# Fast Prediction of Angle Stability Using Support Vector Machine and Fault Duration Data

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***Abstract*—This paper deals with the prediction of the transient stability of power systems using only pre-fault and fault duration data measured by Wide Area Measurement System (WAMS). In the proposed method, the time-synchronized values of voltage and current generated by synchronous generators (SGs) are measured by Phasor Measurement Units (PMUs) installed at generator buses, and given as input to the proposed algorithm in order to extract a proper feature set. Then, the proposed feature set is applied to Support Vector Machine (SVM) classifier to predict the transient stability status after fault occurrence and before fault clearance. The robustness and accuracy of the proposed method has been extensively examined under both unbalanced and balanced fault conditions as well as under different operating conditions. The results of simulation performed on an IEEE 14-bus test system using DIgSILENT PowerFactory software show that the proposed method can accurately predict the transient stability status against different contingencies using only pre-disturbance and fault duration data.**

***Keywords-transient stability; support vector machines; phasor measurement units.***

## I. INTRODUCTION

In recent years, due to the increase in load demand, power systems operate near the stability boundaries that may lead to instability or even blackouts after a fault occurrence [1,3]. Although power systems are designed to be immune against different disturbances, some unexpected ones can lead to angular, frequency or voltage instability [4-7]. Usually, rotor angle instability which is also popularly referred to as transient instability occurs due to large disturbances like three-phase short circuit which depicts itself with an periodic or aperiodic angular separation of some SGs from other ones [7,8].

In order to prevent system instability, operators should execute optimum remedial actions before the operating point leaves the stability boundary. In this respect, early assessment of stability status and timely execution of these actions are of great importance.

Transient stability assessment methods may be divided into two categories which include detection and prediction of stability status. In detection methods, the required data is measured and analyzed to assess the stability status of the system in near future. Methods which estimate critical clearing time (CCT), energy function [9], sensitivity analysis [10,11], and Equal Area Criterion (EAC) [12,13] are included in this category. The main drawback of these methods is that they cannot predict the stability status and hence, they may not provide sufficient time for system operators to take timely suitable control measures, e.g. fast-valve control of turbines, system switching, load shedding, dynamic braking, and intentional islanding [14,15].

Prediction methods which are used to predict the stability status are more effective in analyzing transient stability. Hence, in the last decade, extensive research works have been conducted to formulate efficient algorithms for rotor angle stability prediction [16-18]. Especially, the advent of a Wide Area Measurement System (WAMS), which measures time-synchronized values of system variables and makes the dynamic behavior of power system observable, significantly improves the performance of the artificial intelligence-based methods (like SVM and decision tree) in accurately predicting power systems stability status [19,20].

In [19], a transient stability prediction method is proposed based on the decision tree algorithm, in which, transient stability is investigated only for three-phase short-circuit faults on transmission lines using post-fault information. Also, in [20], SVM algorithm is used to predict transient stability using both post-fault and pre-fault data just for three-phase faults. In [17], after measuring voltage phasors of some buses and generators rotor angles via PMUs, transient stability status prediction is accomplished with a decision tree based algorithm for three-phase short circuit faults on some HV lines with precision of 93%.

When a power system is affected by a disturbance, transient instability is mainly determined by a progressive separation of rotor angles of some SGs from others. As illustrated in Fig. 1, it can be concluded that as time passes and the rotor angle separation increases, prediction of angle stability status of power system becomes easier. Hence, according to the extensive investigation of authors, all methods proposed in the literature used data measured before and after fault clearing time to accurately predict stability status. However, since the required remedial actions should be executed before the operating point leaves the region of attraction [21,22], such a prediction methods reduce the time available to perform remedial actions. In other words, if transient stability is predicted using only data measured before fault clearance, more opportunity will be available to conduct suitable control measures. In addition, the methods proposed in the literature

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usually predict the stability against a limited fault types, e.g. against only LLL [20].

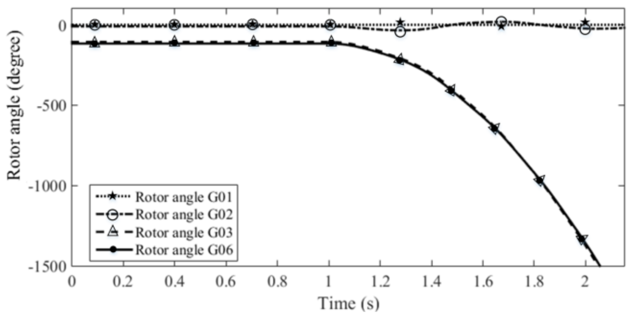



Figure 1. Instability occurrence in IEEE 14-Bus test system.

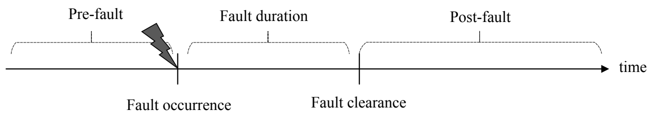



Figure 2. The pre-fault, fault duration and post-fault period.

In order to provide a single comprehensive assessment tool to predict stability status against different fault types (i.e. LLL, LL, LLG, LG) as well as to give more opportunity to system operators to take suitable control measures, this paper proposes an SVM-based algorithm to predict the transient stability using only pre-fault and fault duration data (specified in Fig. 2), i.e. with no need to data measured after fault clearance. Such a prediction tool can be used by special protection systems or power management systems [23] to prevent instability.

It is worth mentioning that that due to the large size of power systems, the use of advanced measuring system has become a necessity for monitoring, maintaining the security and the stability, and enhancing network reliability. Traditional power system measuring tool, namely SCADA, is not suitable for fast dynamic analyzes due to the inability to measure time-synchronized values of system variables and also, the inability to measure voltage and current phasors. With the advent of the WAMS, power system control and monitoring has improved significantly. At the lowest level of this measuring system, Phasor Measurement Units (PMUs) are located to measure voltage and current phasors, frequency and other parameters at specific time instances and send them to a higher stage called Phasor Data Concentrator (PDC). In the second step, PDC receives measurements with a precise time tag from PMUs located on its territory through communication links and prepares synchronous phasors and eliminates false data. Finally, Super Data Concentrator is at the highest level which receives data from all PDCs and proper control actions may be taken at this level [24,25]. In this paper, to gather such time-synchronized data, dynamic simulations have been carried out in DIgSILENT PowerFactory software in which controllers of SGs as well as voltage-dependent loads are accurately modeled to properly simulate the dynamic behavior of test system. Then, the values of currents and voltages generated by SGs are gathered.

The remainder of this article is organized as follows. In Section 2, the SVM classifier needed to carry out this research has been addressed. The complete implementation of the proposed method is explained in Section 3. In Section 4, the simulation results are investigated and finally, the conclusion is presented in Section 5.

## II. SUPPORT VECTOR MACHINE

The SVM classifier is one of the most effective tools for solving the problems of classification, estimation, and regression [16,20]. For this purpose, offline data which is usually obtained from simulation results are used to determine a proper feature set which can properly indicate the operating point condition. Then, the value of this feature set for all feasible operating points are calculated and applied to SVM (or any other classifier) to train it. In online application, based on the data gathered from online operation of network, this trained classifier is used to classify the system stability into different classes (e.g. stable or unstable) with the least error [26].

In SVM, the input data is mapped into a higher dimensional feature space by a kernel function, e.g. Radial Basis Function (RBF). Then, in the higher dimensional space, the SVM classifier separates two classes (i.e. $C_1$ and $C_2$) by constructing an optimal hyper-plane, *h(x)*:

$$h\left(x\right) = \omega^T x^t + \omega_0 \tag{1}$$

Given a set of training data an SVM seeks to construct a hyper plane (i.e. $\omega$, $\omega_0$) that separates the data with the maximum margin of separability. In Fig. 3, a schematic diagram of high dimensional feature space is illustrated where a sample $x^t$, which belongs to $C_1$ or $C_2$ classes and identified by $r^t$ =+1 or -1 respectively, is mapped into the higher dimensional space so that [27]:

$$\begin{aligned} \omega^T x^t + \omega_0 \geq +1 \quad &\text{for} \quad r^t = +1 \\ \omega^T x^t + \omega_0 \leq -1 \quad &\text{for} \quad r^t = -1 \end{aligned} \tag{2}$$

Furthermore, the distance between sample and hyper-plane is determined as follows:

$$r = \frac{\left|\omega^T x^t + \omega_0\right|}{\left\|\omega\right\|} \tag{3}$$

To calculate the optimal hyper-plane, the following constrained optimization formula is used to maximize the distance of the nearest samples to *h(x)*, i.e. support vectors to hyper-plane, which are shown by *h(x)* =±1 [28]:

$$\min \frac{1}{2}\left\|\omega\right\|^2 \quad \text{subject to} \quad r^t\left(\omega^T x^t + \omega_0\right) \geq +1 \tag{4}$$

For this purpose, the Lagrangian multiplication can be written as follows:

$$L_P = \frac{1}{2}\left\|\omega\right\|^2 - \sum_t \alpha^t \left[ r^t\left(\omega^T x^t + \omega_0\right) - 1 \right] \tag{5}$$

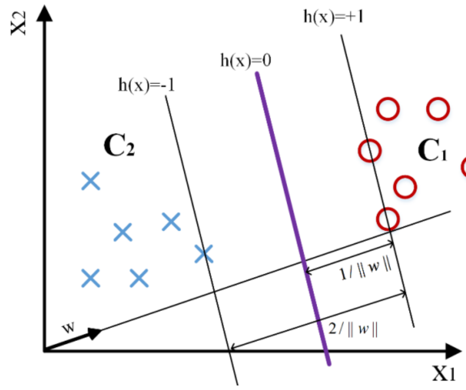


Figure 3. Schematic diagram of high dimensional feature space [29].

To solve (5), a transfer function, $\varphi(x)$, is taken into account to deal with a dual problem as follows [28]:

$$\max : -\frac{1}{2}\sum_t\sum_s \alpha^t\alpha^s r^t r^s K\left(x^t x^s\right)+\sum_t \alpha^t \quad \text{subject to} \sum_t \alpha^t r^t = 0 \text{ and } \alpha^t \geq 0 \tag{6}$$

where $K(x^t\ x^s)$ is known as a kernel function and is defined as follows:

$$K\left(x^t x^s\right)=\varphi\left(x^t\right)^T \varphi\left(x^s\right) \tag{7}$$

Finally, the solution for the optimization problem is:

$$h(x)=\sum_t \alpha^t r^t K\left(x^t x\right) \tag{8}$$

and sample $x$ can be classified arbitrarily by (8) and (2). as mentioned earlier, in online application, the feature set is applied to this trained SVM to predict the transient stability status of power system.

## III. Proposed Method

In this paper, a novel SVM-based algorithm has been proposed which only uses data measured before fault clearance for timely and accurate prediction of angle stability status. The procedure to training the SVM has four steps which are described below.

### A. Operating Points Determination

To obtain all feasible operating points, starting from an operating point at low loading condition, system loading increases successively with variable steps using time-domain simulation. After each step-load change, when the system reaches to a steady state condition, the equilibrium point is considered as a new operating point and the above procedure repeated until instability occurs. It should be noted that in these simulations, as the operating point gets closer to the stability boundary, the load increasing step becomes smaller and hence, in heavily loaded conditions, the density of operating points is high.

### B. Contingency Determination

This paper attempts to prepare a tool for prediction of transient stability status against different fault types at all buses using pre-fault and fault duration data. Table I shows the contingencies considered in this paper, which takes into account all possible faults to train the SVM classifier, to ensure it covers all scenarios.

TABLE I. Fault types and fault location in IEEE 14-bus test system used to train a SVM classifier.

| Fault Type | Fault Location |
|---|---|
| 3 phase short circuit | at 5% and 95% of all transmission lines |
| 2 phase to ground short circuit | |
| 2 phase short circuit | |
| single phase short circuit | |

It should be noted that after determining various operating points and contingencies, time domain simulations are performed offline for all possible scenarios. Therefore, the number of study cases is:

$$StudyCases = N_{op} \times 2N_{line} \times N_{FaultType} \tag{9}$$

where $N_{op}$ is the number of operating points obtained in Section III.A, $N_{line}$ is the number of transmission line, and $N_{FaultType}$ is the number of fault type (=4) mentioned in Table I.

Also, it is worth mentioning that for each dynamic simulation in which a disturbance occurs at an operating point, the stability status of system is determined based on (10):

$$TSI = \frac{360-\left|\Delta\delta_{\max}\right|}{360+\left|\Delta\delta_{\max}\right|} \tag{10}$$

where $\Delta\delta_{max}$ is the maximum angular separation between any two generators rotor angles during the transient period. If *TSI* remains positive, the system will be stable and its class label is tagged as 1. Otherwise, the system will be unstable and its class label is tagged as 0.

### C. Sampling

According to [30], PMUs in 50 Hz systems can perform 25 sampling per second, and 30 samples per second for 60 Hz systems. Therefore, in this paper, it is assumed that the PMUs, installed at generator buses, captures the time-synchronized values every 1/30s which is mentioned in Table II.

TABLE II. The PMUs sampling times in fault duration period.

| Sample number measured in fault duration period | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Sampling time | 1 s | 1.033 s | 1.066 s | 1.099 s |

It is noteworthy that in this paper, assuming that all transmission lines are protected using Direct Under-reaching Transfer Trip (DUTT) scheme. The operating time of Zone 1 of distance relays is set to 100ms, when a short circuit occurs at 1s, it remains for 0.1s and then, the protection system will trip the faulted line.

### D. Feature Selection

Choosing a right feature set is vital to predict transient stability when pre-fault and during-fault information is used. Since the transient instability is directly related to the angular difference between the generator rotor angles [31,32], in the proposed method, variations of generators' active power and terminal voltages are used to select an appropriate feature set to predict the stability status. In the proposed feature set, two types of features are presented to predict the transient stability status which are summarized in Table III:

- Fault-independent features, which have nothing to do with the contingency occurs in the system: generators terminal voltages and generated active power of SGs.
- Fault-dependent features: the fault location and fault type.

Among all available parameters that can be used to predict transient stability, five features have been selected for this purpose and are summarized in Table III. It should be noted that for each case (i.e. for each dynamic simulations in which a disturbance occurs at an operating point), 1st-3rd features are calculated for all generators.

TABLE III. The proposed feature set to predict angle stability status against different contingencies.

| Symbol | Indicator title | Time span |
|---|---|---|
| $V_{G0}$ | Terminal voltage of generators in pre-fault | Before fault occurrence |
| $\frac{dP_G}{dt}=\frac{P_G^{t=1.06\bar{6}}-P_G^{t=1.03\bar{3}}}{0.03\bar{3}}$ | Active power change of generators in fault duration period | (1.033-1.066) s |
| $\frac{dv_G}{dt}=\frac{v_G^{t=1.03\bar{3}}-v_G^{t=1}}{0.03\bar{3}}$ | Voltage amplitude in fault duration period | (1-1.033) s |
| Line | Faulted Line | -------- |
| F.T | Fault type | -------- |

In the pre-fault conditions, as the system loading increases, the amplitude of generators terminal voltages slightly decrease and they drop drastically when the AVR limiters decrease the excitation and/or stator currents to pre-specified thresholds. Therefore, the voltage amplitude in pre-fault conditions is selected as a feature to indicate the closeness of the operating point to stability boundary. Also, results of extensive simulations carried out by authors show that generally, as the stability status of post-disturbance operating point becomes worse, the absolute values of the second and third features increase. Therefore, it seems that these features are proper ones to predict the stability status of post-disturbance operating point.

### *E. Model training*

For all study cases, the feature set along with their class labels (=0,1 for unstable and stable classes, respectively) are used to train an SVM classifier using K-fold cross-validation method [6]. In this method, while the database is divided into K sets, K-1 sets serves as training set to train the classifier and the last set is used to test the trained classifier and to determine its accuracy. This procedure is repeated K times and each time, another set is used for testing and the remaining sets are used to train a new classifier. Finally, the average of the accuracy of the above mentioned K trained classifiers is considered as the overall accuracy of a classifier trained with all K sets [33].

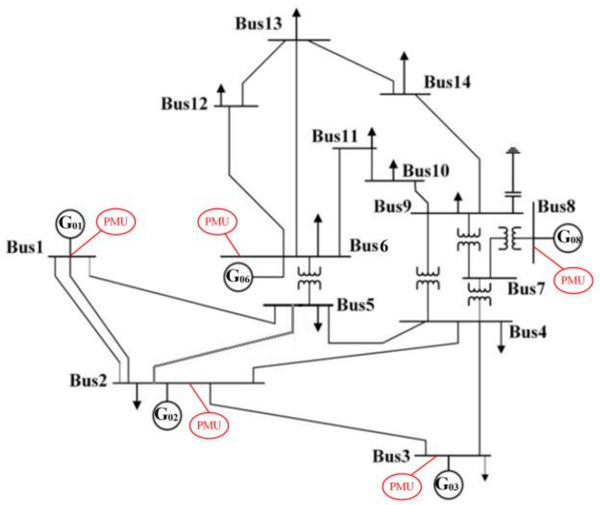


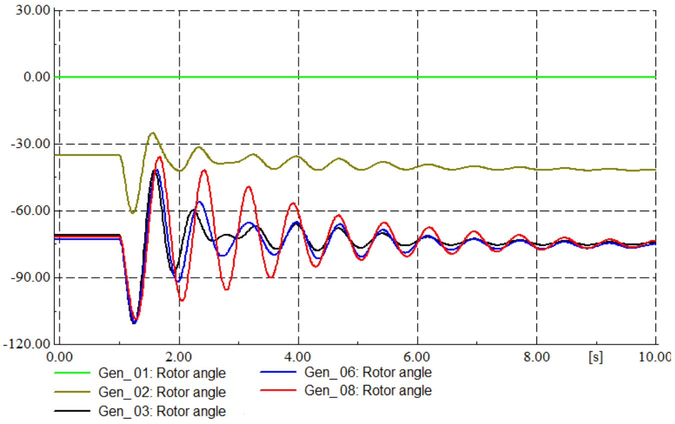

Figure 4. Single line diagram of IEEE 14-bus test system and PMU locations.

## IV. SIMULATION RESULTS

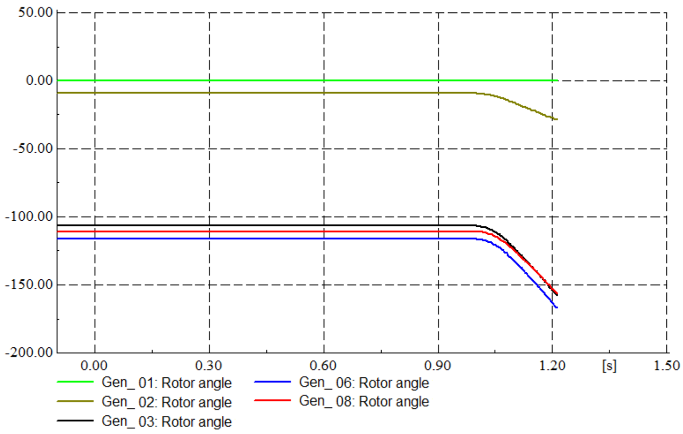
The proposed method has been tested on IEEE 14 Bus test system. By performing offline time domain simulations for various disturbances at different operating points, the database is collected. These collected data is given as input to the SVM to be trained and used in online application to predict stability status. As mentioned, in this paper, dynamic simulations are performed using DIgSILENT PowerFactory software in which all generators' controllers and voltage-dependent loads are modeled accurately and the proposed SVM based classifier is realized in WEKA software.

Following the procedure mentioned in Section III, 13 operating points are generated in IEEE 14-bus test system and 5 PMUs are installed at generators buses (Fig. 4) to measure generators active power generation and bus voltages. For each generated operating point, a fault type and a fault location is selected from table I and time domain simulation is performed to calculate the feature set mentioned in Table III. In these simulations, there are 1664 case studies which include 629 stable and 1035 unstable ones. In Fig. 5, two time-domain simulation results for stable and unstable cases have been shown, which are related to 3 phase short-circuit fault on 0.1% of the line 1-2 in low and heavy loading conditions, respectively. It should be stated that in this database, the number of different fault types (LLL, LL, LLG, and LG) is 416.

Finally, the accuracy of the feature set that was used to train an SVM classifier is given in Table IV. As shown in this table, among different kernel functions, the best prediction is achieved when the polynomial kernel function is used with 10-fold cross validation. In this case, although the proposed SVM-based classifier does not use any post-fault measured data, it can predict the stability against different types of short-circuit types with the accuracy of 99.38 %.




(a)




(b)

Figure 5. Three-phase short circuits contingency in low loading condition leads to a stable equilibrium point b) Three-phase fault in high loading condition results in instability.

TABLE IV. The accuracy of the trained classifier against different SVM kernel functions.

| Kernel Function | classes | No. each label | accuracy |
|---|---|---|---|
| RBF | stable | 629 | 99.34 % |
| | unstable | 1035 | |
| Linear | stable | 629 | 99.34 % |
| | unstable | 1035 | |
| Polynomial | stable | 629 | 99.38 % |
| | unstable | 1035 | |

## V. CONCLUSION

In this paper, a precise and fast algorithm has been proposed to predict the transient stability status of a power system without any post-fault measured data. In this method, assuming that PMUs have been installed only at generators terminal buses, time-synchronized values of active power generation and terminal voltage of SGs are used to calculate the proposed feature set. Then, this feature set is used to train an SVM classifier. The results of simulations performed in IEEE 14-bus test system show that the suggested method is robust under the presence of different faults types and network topology changes and can predict the stability status of test system against different fault types (i.e. LLL, LL, LLG, LG) with accuracy of 99.38%.

## REFERENCES

[1] D. Huang, X. Yang, S. Chen, and T. Meng, "Wide-area measurement system-based model-free approach of post-fault rotor angle trajectory prediction for on-line transient instability detection," IET Generation, Transmission & Distribution, vol. 12, no. 10, pp. 2425-2435, 2018.

[2] H. Khoshkhoo, S.M. Shahrtash, "On-line dynamic voltage instability prediction based on decision tree supported by a wide-area measurement system," IET Generation, Transmission & Distribution, vol. 6, Issue 11, pp. 1143-1152, 2012.

[3] H. Khoshkhoo and S. M. Shahrtash, "Fast online dynamic voltage instability prediction and voltage stability classification, " IET. Gen. Transm. Distrib, vol. 8, no. 5, pp. 957-965, 2014.

[4] S. Yari and H. Khoshkhoo, "A Comprehensive Assessment to Propose an Improved Line Stability Index, " International Transactions on Electrical Energy Systems, p. e2806, 2019.

[5] S. Yari and H. Khoshkhoo, "Assessment of line stability indices in detection of voltage stability status,"IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe) and IEEE International Conference, in Environment and Electrical Engineering,pp. 1-5, 2017.

[6] A. D. Rajapakse, F. Gomez, K. Nanayakkara, P. A. Crossley, and V. V. Terzija, "Rotor angle instability prediction using post-disturbance voltage trajectories," IEEE Transactions on Power Systems, vol. 25, no. 2, pp. 947-956, 2010.

[7] J. C. Cepeda, J. L. Rueda, D. G. Colomé, and D. E. Echeverría, "Real-time transient stability assessment based on centre-of-inertia estimation from phasor measurement unit records," IET Generation, Transmission & Distribution, vol. 8, no. 8, pp. 1363-1376, 2014.

[8] P. Kundur et al., "Definition and classification of power system stability," IEEE transactions on Power Systems, vol. 19, no. 2, pp. 1387-1401, 2004.

[9] D. Fang, J. Yang, W. Sun, Z. Xue, and S. Yuan, "Transient stability assessment using projection formulations," IET generation, transmission & distribution, vol. 3, no. 6, pp. 596-603, 2009.

[10] K. Shubhanga and A. M. Kulkarni, "Determination of effectiveness of transient stability controls using reduced number of trajectory sensitivitycomputations," IEEE Transactions on Power Systems, vol. 19, no. 1, pp. 473-482, 2004.

[11] G. Hou and V. Vittal, "Determination of transient stability constrained interface real power flow limit using trajectory sensitivity approach," IEEE Transactions on Power Systems, vol. 28, no. 3, pp. 2156-2163, 2013.

[12] L. Mariotto, H. Pinheiro, G. Cardoso, A. Morais, and M. Muraro, "Power systems transient stability indices: an algorithm based on equivalent clusters of coherent generators," IET generation, transmission & distribution, vol. 4, no. 11, pp. 1223-1235, 2010.

[13] D. E. Echeverría, J. L. Rueda, J. C. Cepeda, D. G. Colomé, and I. Erlich, "Comprehensive approach for prediction and assessment of power system transient stability in real-time," IEEE/PESin 4th Innovative Smart Grid Technologies Europe (ISGT EUROPE), 2013.

[14] S. Rovnyak, S. Kretsinger, J. Thorp, and D. Brown, "Decision trees for real-time transient stability prediction," IEEE Trans. Power Syst., vol.9, no. 3, pp. 1417–1426, Aug. 1994.

[15] A. A. Grobovoy, "Russian far east interconnected power system emergencystability control," in Proc. IEEE Power Engineering SocietySummer Meeting, Jul. 2001, vol. 2, no. 15–19, pp. 824–829.

[16] F. R. Gomez, A. D. Rajapakse, U. D. Annakkage, and I. T. Fernando, "Support vector machine-based algorithm for post-fault transient stability status prediction using synchronized measurements," IEEE Transactions on Power Systems, vol. 26, no. 3, pp. 1474-1483, 2011.

[17] I. Kamwa, S. Samantaray, and G. Joos, "Development of rule-based classifiers for rapid stability assessment of wide-area post-disturbance

records," IEEE Transactions on Power Systems, vol. 24, no. 1, pp. 258-270, 2009.

[18] F. Hashiesh, H. E. Mostafa, I. Helal, and M. M. Mansour, "A wide area synchrophasor based ANN transient stability predictor for the Egyptian Power System," in Innovative Smart Grid Technologies Conference Europe (ISGT Europe), IEEE PES, 2010.

[19] H. Suprême, A. Heniche-Oussédik, I. Kamwa, and L.-A. Dessaint, "A novel approach for instability detection based on wide-area measurements and new predictors," IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 2016.

[20] E. A. Frimpong, P. Y. Okyere, and J. Asumadu, "Prediction of transient stability status using Walsh-Hadamard transform and support vector machine," in IEEE PES PowerAfrica, pp. 301-306, 2017.

[21] N. Amjady and S. F. Majedi, "Transient stability prediction by a hybrid intelligent system," IEEE Transactions on Power Systems, vol. 22, no. 3, pp. 1275-1283, 2007.

[22] C.-W. Liu, M.-C. Su, S.-S. Tsay, and Y.-J. Wang, "Application of a novel fuzzy neural network to real-time transient stability swings prediction based on synchronized phasor measurements," IEEE Transactions on Power Systems, vol. 14, no. 2, pp. 685-692, 1999.

[23] A. Parizad, H. Khoshkhoo, N.T. Sahand, S. Dehghan, R. Moradtalab, "An Intelligent Load and Generation Shedding Procedure in an Islanded Network Using a Smart Power Management System," Smart Grid Conference (SGC), 2017.

[24] K. E. Martin, "Synchrophasor standards development-IEEE C37. 118 & IEC 61850," System Sciences (HICSS), 44th Hawaii International Conference on, 2011.

[25] H. Khoshkhoo and S. M. Shahrtash, "Fast online dynamic voltage instability prediction and voltage stability classification," IET Generation, Transmission & Distribution, vol. 8, no. 5, pp. 957-965, 2014.

[26] C. J. Burges, "A tutorial on support vector machines for pattern recognition," Data mining and knowledge discovery, vol. 2, no. 2, pp. 121-167, 1998.

[27] H. Khoshkhoo, S.M. Shahrtash, "Dynamic small disturbance voltage instability prediction based on wide area measurement system," IEEE International Power Engineering and Optimization Conference (PEDCO) Melaka, Malaysia, 2012.

[28] Q.H. Wu, Z. Lu and T.Y. Ji, "Protective Relaying of Power Systems Using Mathematical Morphology," Springer, 2009.

[29] E. Alpaydin, "Introduction to Machine Learning," MIT Press, 2005.

[30] S. Tripathi and S. De, "Assessment of power system stability using reduced-rate synchrophasor data," IEEE International Conference in Advanced Networks and Telecommuncations Systems (ANTS), 2015.

[31] P. Kundur et al., "Definition and classification of power system stability," IEEE transactions on Power Systems, vol. 19, no. 2, pp. 1387-1401, 2004.

[32] K. Sun, S. Likhate, V. Vittal, V. S. Kolluri, and S. Mandal, "An online dynamic security assessment scheme using phasor measurements and decision trees," IEEE Transactions on Power Systems, vol. 22, no. 4, pp. 1935-1943, 2007.

[33] V. Kecman, "Learning and soft computing: support vector machines, neural networks, and fuzzy logic models.", MIT press, 2001.