On-line Voltage Stability Monitoring Using an Ensemble Adaboost Classifier

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Abstract—**Predictive modeling in an electrical power systems is currently gaining momentum especially as Phasor Measurement Units (PMUs) are being deployed in modern electrical grids to replace the Supervisory Control and Data Acquisition System (SCADA). This paper evaluates machine learning algorithms for the task of monitoring voltage instability for online decision making. In particular the performance of the Naïve Bayesian, K-Nearest Neighbors, Decision Tree and Ensembles classifiers (XGBoost, Bagging, Random Forest, and AdaBoost) were compared. Performance evaluation measures of Precision, Recall, F1-score, and Accuracy were adopted to evaluate the performance of the classifiers. In this paper, a number of voltage stability operating points were generated with different variations of load/generation, using the PSSE Power-Voltage (PV) analysis tool. An IEEE 39 bus was used as a test system. Sufficient training patterns that captured different Operating Points (OPs) at base-case and at multiple contingencies (N-k) were gathered to train machine learning methods to identify acceptable operating conditions and near collapse situations. Experimental results show that AdaBoost achieved the highest classification accuracy, i.e. 96.02%, compared to the other classifiers.**

Keywords— ***Adaboost, Decision Tree, Phasor Measurement Units, Power-Voltage Analysis, PSSE, Support Vector Machines***

I. INTRODUCTION

Electrical systems around the world are under increasing stress, and one of the strongest drivers is the growing role of decentralized energy sources. The decentralized energy sources increase instability on the grid but encourages grid operators to operate the network close to its stability limit. When this limit is breached the entire system may experience voltage collapse which could result in total power failure. An electrical grid is normally designed to maintain stability when a few elements such as transmission line and transformer are removed, however, when the system is under stressed condition due to heavy loads and outages of equipment, large disturbance and subsequent tripping of other elements may occurred. This condition causes cascading power failure. A contingency in anelectrical power system is a specified set of events that occur as a result of unexpected failure or removal of electrical components on an electrical grid. A contingency resulting in the loss of one element is referred to as an N-1contingency or N-1 secure. A contingency resulting in the loss of more than one component is referred to N-k, whereby k>1 [1]. In contingency analysis, computer models are used to investigate the effect of the failure of a particular element. Voltage stability is the required characteristic of power system to maintain stable voltage at all buses despite being subjected to disturbances [2]. Most of the recent blackouts observed in North America and Canada August 2003, Europe November 2006, Brazil November, 2009 and India July, 2012 occurred as a result of voltage instability [3]. The root causes of the August 2003, America and Canada blackout were attributed to ineffective monitoring of the grid by operators. More specifically, failure in identifying emergency conditions and ineffective communication of the current status to neighboring systems [4]. In Europe, the European Commission is promoting ambitious plans in the member states to renovate the generation portfolio [5]. In this

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new scenario, electrical grid systems are moving toward infrastructural change to better cope with the current operating conditions. One of the vital parts of this modernization is the effective and efficient monitoring of the power grid, particularly for transmission and distribution. More specifically, Phasor Measurement Units (PMUs), are being deployed in modern electrical power systems to replace the Supervisory Control and Data Acquisition (SCADA) system. SCADA is used to provide data for stability analysis on an electrical grid, but it is known to be very slow in sampling and incapable of monitoring modern electrical grids and provides in effect limited decision making capability [6], [7]. In contrast, PMUs provide real time information of the grid in a synchronized manner at PMU is between 30 and 240 samples per second[9],[10]. High frequency and high precision [8]. The sampling rate of a As a consequence, PMU technology is aimed at replacing SCADA entirely for smart grid implementation. However, because of its high sampling rates, speed and complexity [11], PMU generates unprecedented data volume and requires fast decision making capabilities to transform the data collected for better understanding of physical grid dynamic behavior. Voltage security monitoring of power systems is a task that must be performed regularly at control centers by grid operators. This task can be very time consuming and memory intensive. Electrical systems may be stable for a given large physical disturbance and unstable to another. Due to this unpredictable nature, researchers are now turning to Machine Learning (ML) approaches for very fast monitoring and prediction of vulnerability in real time for an electrical system. ML algorithms have the ability to achieve complicated input-output mappings through adaptive learning. Several data mining and prediction algorithms using ML, have been proposed for online monitoring and decision making [12], [13]. These algorithms are also proposed for voltage stability prediction [7], monitoring of smart grid false data injection attack [14], [15], and the prediction of household load forecasting [16]. However, detailed pre- and post- contingency assessments in real time for identification of near voltage collapse for situational awareness, and understanding systems condition and projection of its future status is not yet fully analyzed.

The main objective of this paper is to explore and evaluate different machine learning algorithms and their accuracy in an online monitoring of voltage stability at base-case when the system is intact and at multiple contingencies for identification of a near voltage collapse condition. Such algorithms will enable grid operators to analyze and manage huge data generated by PMUs for fast decision and solution to the problems related to voltage instability in real time. The remainder of this paper is organised as follows: Section II presents a literature review on power system stability and conventional machine learning algorithms. Section III discusses the experimental methodology. Results and discussion are presented in Section IV. Concluding remarks are given in Section V.

II. LITERATURE REVIEW

In order to optimize grid functionality, modern utility industries must deal with high-volume data management, and be able to analyse and evaluate patterns in the collected data within a specified period of time. The data generated by PMUs must be transformed into actionable insights to increase situational awareness. These insights help operators to protect the grid from chain reactions that may be initiated by various perturbations, for example a faulty transmission line, and later propagate and weaken the system, which could lead to instability or cascading power failures. An electrical power system is highly non-linear and operates in constantly changing operating conditions. The key operating parameters such as load, generator outputs and unpredictable behavior of intermittent energy sources changes continuously. Although there are different factors contributing to voltage instability such as rotor angle instability and self excitation of synchronous machine, these factors are becoming difficult for grid operators to handle. However, the driving force for voltage instability is generally the magnitude of the load in response to a disturbance. A progressive voltage drop occurs when load dynamics attempt to deliver power beyond the capability of the transmision network and also when generators hit their field or armature current time-overload capability limits. In addition, voltage drops occur when a disturbance increases the reactive power demand beyond the limit of the available reactive power resources [2]. This section provides a background on Voltage Stability and discusses related works.

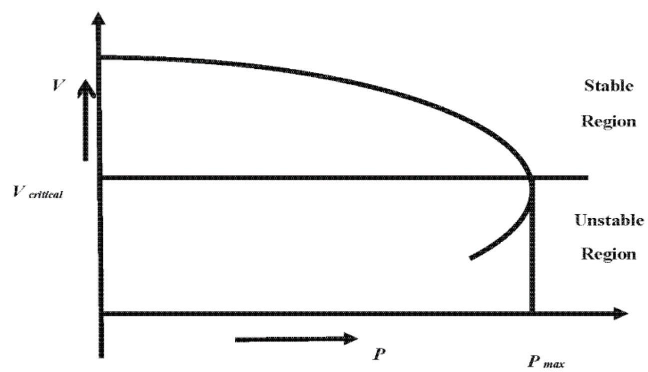

Figure 1. PV curve shows the relationship between incremental power (P) and receiving end voltage (V) [17].

A. *Voltage Stability*

Voltage stability is one of the classifications of power system stability. For a system to be voltage stable, it has to maintain steady voltage at all buses despite being subjected to disturbance [2]. Voltage instability is considered as one of the most challenging aspects faced by the electrical utility industry [7]. Several techniques and approaches have been put forward by researchers to address the issue of voltage instability. The PV curve i.e. transmitted power (P) and receiving end voltage (V) curve, is one of the most widely accepted measures to analyse voltage instability or collapse [18]. The process involves monitoring the voltage as the power or load increases. Fig. 1 shows a typical PV curve.

The characteristic of interest in the PV curve is the relationship between incremental power (P) and receiving end voltage (V). As it can be seen in the curve, when the transfer of power flow increases, the voltage starts to drop, until reaches the extreme drops of the curve known as the knee point or collapse point; at this region the voltage drops rapidly, and hence instability occurs. Only operating points above the knee point represent satisfactory operating conditions. Voltage instability may occur in different forms; however the simplest can be demonstrated using a simple terminal network. The mathematical relationship for the network can be expressed using equations (1) to (5). Assuming (E_S) is a constant voltage source, supplying to a receiving load (Z_{LD}) with its phase angle (ϕ). (Z_{LN}) is a series impedence with its phase angle (θ), (V_R) is the receiving end voltage and the power supplied to the load is (P_R). The magnitude of the current flowing in the electrical network can be written as:

$$I = \frac{E_S}{\left(\sqrt{Z_{LN}\cos(\theta) + Z_{LD}\cos(\phi)}\right)^2 + \left(\sqrt{Z_{LN}\sin(\theta) + Z_{LD}\sin(\phi)}\right)^2} \quad (1)$$

Equation (1) can be simplified as follows.

$$I = \frac{1}{\sqrt{F}}\frac{E_S}{Z_{LN}} \quad (2)$$

Where

$$F = 1 + \left(\frac{Z_{LD}}{Z_{LN}}\right)^2 + 2\left(\frac{Z_{LD}}{Z_{LN}}\right)COS(\theta - \phi) \quad (3)$$

$$V_R = \frac{1}{\sqrt{F}}\frac{Z_{LD}}{Z_{LN}}E_S = Z_{LD}I \quad (4)$$

Hence the receiving power can be expressed as:

$$P_R = V_R I COS\phi = \frac{Z_{LD}}{F}\left(\frac{E_S}{Z_{LN}}\right)^2 COS\phi \quad (5)$$

Power transmitted in the circuit is maximum when the voltage drop in the line is equivalent to the magnitude of V_R, i.e $Z_{LN}/ Z_{LD} =1$. As Z_{LD} gradually decreases, *I* increases in Equation (1) and V_R decreases in Equation (4). When Z_{LD} is less than Z_{LN}, P_R decreases in Equation (5). When the load demand is higher than the maximum deliverable power, instability may occur. Further details of the relationship can be found in [17].

B. Related Works

Several machine learning techniques have been proposed for online decision making. The Decision Tree (DT), a tree-structured predictive model, is also one of the most widely used machine learning algorithms which have been proposed for online security assessment of an electrical grid [19]. Diao et al. [19] proposed a Decision Tree assisted scheme for voltage security assessment. Regression Trees are trained to analyze post contingency issues such as voltage magnitude violation and thermal limit violation. Classification Trees are trained for voltage stability and transient stability analysis. From the result obtained, DT was able performed different security assessment in near real time. Kamwa et al. [20] proposed a Random Forest leaning approach to improve the reliability margin and instability experienced when using DTs in an online stability prediction, i.e. shifting from single tree learning to ensemble decision trees. According to the authors, DTs has instability issues when it comes to small changes in leaning data; the entire tree structure can easily be altered if the first cut point is chosen differently. The authors also claim that RF has a large combination of de-correlated predictors, such that each tree depends on the values of a random vector sampled independently, and thus assume the RF method is more robust and reliable. Mohammadi et al. [21] proposed a method using Principal Component Analysis (PCA) to drastically reduce the dimension of the data collected by PMU using correlation analysis before feeding it to a DT. The reduced data is used to train the DTs and develop a classifier for online security assessment. Ashraf et al. [7] and Zhou et al. [12] adopted Artificial Neural Networks for large power network monitoring. ANNs were trained to predict loading margin for voltage stability prediction using data generated from PSAT simulation software. Zhou et al. [12] used nodal voltage magnitude and phase angle obtained as an input to train the machine. Different cases that captured sufficient scenarios for the training were generated using conventional power flow solution software. ANNs were trained using the generated data to learn the I/O mapping. However, the methodology requires a large number of ANNs for real online stability monitoring. Malbasa et al. [10] proposed a methodology to improve conventional machine learning tools, by optimizing the training data set to predict system stability more efficiently. Instead of using a comprehensive simulation method, the authors select most relevant operating points along the PV curve to generate the training data sets, and to train a Neural Network. Bus voltage and power margin are used as an input to the Neural Networks. The system is tested using data obtained from detailed simulation of a power system.

III. Experimental Methodology

This section discusses the methods used for collecting the data which is used for training and testing the machine learning classifiers. The proposed approach is evaluated using synthetic data obtained from simulations using Siemens Power Transmission System Planning Software (PSSE) [22]. The experiment focuses on training Machine Learning algorithms to identify voltage conditions, such as “acceptable/stable”, and “near collapse” points before and after system disturbances. In order to generate the data the New England (IEEE 39 test bus system) was used [23]. The network consists of 31 loads, 46 branches, 12 transformers, and 9 generators.

A. Data Processing

Traditionally electrical power systems are designed to operate at normal conditions and at different contingencies.

The standard procedure in the utility industry is to consider N-1 contingencies, i.e. an electrical system minus a single element [17]. The process of generating data for stability training in this paper involves three stages.

Stage 1: In order to train the machine learning algorithm for normal operating condition and at contingencies, power flow is solved using the Full Newton-Raphson method in the PSSE simulation software to ensure the system under test converges within minimal computational cost. To generate a substantial amount of data that captures different Operating Points (OPs) along the PV-curve for training and voltage stability prediction, PV analysis was carried out using the PV tool, a power flow base analysis tool used in PSSE to investigate maximum power transfer before voltage collapse. A large number of cases with different values of load/generation were automatically generated for base-case and multiple contingencies. The N-k contingencies considered in this paper are single and multiple outages of transmission line and other electrical components.

Stage 2: As the transfer of power flow increases, voltage started to drops until a collapse point of the 39 buses is identified. Corresponding voltage magnitudes, branch reactive power flow (MVA) and generators outputs (MW) were calculated.

Stage 3: To create a dataset for training, the synthetic data obtained from the simulation, using PV analysis tool for different voltage variation, was stored.

TABLE II. DATASET CHARACTERISTICS

Dataset	Input Dimension	No. of samples	
		Training	*Testing*
Class 0 Acceptable	*(1455, 3)*	*1014*	*441*
Class 1 Near Collapse	*(302, 3)*	*215*	*87*
Total	**(1757, 3)**	**1229**	**528**

The experiment focused solely on identifying Operating Points (OPs) categorized as stable points which are within acceptable variation limit ±5 % per unit voltage magnitude, i.e. the system buses must be in the range of. 1.05 per unit to 0.95 per unit. Also, critical points and collapse points in accordance with the theory of voltage stability and PV curve were identified.

Comparable to the work of Dinavahi and Srivastava [24], also in this paper, real power incremental transfer (MW) and reactive power injections to all buses (MVA) are used as inputs into the algorithms.

B. Dataset

The proposed approach for online voltage stability monitoring has been applied to the New England 39-bus test system. After simple preprocessing 1757 labeled samples were generated. Each sample belongs to one of two classes (i.e. labels): the 'acceptable' class (class 0), or the 'near collapse' class (class 1). A total of 70% of cases were randomly selected as the training data and the remaining 30% of the samples were used as the test cases. A total of 1229 samples were used for training, and the rest of the data, 528 samples, were used for testing, see Table II. Each input sample has three features, as illustrated in Table I.

C. Machine Learning Methods

This section describes the machine learning methods which are used for the experiments. Two groups of machine learning methods are used – single and Ensemble leaning classifiers.

Gaussian Naive Bayes: is a powerful algorithm for predictive modelling and classification. It is appropriately used when the dimension of the feature space is high, making the density space unattractive. To simplify the estimation, the algorithm makes strong assumptions about the independence of each input variable.

K-nearest neighbour (KNN): an algorithm for classification and regression, is a classifier that discriminates classes considering the distance measured between the feature vectors on the feature space. The classifier places an unknown class in the same group. The number of k nearest neighbours was set to 5, and *k* was chosen experimentally.

Decision Tree algorithm or Classification and Regression Trees (CART): is a tree structured inspired algorithm. It is used for classification or regression predictive modelling and for approximating discrete-valued target functions. The tree is designed in such a way that, each node in the tree represents a test of an instance on selected attributes, while each branch descending from the node corresponds to one of the possible values for this attributes.

eXtreme Gradient Boosting (XGBoost): is an ensemble learning method, and it is advanced implementation of gradient boosted decision trees used for speed and performance. The algorithm is mainly designed for regression, and classification problems. One of the advantage of this machine learning algorithm is its scalability in all scenarios which is due to the several systems and algorithmic optimisation.

Bagging Classifier: is an ensemble general purpose procedure that is used for reducing the variance of statistical learning method. This algorithm come in handy as Decision Trees suffer from high variance. Bagging provides an effective way to create robust decision by aggregating the randomized original data.

Random forests: or random decision forest is an ensemble learning method for classification and regression. The algorithm evolves from several individual Decision Trees, each tree is trained on a boostrapped sample, and leaf on each tree is split by randomly selected features. The algorithm is insensitive to high dimensional features and requires only slight parameter tuning.

AdaBoost (Adaptive Boosting): uses a sequence of weak learners to construct a stronger classifier. Different training samples are assigned different weights. Each weak classifier focuses on different samples using the different weights. The training samples that are not trained perfectly with the previous weak classifier will get a higher weight for the next weak classifier. However, the training samples that are predicted correctly will get lower weight for the next weak classifier. The weights are adjusted in different steps based on the accuracy of each weak classifier.

D. Performance Evaluation Measures

Different measures were adopted to evaluate the performance of the proposed scheme. These were Precision, Recall, F1-score, and Accuracy. Let |P| be the total number of 'near collapse' cases. Let |N| be the total number of 'acceptable' cases. Let, |TP|, be the total number of 'near collapse' cases correctly identified as 'near collapse'. Let, |TN| be the total number of 'acceptable' cases correctly identified as 'acceptable'. Let, |FP|, be the total number of 'acceptable' cases incorrectly identified as 'near collapse'. Let, |FN| be the total number of 'near collapse' cases incorrectly identified as 'acceptable'. Where, P is Positive; N is Negative; TP is True Positive; TN is True Negative; FP is False Positive; and FN is False Negative.

Precision, also called the Positive Predictive Value, is the fraction of True Positive (TP) predictions divided by the total number of positive class values predicted as shown in (6).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{6}$$

Recall, is also known as Sensitivity, is the fraction of the number of True Positive predictions divided by the number of positive class values in the test data.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{7}$$

F1-score is also called the F-score or F-measure conveys the balance between Precision and Recall. The value of F1-score becomes high only if the values of both Precision and Recall are high. F1-score values fall in the interval [0,1], and the highest the value, the better the classification accuracy. The formula for F1-score formula (8).

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

Precision, Recall, and F1-score ranges from 0 to 1.0 values. The closer the value is to 1.0 the better the performance of the method.

Accuracy is the percentage of correct classifications out of testing samples. The closer the Accuracy value is to 100, the better the performance of the classifier.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \tag{9}$$

IV. Results and Discussion

The machine learning models used in the experiments were implemented in the Python programming language. Data was randomly partitioned into 70% training samples, and 30% testing samples. The classification models adopted for the experiments belong into one of two groups. The first group includes the single classifiers: Naïve Bayesian, k-NN classifier, and Decision Tree. The second group of classification methods contains Ensemble classifiers. The Ensemble classifiers adopted were the XGBoost Classifier, Bagging Classifier, Random Forest, and AdaBoost Classifiers. For a fair comparison, all classifiers were tuned to achieve their best performance. The results are presented in Table III. From the first group of classifiers, the best result was given by the Decision Tree classifier which returned Precision: 0.86, Recall: 0.87, F-measure: 0.86, Accuracy: 86.55%. However, a single classifier is sensitive to noise and has a strong tendency to learn both the relationships between the data and noise in the training set.

The second part of Table III shows the classification accuracy of the Ensemble classifiers. From the table it can be seen that the classification accuracy of the AdaBoost is better than that of all other methods, Precision: 0.96, Recall: 0.96, F-measure: 0.96, Accuracy: 96.02%. Thus the AdaBoost is able to classify power system stability using IEEE 39 test bus system (New England) more accurately than the alternative machine learning models. Fig. 2 and Fig. 3, show the confusion matrix derived from applying the best two classifiers on the dataset, which were the AdaBoost and Random Forest, respectively. The vertical axis shows the true label and the horizontal axis shows the predicted label. The confusion matrix of the AdaBoost classification model shows that for the class 'acceptable' class, 433 samples (out of 441 samples) are classified correctly. For the class 'near collapse' class, 74 samples (out of 87 samples) are classified correctly. The overall classification accuracy of the AdaBoost method on the Voltage stability monitoring data is 96.02%. The Random Forest classifier was the second-best classifier, and achieved classification accuracy of 94.89%. Table IV shows that the Adaboost model performed better in predicting the 'acceptable' cases than 'near collapse' cases. Although the accuracy of the 'near collapse' class is very high, with more samples this accuracy can be increased even further.

TABLE III. Performance Measures for Evaluating Real Time Voltage Stability

Single Classifiers				
Models	***Precision***	***Recall***	***F-score***	***Accuracy***
Naïve Bayesian	0.80	0.82	0.81	81.82
K-Nearest Neighbors Classifier	0.85	0.86	0.86	86.17
Decision Tree	0.86	0.87	0.86	86.55
Ensemble Classifiers				
Models	***Precision***	***Recall***	***F-score***	***Accuracy***
XGBoost Classifier	0.91	0.91	0.91	91.29
Bagging Classifier	0.95	0.95	0.95	94.70
Random Forest	0.95	0.95	0.95	94.89
AdaBoost Classifier	**0.96**	**0.96**	**0.96**	**96.02**

V. Conclusion

This paper has compared several data mining and machine learning algorithms for online stability of power distribution systems. A number of credible contingency cases were gathered with different variations of load/generation, using PSSE Power-Voltage (PV) analysis tool, IEEE 39 bus was used as a test system. Sufficient training patterns that captured different operating points (OPs) at base-case and at multiple contingencies (N-k) were gathered. Machine learning methods were trained to identify voltage stability operating conditions. The experiment focused mainly on identifying acceptable voltage variation limit which is between ±5 % per unit voltage magnitude, and to identify critical points (near voltage collapse) and collapse points. The performance of the Naïve Bayes, K-Nearest Neighbors, Decision Tree and Ensembles classifiers (XGBoost, Bagging, Random Forest, and AdaBoost) was compared. Performance evaluation measures of Precision, Recall, F1-score, and Accuracy were adopted to evaluate the performance of the classifiers. Out of all the single classifiers used in the experiment i.e. Decision Tree, Naïve Bayesian and k-Nearest Neighbors Classifier, the best result of 86.55% accuracy was achieved by Decision Tree. Since single classifiers are sensitive to noise, several learning algorithms were combined, using Ensemble classifiers, to achieve better classification accuracy. The classifiers used are AdaBoost, Bagging, Random Forest, and XGBoost classifier. Experimental results demonstrated that AdaBoost achieved the highest classification accuracy, i.e. 96.02%, compared to the other classifiers. In future work, more simulations will be carried out to explore use of the learning algorithms with more complex data, using more input variables.

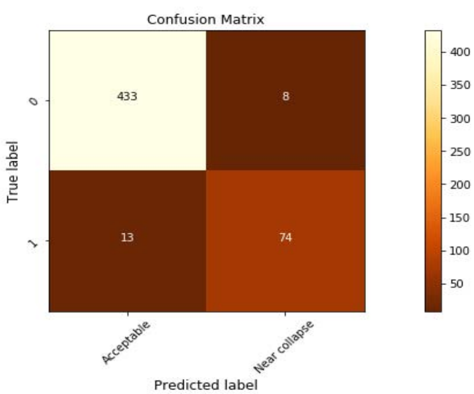

Figure 2. Confusion matrix for the AdaBoost Classifier

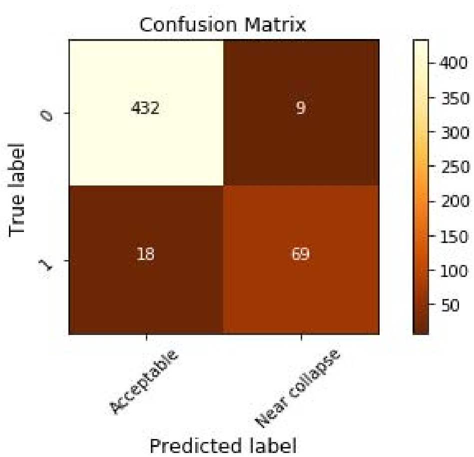

Figure 3. Confusion matrix for the Random Forest Classifier

TABLE IV. PRECISION, RECALL AND F1-SCORE OF ADABOOST ON THE 528 TEST CASES

	Precision	*Recall*	*F1-score*	**#Testing Samples**
Acceptable	0.97	0.98	0.98	441
Near Collapse	0.90	0.85	0.88	87
Average/total	**0.96**	**0.96**	**0.96**	**528**

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REFERENCES

[1] Q. Chen and J. D. McCalley, "Identifying high risk N-k contingencies for online security assessment," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 823–834, 2005.

[2] P. Kundur *et al.*, "Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1387–1401, 2004.

[3] Y. Jia, Z. Xu, L. L. Lai, and K. P. Wong, "Risk-Based Power System Security Analysis Considering Cascading Outages," *IEEE* Trans. *Ind.* Informatics, vol. 12, no. 2, pp. 872–882, 2016.

[4] U.S.-Canada Power System Outage Task Force, "Final Report on the August 14, 2003 Blackout in the United States and Canada: Causes and Recommendations," 2004.

[5] F. P. Antonello Monti, Carlo Muscas, *Phasor Measurement Units and Wide Area Monitoring Systems*. Elservier Inc, 2016.

[6] B. Wang, B. Fang, Y. Wang, H. Liu, and Y. Liu, "Power System Transient Stability Assessment Based on Big Data and the Core Vector Machine," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2561–2570, 2016.

[7] S. M. Ashraf, A. Gupta, D. K. Choudhary, and S. Chakrabarti, "Voltage stability monitoring of power systems using reduced network and artificial neural network," *Int. J. Electr. Power Energy Syst.*, vol. 87, pp. 43–51, 2017.

[8] J. Ma, P. Zhang, H. j. Fu, B. Bo, and Z. y. Dong, "Application of Phasor Measurement Unit on Locating Disturbance Source for Low-Frequency Oscillation," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 340–346, 2010.

[9] "IEEE Standard for Synchrophasor Measurements for Power Systems," *IEEE Std C37.118.1-2011 (Revision of IEEE Std C37.118-2005)*. pp. 1–61, 2011.

[10] V. Malbasa, C. Zheng, P. C. Chen, T. Popovic, and M. Kezunovic, "Voltage Stability Prediction Using Active Machine Learning," *IEEE Trans. Smart Grid*, vol. 8, no. 6, pp. 3117–3124, 2017.

[11] M. H. F. Wen and V. O. K. Li, "Optimal Phasor Data Compression Unit Installation for Wide-Area Measurement Systems—An Integer Linear Programming Approach," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2644–2653, 2016.

[12] D. Q. Zhou, U. D. Annakkage, and A. D. Rajapakse, "Online Monitoring of Voltage Stability Margin Using an Artificial Neural Network," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1566–1574, 2010.

[13] C. Zheng, V. Malbasa, and M. Kezunovic, "Regression tree for stability margin prediction using synchrophasor measurements," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1978–1987, 2013.

[14] M. Esmalifalak, N. T. Nguyen, R. Zheng, and Z. Han, "Detecting stealthy false data injection using machine learning in smart grid," in

2013 IEEE Global Communications Conference (GLOBECOM), 2013, pp. 808–813.

[15] Y. He, G. J. Mendis, and J. Wei, "Real-Time Detection of False Data Injection Attacks in Smart Grid: A Deep Learning-Based Intelligent Mechanism," *IEEE Trans. Smart Grid*, vol. 8, no. 5, pp. 2505–2516, 2017.

[16] H. Shi, M. Xu, and R. Li, "Deep Learning for Household Load Forecasting – A Novel Pooling Deep RNN," *IEEE Trans. Smart Grid*, vol. PP, no. 99, p. 1, 2017.

[17] M. G. L. Prabha Kundur, Neal J. Balu, *Power system stability and control*. Michigan: McGraw-Hill, 1994.

[18] C. W. Taylor, *Power System Voltage Stability'*. Singapore: McGraw-Hill, 1994.

[19] R. Diao, V. Vittal, and N. Logic, "Design of a Real-Time Security Assessment Tool for Situational Awareness Enhancement in Modern Power Systems," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 957–965, 2010.

[20] I. Kamwa, S. R. Samantaray, and G. Joos, "Catastrophe Predictors From Ensemble Decision-Tree Learning of Wide-Area Severity Indices," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 144–158, 2010.

[21] H. Mohammadi and M. Dehghani, "PMU based voltage security assessment of power systems exploiting principal component analysis and decision trees," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 655–663, 2015.

[22] Siemens Industry Inc, "PSSE." Siemens Industry Inc, 2017.

[23] T. Athay, R. Podmore, and S. Virmani, "A Practical Method for the Direct Analysis of Transient Stability," *IEEE Trans. Power Appar. Syst.*, vol. PAS-98, no. 2, pp. 573–584, 1979.

[24] V. R. Dinavahi and S. C. Srivastava, "ANN based voltage stability margin prediction," in *2001 Power Engineering Society Summer Meeting. Conference Proceedings (Cat. No.01CH37262)*, 2001, vol. 2, pp. 1275–1280 vol.2.