delay compensation problem reduces to a time series prediction problem. In this scenario

$$\delta(t) = f\big(\delta(t-1), \delta(t-2), \dots, \delta(t-n)\big) + \varepsilon_t \qquad (1)$$

Where f is an arbitrary nonlinear function, and ε_t is the independent and identically distributed random error. This error is a result of the modeling error and compensates the effect of neglecting the effects of other variables in the estimation of $\delta(t)$. In this formulation, the delay compensation problem translates to finding a nonlinear function f based on the past values of δ.

2.1 Online Time Series Prediction Using Incremental Support Vector Regression

Born in the field of statistical learning theory, Support Vector Regression (SVR) is a popular method for solving nonlinear regression problems. Considering a finite training sample $S = \{x_i, y_i\}_{i=1\dots N}$, it first maps the input into a high dimensional space using a nonlinear mapping ϕ, and then solves the linearized problem in this space. The linearized model is given by

$$f(x, \omega) = <\omega, \phi(x)> + b \qquad (2)$$

Where ω represents the weight vector, b is the bias term, and $<.,.>$ denotes a dot product in the high dimensional space. The weight vector and the bias term are calculated by minimizing a convex cost function, consisting of terms for model complexity and empirical risk. The optimization problem for the weight vector can be defined as follows [20]:

$$min\, R = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \qquad (3)$$

$$subject\ to \begin{cases} y_i - f(x_i, \omega) - b \le \varepsilon + \xi_i \\ f(x_i, \omega) + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \qquad (4)$$

In this formulation, *C* is the regularization parameter which determines the trade-off between the model complexity and the error toleration up to the amount specified by ε. This optimization problem is solved for ω and b and then the nonlinear function *f(.)* is calculated as a function of training samples x_i.

However, in the case of online time series prediction problem, one would like to update the model from incoming data in real time to make predictions based on this model. For this purpose, Accurate Online Support Vector Regression (AOSVR) is used to update the trained SVR function whenever a new sample is added to the training set S [21]. The online algorithm produces the exact same SVR function as the batch algorithm with a significant reduction of computational cost and thus is well suited to a real time prediction paradigm.

2.2 Delay Compensation Using SVR

The expected delay of the data transfer is 150ms. Assuming a sampling time of 10ms, this means that we have to predict the value of rotor angles 15 steps ahead. The regression problem defined in (1) can be solved using AOSVR, which compensates the expected delay and predicts the rotor angles of the

Table 1 the prediction of the rotor angles using AOSVR

	Stable faults	Unstable faults
$MAPE_{error}$	5.45%	9.32%

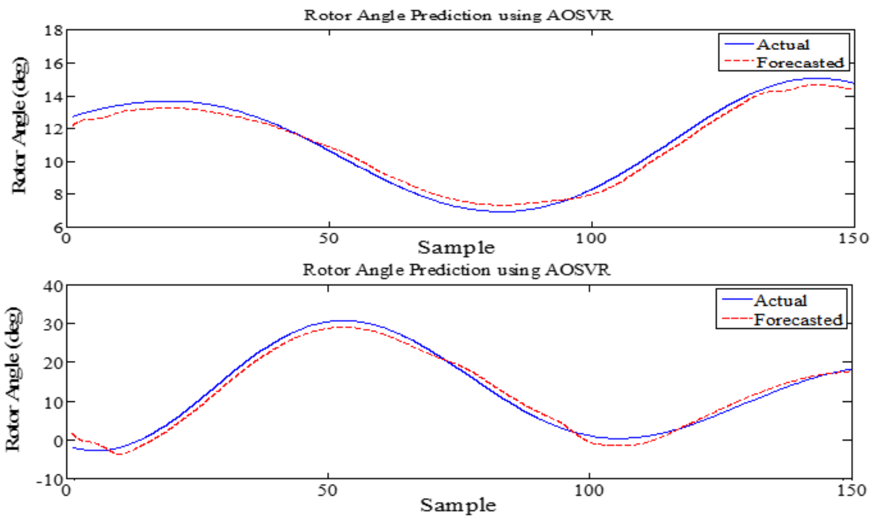

Figure 1. The delay compensation of the rotor angles using AOSVR (a) the prediction result during a stable fault occurrence and (b) an unstable case.

generators in New England System. Figure 1 shows the prediction results of the rotor angles during a stable and unstable fault occurrence, and

Table 1 reports the prediction error for the stable and unstable cases in terms of mean absolute percentage error (MAPE). The results show that the delay of the rotor angles can be reliably compensated for either stable or unstable fault conditions.

Before introducing this method, delay of PMUs was a huge problem for transient stability prediction. It always caused time limitations for prediction and remedial control actions and thus, often blackout occurred. On the other hand, according to table I, the rotor angles of stable and unstable generators are predictable with a high accuracy by our explained approach. Therefore, if an exact method is utilized, the available data will be sufficient to predict stability status of power system.

3. Proposed Method

Because of time limitation for remedial action to prevent instability and loss of synchronism in a power system, prediction of stability must be done in a short time interval after occurring a disturbance. Therefore, precision of the prediction and selecting the true generator for generator shedding in an emergency situation are two main issues in transient stability analysis. This paper offers a new algorithm for prediction of transient stability status of power systems and generators. Different steps of the algorithm are explained one by one in the following sections.

3.1 Prediction of Transient Stability Status of Power System

As already mentioned, definition of transient instability and loss of synchronism is an important issue. Loss of synchronism generally depends on maximum deviation of machine rotor angles [22].

This maximum value may differ from one power system to another.

$$\Delta\delta_{i-j} = \delta_{Gi} - \delta_{Gj} \tag{5}$$

$$A = \begin{Bmatrix} \Delta\delta_{1-2}, \Delta\delta_{1-3}, \ldots \Delta\delta_{1-n}, \Delta\delta_{2-1}, \\ \ldots, \Delta\delta_{2-n}, \ldots\ldots, \Delta\delta_{n-(n-1)} \end{Bmatrix} \tag{6}$$

$$\begin{aligned} &\max(\Delta\delta_{ij})^{(t_m)} - \max(\Delta\delta_{ij})^{t_m+1} \geq k \\ &\max(\Delta\delta_{ij})^{(t_m+1)} - \max(\Delta\delta_{ij})^{t_m+2} \geq k \end{aligned} \quad (7)$$

All values of set A should be less than the defined threshold value. Maximum value of matrix A is determined and compared with the obtained threshold value [23]. The threshold value depends on network and, for each system, can be determined using trial and error method. If any instantaneous value of A becomes greater than the threshold value, a warning is being issued, otherwise/then, the matrix will be updated and next sample is checked. This process continues until (7) is satisfied. Figure 2 illustrates the rotor angles change versus time. Also, it shows the maximum value of set A for a three phase short circuit at a 39-Bus system.

According to (7), if the maximum value of A at $t = t_m$ becomes greater than the maximum value of A at, and for next sample, this trend $t = t_m + 1$ continues, the algorithm stops. IEEE 9-Bus, IEEE 39-Bus and Khorasan power system [24] are considered as case studies in this paper. Threshold values for these systems are obtained by trial and error using numerous and different simulations. Obtained threshold values are shown in table 2. Values of k in (7) are similar to the threshold value and depend on the particular system that is being studied.

In the following sections, simulation studies of IEEE 39-Bus system are provided where the obtained threshold values for that has been approved. To achieve this goal, a sample for both marginal stable and unstable cases for this network is intended. Regarding this issue, which measurement of rotor angle is difficult, voltage phase angle is used instead of rotor angle.

In the following Figure, a three phase short circuit is applied to line 23-24 of IEEE 39-Bus system for 260 ms in (a) and 270 ms in (b).

As shown in Figure 3, voltage angles of different generators in (a) are stable as a result of which the system is stable, too. However, in (b), voltage angles of two generators are unstable and thus, the system is unstable. Now, these two cases are checked with the threshold value. The difference between mutual generators in these cases is shown in table 3.

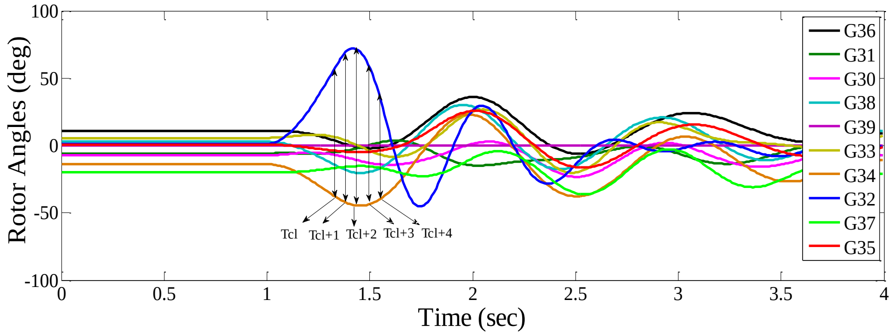

Figure 2. Calculation of maximum value of matrix A base on time

Table 2 Obtained threshold value for studied systems

Studied systems	Threshold value	k
IEEE 9-Bus system	175	2
IEEE 39-Bus system	190	2.5
Khorasan power system	205	3

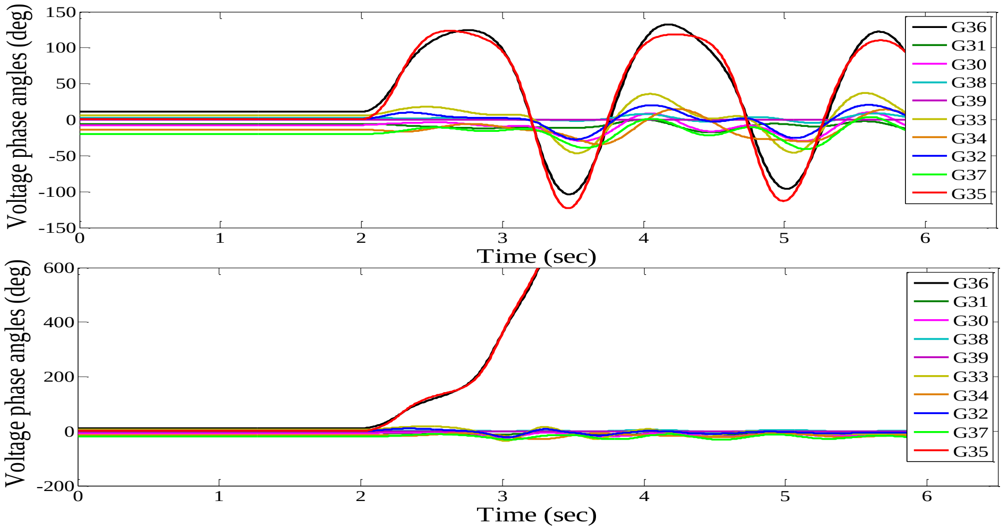

Figure 3. Voltage phase angles after three phase short circuit for 260ms (a) and 270ms (b) on line23-24

Maximum value of matrix *A* for case (a) is 141 degrees and it is related to G34 and G35. Two samples later, the maximum of A has changed to 138.2 degrees and three samples after that, it is 136.8 degrees. Therefore, the algorithm stops and the system status is indicated as stable. But maximum value of matrix *A* in case (b) is 192 degrees which exceeds from the obtained threshold. Therefore, the algorithm stops and the system status is indicated as unstable. After this indication, the difference between G34 and G35 is increased and the required remedial action is done.

B. Recognizing Critical Generators

In this section, it is explained that after fault detection and obtaining the fault clearing, data of all generators, at these times with time tag sending to control center and then using (8), (9) and (10) critical generators are recognized.

$$\delta_i = \delta_i(t_{cl}) - \delta_i(t_f) \qquad i = 1,2,\ldots,n$$

(8)

$$B_{ij} = (\delta_i - \delta_j)$$

(9)

$$b_i = \frac{\sum_{j=1}^{n} b_{ij}}{\max_{j=1:n}(b_{ij})} \tag{10}$$

Applying above equations (i.e., (8)-(10)) for all generators, the generator group which has a maximum of b_i is determined as the critical generator group. Once b_i for two or three generators is identified to be more than the rest of generators, the group of critical generators should be defined.

Therefore, status of generator groups is recognized and the

$$If\ |b_i - b_j| < 0.4\ i\ and\ j\ are\ coherent \tag{11}$$

Therefore, status of generator groups is recognized and the group which contains the most b_i value is considered as the critical group.

C. Prediction of Generator Stability Status

Decision boundaries indicate the stability border of system. They are defined using optimization problems which, themselves, are solved using numerous kinds of criteria e.g. voltage magnitude, voltage phase angle and their derivatives. The goal of this section is to determine decision boundaries for generators. In the following, the optimization problem is explained, and is then solved considering different criteria and at the end, the best boundary with the least error for prediction is selected for each generator.

This problem can be defined in the form of a binary classification.

$$generator\ \ status = \begin{cases} 1 & generator\ \ is\ \ stable \\ 0 & generator\ \ is\ \ unstable \end{cases}$$

(12)

To cope with this issue, logistic regression is often used [25]. This method is one of the pattern recognition methods in which defined function should be between zero and one. The considered function is a sigmoid which is stated as

$$h_\theta(x) = \frac{1}{1 + \exp(-\theta^T \times X)} \tag{13}$$

$$y=\begin{cases}0 & 0\le h_\theta(X)\le 0.5\\ 1 & 0.5\le h_\theta(X)\le 1\end{cases} \tag{14}$$

Cost function is defined by (15) and it shows the prediction error of generator stability status.

$$Cost\ Function=\frac{1}{2m}\times\sum_{i=1}^{m}(h_\theta(X(i))-y(i))^2 \tag{15}$$

Since $h_\theta(x)$ is nonlinear, cost function is non-convex and thus finding the global optimum is hard, the obtained answer may stay in the local optimum.

To avoid this issue, the cost function is rewritten as

$$Cost\quad Function=\frac{1}{m}\times\sum_{i=1}^{m}-y(i)\times\log(h_\theta(x(i)))-(1-y(i))\times\log(1-h_\theta(x(i))) \tag{16}$$

Therefore, the problem changes into a convex function optimization for which, using a genetic algorithm, the optimum result can be achieved. This value can be determined using the offline data boundary and then, it can be evaluated using the test data. The prediction error is defined by that p is number of test case.

$$e=\frac{1}{p}\sum_{i=1}^{p}\left(\frac{\operatorname{sgn}(\theta(i)\times X(i))+1}{2}-y(i)\right)^2 \tag{17}$$

In the following, performance of the explained method is evaluated and the decision boundary of generators for the system under study is obtained. For this goal, 272 contingencies are applied 193 cases of which are stable and the other 79 cases are unstable. For creating the decision boundary of different generators, 75% of the data was used for training and the stability border was tested by rest of the data. Now, the decision boundary for the voltage magnitude, the voltage phase angle (δ,V)in two-dimensional plane is obtained for generator 36 of IEEE 39-Bus system. Also, precision of generator status prediction with these two criteria is obtained.

The obtained decision boundary using (δ,V): voltage magnitude and voltage phase angle are applied to the algorithm 150ms after clearing the fault. Then, using optimization, coefficients of decision boundary are calculated. 150ms after clearing the fault (this time was obtained by simulation), the test data is compared with the pre-determined boundary and stability status of generators are predicted. For this indicator, decision boundary is obtained by a first-degree polynomial, a quadratic polynomial and a third-degree polynomial. The obtained decision boundary and the test data are shown in Figure 4.

Moreover, precision of boundaries for these two criteria are calculated and illustrated in Table 3.

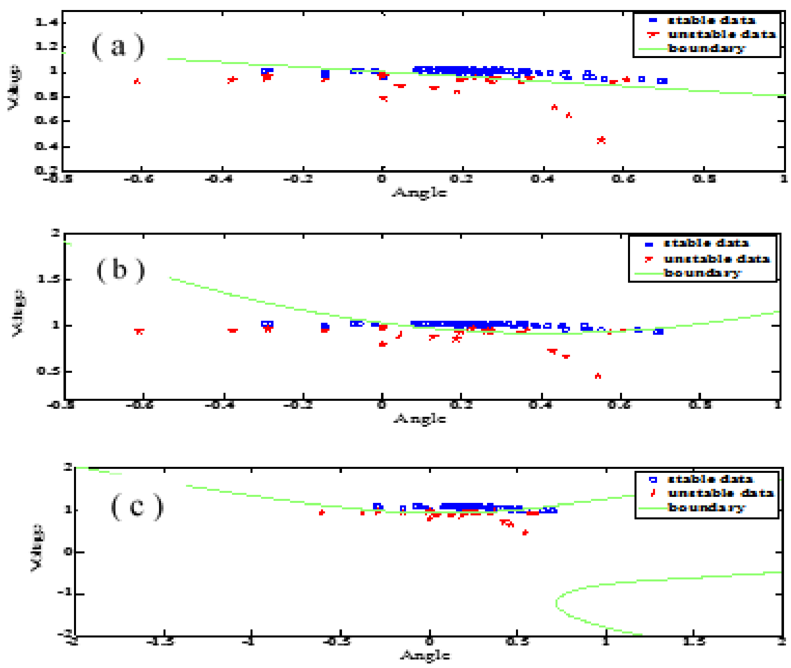

Figure 4. Decision boundary for (δ,V) criteria. (a) First-degree polynomial, (b) quadratic polynomial and (c) third-degree polynomial

Table 3. Prediction error of stability status for generator 36 with (δ, V) criteria

Order of polynomial	Precision of Prediction (%)
1	86.28
2	88.34
3	89.17
4	87.08

Table 4. Prediction error of stability status of generator 36 with different criteria

Criterion	Order of polynomial	Precision of prediction (%)
$(\delta,\dot{\delta})$	1	86.72
	2	88.07
	3	88.54
	4	87.48
$(\delta,\ddot{\delta})$	1	84.43
	2	86.91
	3	86.56
	4	87.31
$(\dot{\delta},\ddot{\delta})$	1	88.57
	2	88.79
	3	90.46
	4	89.56
$(V,\dot{V})$	1	90.38
	2	91.77
	3	91.04
	4	91.44
$(\delta,\dot{\delta},\ddot{\delta})$	1	88.61
	2	89.31
	3	90.69
$(\delta,\dot{\delta},V)$	1	89.37
	2	89.93
	3	90.12
$(\delta,\dot{\delta},\dot{V})$	1	91.23
	2	91.54
	3	91.82
$(\dot{\delta},V,\dot{V})$	1	90.55
	2	91.71
	3	92.38
$(\delta,\dot{\delta},V,\dot{V})$	1	94.74
	2	94.95
	3	**96.26**
$(\delta,\ddot{\delta},V,\dot{V})$	1	91.09
	2	90.87
	3	91.76
$(\dot{\delta},\ddot{\delta},V,\dot{V})$	1	91.73
	2	92.21
	3	92.77

The algorithm is applied to different generators with different criteria in a similar way. Results of this method are shown in table 4. Finally, according to these results, the best criterion with the most accuracy is selected for prediction of generator stability status. According to above results for generator 36, the best criterion is $(\delta,\dot{\delta},V,\dot{V})$ with a third-degree polynomial. Using this boundary, stability status of generator 36 is predicted for the tested data with the accuracy of 96.26%. This algorithm applies to other generators of study system as well. The performance precision of the decision boundary for different generators is shown in table 5. Eventually, decision making for generators is based on results of table 5.

Table 5. Precision of decision boundary for different generators of IEEE 39-Bus system

Generators	Precision of prediction (%)
30	96.55
31	95.9
32	97.18
33	95.38
34	96.81
35	96.3
36	96.26
37	96.94
38	95.89

D. Decision Procedure

So far, the algorithm for prediction of system stability status, algorithm for recognizing the critical generator and the algorithm for prediction of the generator transient stability status have been introduced. Here, the general method for decision making is explained. After fault detection, online prediction of the system stability status is started. Determination of critical generator using data of occurring fault and clearing fault is done separately. Furthermore, using data of 150ms after clearing the fault and obtained optimizing decision boundary for different generators, transient stability status of generators are predicted.

Graphic chart for the decision algorithm is shown in figure 5. As can be seen, when rotor angles difference of two generators exceeds from the threshold value, an alarm is sent to the control center and then, the critical and unstable generators should be shed quickly. Once one generator is predicted as unstable and critical, it should be shed immediately.

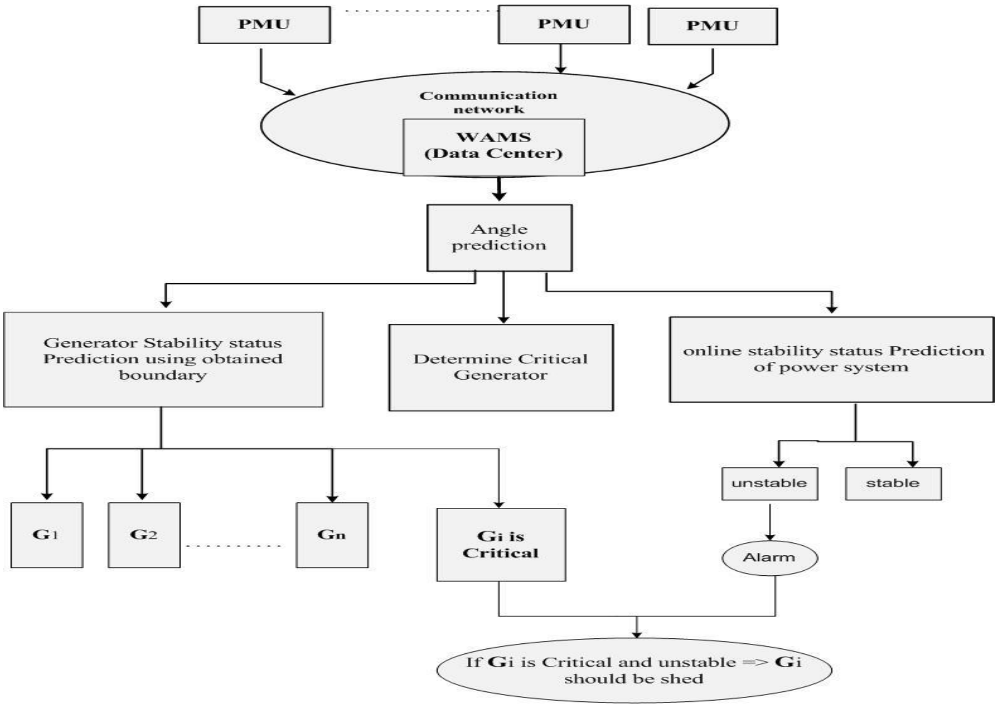

Figure 5. Graphic chart for decision algorithm

V. Simulation Result

IEEE 39-Bus system

IEEE 39-Bus system (see Figure 7) is used to verify the proposed method. This system is well-known as 10-machine New-England Power System and is used widely for transient stability assessments. It has 10 generating units, 39 buses, 19 loads and 46 transmission lines [26]. It is assumed that all generator buses are equipped with PMU and five indicators ($\delta, V, \dot{\delta}, \dot{V}, \ddot{\delta}$) would be measured and sent by PMUs to the control center. Performance of the algorithm is evaluated on a contingency, and the results are shown in the following.

Scenario

a) Two faults is applied to 19-16 and 3-2 transmission lines at t=2s. Then, after 200ms, fault became cleared. After the fault detection, the algorithm is initiated. At this stage, rotor angles of generators are shown in Figure 7. And the maximum difference between them is revealed in table 6.

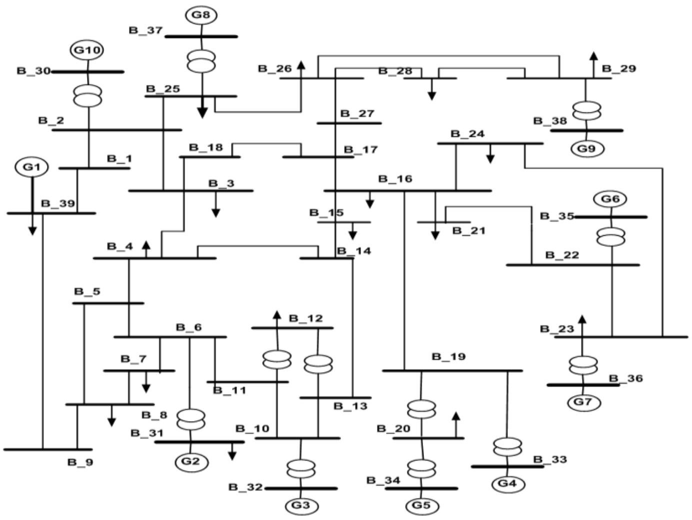

Figure 6. New England 39 bus test system

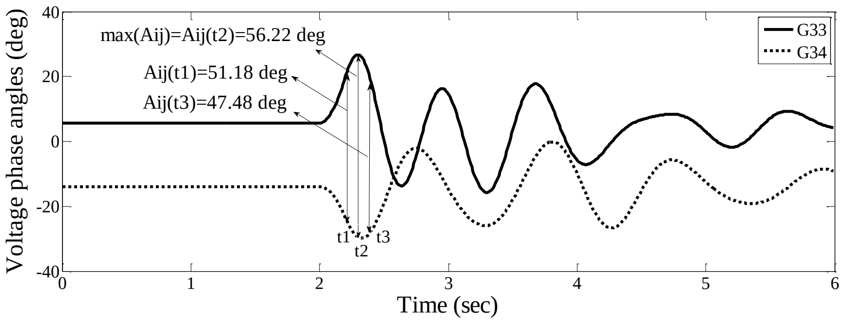

Figure 7. Voltage phase angles of generators for scenario a

Table6. The maximum difference between voltage phase angles of generators versus time in scenario a

Time (s)	Maximum difference between voltage phase angles of generators (deg)
2.22	47.78
2.24	51.18
2.26	53.78
2.28	55.48
2.30	56.22
2.32	55.97
2.34	54.72
2.36	52.49
2.38	49.36
2.40	45.41

According to the results in the table11, it can be seen that the maximum difference decreases over time after $t = 2.3s$. Therefore, the system is stable and no remedial action is required. In addition, the algorithm has stopped waiting for the next fault detection. The algorithm recognizes the critical generator and its stability status, individually, but according to stability status of the system, it does not have to determine generator stability status and critical generators.

b) Now, the clearing time increases to the edge of stability border. In this situation, the system is stable but if clearing time increases by 10ms, the system will be unstable. In this case, the fault is cleared at $t = 2.54s$. Rotor angles of the generators are shown in Figure 8.

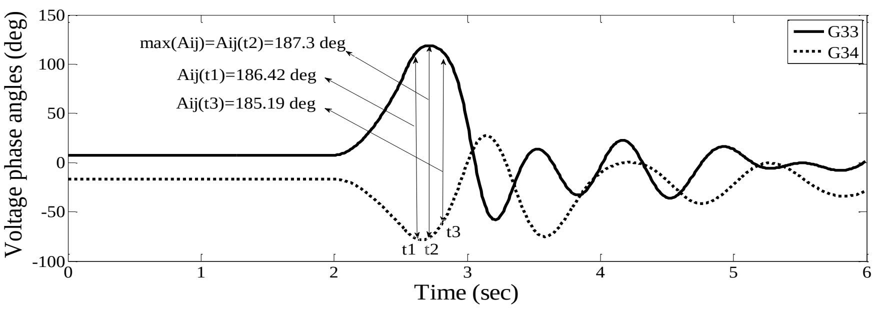

Figure 8. Voltage phase angles of generators for scenario b

Table 7. The maximum difference between voltage phase angles of generators versus time in scenario b

Time (s)	Maximum difference between voltage phase angles of generators (deg)
2.56	167.21
2.58	174.98
2.62	184.28
2.64	186.42
2.66	187.3

Also, after fault detection, the algorithm is initiated. The maximum voltage phase angle difference between the generators which is monitored online is shown in table 7.

In this case, the system is stable and no remedial action is required. Results of the algorithm actions for determination of the critical generator are collected in table 8.

Table 8. Value of definition index for determining critical generator in scenario b

G_i	G30	G31	G32	G33	G34	G35	G36	G37	G38
b_i	2.75	2.24	2.44	3.41	3.11	2.53	2.56	2.44	2.54

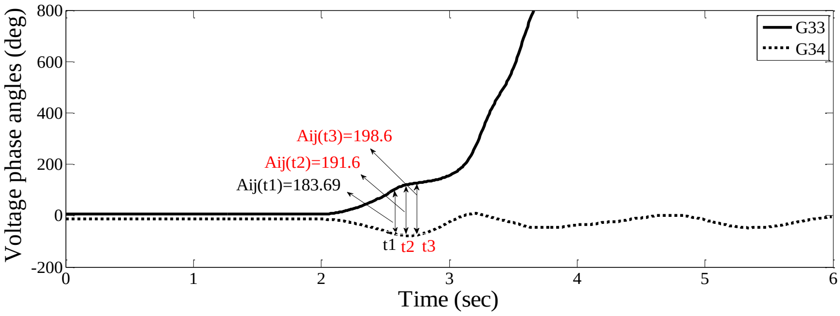

Figure 9. Voltage phase angles of generators for scenario c

Table 9. The maximum difference between voltage phase angles of generators versus time in scenario c

Time (s)	Maximum difference between voltage phase angles of generators (deg)
2.56	168.6
2.58	176.72
2.60	183.69
2.62	189.16
2.64	194.27
2.65	197.43
2.66	199.96
2.67	203.38

Table 10. Value of definition index for determine critical generator in scenario c

G_i	G30	G31	G32	G33	G34	G35	G36	G37	G38
b_i	2.75	2.24	2.42	3.43	3.05	2.23	2.55	2.44	2.5

It can be seen from table 8 that G33 and G34 are the critical generators. Also, using the obtained decision boundary and data at $t = 2.69s$, G33 is identified as unstable, while the rest of the generators are identified as stable. According to the system stability status, the system is, in sum, identified as stable and not any tripping or remedial action is required for any of the generators (even G33).

c) Now, if the clearing time increases, the system will be unstable. In this case, fault clearing occurs at $t = 2.55s$. Voltage phase angles for this situation are shown in Figure9. In this situation, the maximum voltage phase angle difference between different generators is monitored online as shown in table 9.

In this case, the system is unstable and some remedial action is required. The result of the algorithm application for this case is illustrated the determination of critical generator in Table 10.

It can be seen from Table 10 that G33 and G34 are the critical generators and G33 is the most critical one. Also, using the obtained decision boundary and the data at $t = 2.70s$, G33 is identified as unstable, whereas the rest of the generators are identified as stable.

According to the system stability status, the system is identified as unstable and loses synchronism. Therefore, an alarm is sent it to the control center and then, G33 would be shed quickly. By using this algorithm and considering delays of PMU and communication links, G33 is shed at $t = 2.85s$

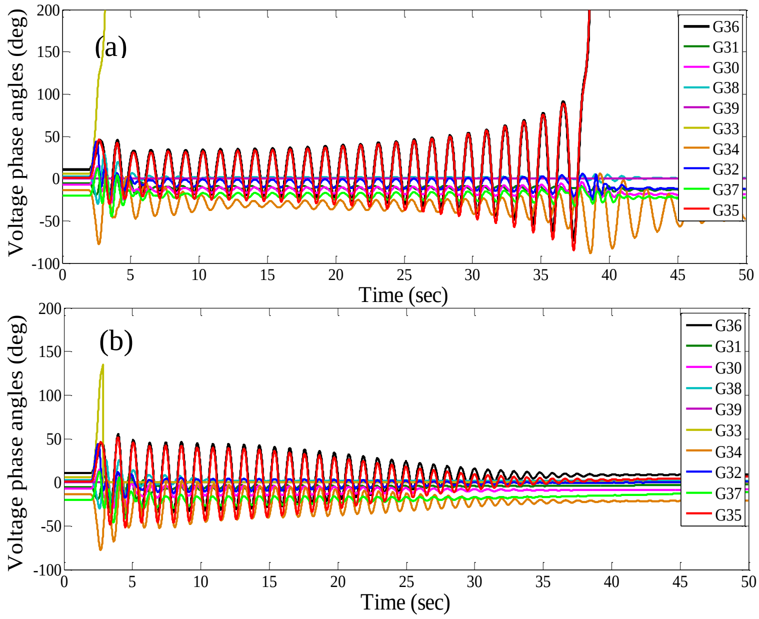

Figure 10. Voltage phase angle of generators. (a) Without generator shedding (b) G33 is shed by the algorithm

No remedial action is taken at this stage, the system will be unstable and loss of synchronism will be inevitable. Results of these two mentioned cases are shown in Figure 10.

According to Figure 10, performance of the algorithm is acceptable and it prevents spreading out the instability to the rest of the system.

VI. Conclusion

This paper introduces a novel method to predict the stability status of a power system and a generator system individually. The proposed method compensates delay of PMU and transferring data, thus generator's data are accessible with high accuracy. Using the provided highly accurate online data, the algorithm is able to predict the generators instability in a short period of time. Besides, it can predict the stability status of power systems online. The proposed method was tested on IEEE 39-Bus system where acceptable performance was verified. It is shown that the proposed algorithm provides very high reliability since its different parts support each other; a fact which augments the accuracy of decision making.

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