A Machine Learning–Based Approach for Fault Detection in Power Systems

Pathan Ilius
King Fahd University of Petroleum and Minerals, Saudi Arabia
g201408000@kfupm.edu.sa

Mohammad Almuhaini
King Fahd University of Petroleum and Minerals, Saudi Arabia
muhaini@kfupm.edu.sa (corresponding author)

Muhammad Javaid
King Fahd University of Petroleum and Minerals, Saudi Arabia
mjavid@kfupm.edu.sa

Mohammad Abido
King Fahd University of Petroleum and Minerals, Saudi Arabia
mabido@kfupm.edu.sa

Received: 27 April 2023 | Revised: 14 May 2023 | Accepted: 17 May 2023

 DOI: https://doi.org/10.48084/etasr.5995

ABSTRACT

Machine learning techniques are becoming popular for monitoring the health and faults of different components in power systems, including transformers, generators, and induction motors. Normally, fault monitoring is performed based on predetermined healthy and faulty data from the corresponding system. The main objective of this study was to recognize the start of a system fault using a Support Vector Machine (SVM) approach. This technique was applied to detect power system instability before entering an unstable condition. Bus voltages, generator angles, and corresponding times before and after faults were used as training data for the SVM to detect abnormal conditions in a system. Therefore, a trained SVM would be able to determine the fault status after providing similar test data once a disturbance has been resolved.

Keywords-support vector machine; python software; fault detection

I. INTRODUCTION

Stability monitoring of power systems has become a topic of keen interest for the power industry and researchers, resulting in the practical implementation of new devices and techniques in power systems. Given the introduction of microgrid and smart grid technologies in power systems, constraints have been introduced to meet the increasing demand, increasing the complexity of a power system. Transmission over interconnected systems has become a significant challenge to system reliability, which is the ultimate goal. Researchers are currently monitoring the stability of systems using Phasor Measurement Units (PMUs). In [1], an equivalent analytical circuit was presented to monitor and assess the voltage stability of a power system, optimizing the positions of the PMUs of a system. Mode frequency, mode damping, and mode shape are the key properties of an oscillating signal in a power system. These properties were analyzed to monitor the real-time inter-area oscillations in [2]. In this case, a graphical-based display is used to monitor the overall stability condition of the operator. The same concept has been used in the power grid in western North America. Fast Fourier Transform (FFT) is applied to monitor the stability of the power system using real-time data taken by PMUs [3]. In this case, the Discrete Fourier transform (DFT) is calculated using the FFT, and the method is validated using a combination of a Real-Time Digital Simulator (RTDS), PMU, and Phasor Data Concentrator (PDC). The FFT is applied to the PMU data to obtain the response in the frequency domain, considering the frequency at which the disturbance occurs to monitor the stability. In this method, an unbound amplitude of the frequency indicates instability.

In [4], an Artificial Neural Network (ANN) was used to predict the online voltage stability margin based on PMU data. The ANN was trained based on several random known operating points and then implemented on unseen test data. Four types of combinations were used as inputs of the ANN to select the operating points of the system and 100 test cases were carried out to validate the network. A similar type of voltage stability monitoring based on different performance indices was proposed in [5], where the ANN was first trained using a huge amount of training data, including a validation check. The Power System Analysis Toolbox (PSAT) was used to generate the training data, and the standard IEEE 14-bus system was used to test the system. In [6], a method was proposed to monitor the stability of the power system, especially in the case of low-frequency oscillations in local and global modes, using the FFT of the original and filtered signals considering the damping ratio at a specified frequency. When determining the stability margin, less damping is considered to represent an unstable situation compared to a certain specified high damping at a certain frequency. High- and low-pass filtering blocks were used to separate the local and global modes of the signal to send them to the system identification block, which identifies the condition as stable or unstable after clearing the faults of the system while monitoring the damping ratio at a certain frequency. In this case, a synthesis signal and an analog simulator were used in a research laboratory.

Various online stability monitoring methods have been modeled and analyzed using GPS for reliable power system operation based on previously published PMU data [7-12]. Multilayer Perceptron (MLP) Neural Network (NN)–based quantification of the proximity of power system voltage instability was proposed in [13], where the quasistatic operating condition was considered and achieved using a reduced Jacobian matrix. In [14], a forecasting-aided state estimator was proposed to predict the state necessary to monitor the system. The tangent vectors of each state and extrapolation techniques play an important role in this regard. In [15], the stability of the online voltage was monitored using a single Radial Basis Function Network (RBFN), separately calculating the weights of the hidden and output layers. Today, classification algorithms are used not only in various types of data classification but also in medical sciences. In [16], a Support Vector Machine (SVM) was used to detect QRS in single-lead and 12-lead ECG signals. In [17], SVM and HMM machine learning techniques were implemented in image classification for two cases, either in authentic or forged mode.

Several studies attempted to monitor the stability of power systems as early as possible after clearing faults using intelligent techniques and optimization algorithms [18-19]. However, the utilization of machine learning techniques to monitor and detect abnormal instability has not received sufficient attention yet. In this study, SVM, kernel trick, and optimization of SVM parameters were used to provide a prediction after monitoring stability schemes in advance when the fault was cleared after a disturbance, regardless of whether the system was transiently unstable. The contribution of this study lies in the proposition of a machine learning-based framework that classifies and detects faulty unstable conditions in power systems by implementing a hybrid action of an SVM with Python, which optimizes the SVM's parameters, while the SVM acts as an abnormality detector. The kernel trick is used to convert the nonlinear space into a multidimensional feature space and can be used for both types of data; thus, it can easily detect the condition of a power system regarding the occurrence of a fault or its stability after clearing it, depending on the datasets used for training and testing the detector.

II. THE PROPOSED SVM FOR FAULT DETECTION

Abnormality detection is one of the main concerns in the area of power systems, where a fault may occur in transmission lines, transformers, synchronous machines, or any device related to the power system that causes an abnormality. Therefore, identifying system faults is the key step in protecting such a system from collapse. In this case, there are two scenarios; one is the stable case, which is normally expected at all times and maintains specific profiles for each parameter in a specific system, and the other is the unstable case, which shows parameter profiles that are entirely different from the stable case for the corresponding times. Thus, binary classification is one way to detect system faults. In this study, this type of classification was evaluated using an SVM to detect a faulty condition. SVM can be used to classify binary class data by separating hyperplanes. In such cases, a healthy system provides a single class of data to the SVM. When there is a fault or any abnormality, the SVM obtains different types of data profiles from those it previously had. These two types of mixed data are used by the SVM to train the network and for classification prediction. In this regard, the SVM shows a very high classification accuracy for severe types of faults because the values of different parameters for this case are vastly different from the data of a healthy system. Thus, the SVM can correctly classify the state of the system with high accuracy for such cases. If some minor problems occur in the system, then some data are similar to those of the healthy system, and the SVM separates these data with low accuracy. Thus, the SVM can predict any type of power system abnormality leading to taking preventive actions before entering an unstable condition.

SVM is a statistical learning process used for classification problems, based on the separation of data by a hyperplane margin. The width of this margin separates the data, depending on the parameters of the SVM and the class of the data. SVM uses kernel tricks for nonlinear types of data to create a high-dimensional feature space model from its input space model.

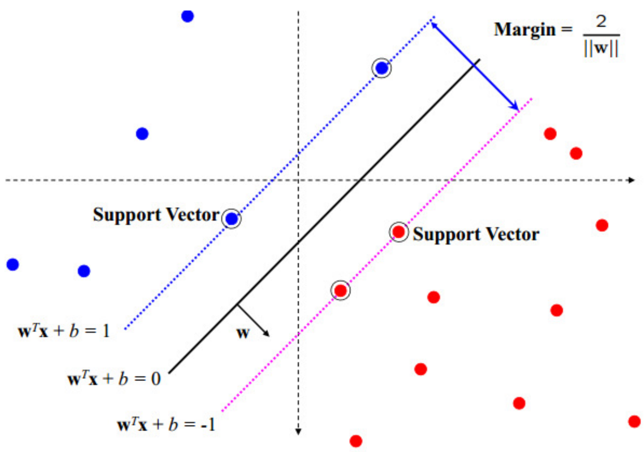

Fig. 1. Typical SVM architecture.

A. Support Vector Machine (SVM)

The main challenge in designing an SVM is to optimize the magnitude of the weight vector, $\|w\|$, which controls the width of the margin considering the proper separation of input or feature vectors. Another challenge is to properly choose the bias b for the positive and negative hyperplanes and the main separation hyperplane. Considering these constraints, the SVM model in this study was developed as outlined below [21-22]: Two classes of data are considered, a positive class and a negative class, separated by a straight line:

$$w^T x + b = 1 \tag{1}$$

$$w^T x + b = -1 \tag{2}$$

Both lines are equally spaced from the origin line:

$$w^T x + b = 0 \tag{3}$$

Thus, the decision boundary is obtained to satisfy the separation lines for all points correctly as in the following form:

$$y_i(w^T x_i + b) \geq 1, \quad \forall i \tag{4}$$

where $y_i \in \{1, -1\}$ and all data points $\{x_1, x_2, \ldots\ldots x_n\}$ are indicated for x_i.The decision margin m is maximized according to the following constraints:

Minimize: $\frac{1}{2}||w||^2$

Subject to: $y_i(w^T x_i + b) \geq 1, \quad \forall i$

Therefore, the Lagrangian is:

$$L = \frac{1}{2} w^T w + \sum_{i=1}^{n} \alpha_i (1 - y_i(w^T x_i + b)) \tag{5}$$

where α_i is the Lagrangian multiplier and $\left||w|\right| = w^T w$. After taking the gradient of the Lagrangian with respect to w for minimization, we have:

$$w + \sum_{i=1}^{n} \alpha_i (-y_i) x_i = 0 \tag{6}$$

$$w = \sum_{i=1}^{n} \alpha_i y_i x_i \tag{7}$$

where $\sum_{i=1}^{n} \alpha_i y_i = 0$ for all vectors on the margin. Substituting (5) into the Lagrangian, the original problem is converted into a dual-optimization problem:

$$L = -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j + \sum_{i=1}^{n} \alpha_i \tag{8}$$

$$L = \frac{1}{2} \sum_{i=1}^{n} \alpha_i y_i x_i^T \sum_{j=1}^{n} \alpha_j y_j x_j + \sum_{i=1}^{n} \alpha_i \left(1 - y_i \left(\sum_{j=1}^{n} \alpha_j y_j x_j^T x_i + b\right)\right) \tag{9}$$

Therefore, the dual problem is to maximize:

$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{10}$$

subject to: $\alpha_i \geq 0$ and $\sum_{i=1}^{n} \alpha_i y_i = 0$

B. SVM Configuration with Error Consideration

The error, ζ_i, in the proposed classification is based on the function $y_i(w^T x_i + b) \geq 1$, which approximates the number of misclassified samples [22].

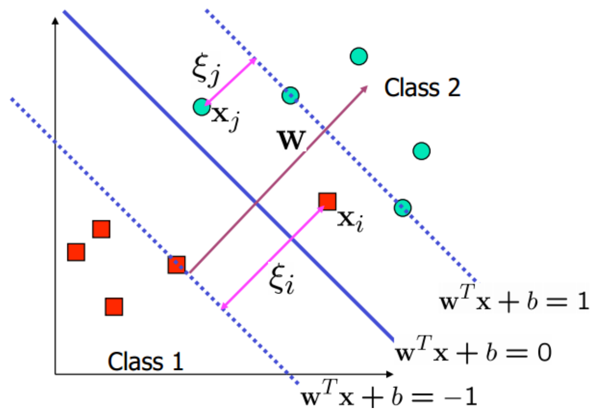

Fig. 2. SVM architecture with misclassification.

The hyperplane is now considered to be a soft margin hyperplane because of the error consideration, which must be minimized. Thus, the optimization equation for SVM becomes:

$$\text{Minimize: } \frac{1}{2}||w||^2 + C \sum_{i=1}^{n} \zeta_i \tag{11}$$

subject to: $y_i(w^T x_i + b) \geq 1 - \zeta_i$, $\zeta_i \geq 0$ and $\forall i$, where ζ_i represents the slack variables and C is the cost or tradeoff parameter between the error and margin. Accordingly, the dual-optimization equation becomes:

Maximize:

$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{12}$$

subject to: $C \geq \alpha_i \geq 0$ and $\sum_{i=1}^{n} \alpha_i y_i = 0$.

C. Kernel Trick

The kernel trick arises from the nonlinearity of the data in most cases, where the nonlinear data input is converted into a high-dimensional feature space. In such cases, the data can be separated linearly.

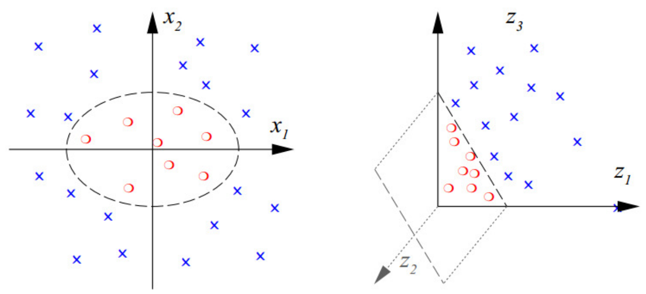

Fig. 3. Nonlinear two-dimensional data are transformed into a three-dimensional feature map.

$$(x_1, x_2) \to (z_1, z_2, z_3) = \left(x_1^2, \sqrt{2} x_1 x_2, x_2^2\right) \tag{13}$$

This transformation from input data to feature mapping facilitates similarity based on the dot product. It is formulated as follows:

$$\phi: R^2 \to R^3 \tag{14}$$

K is a function, known as the kernel function, that is mapped for all $x, y \in X$ such that:

$$K(x, y) = \phi(x).\phi(y) \quad (15)$$

where ϕ is a map for the dot product in the feature space in X, and:

$$\phi(x) = \left(x_1^2, \sqrt{2}x_1x_2, x_2^2\right), \quad x = (x_1, x_2) \quad (16)$$

Thus, a two-dimensional input is converted into three-dimensional space and a similarly higher-order feature space in F.

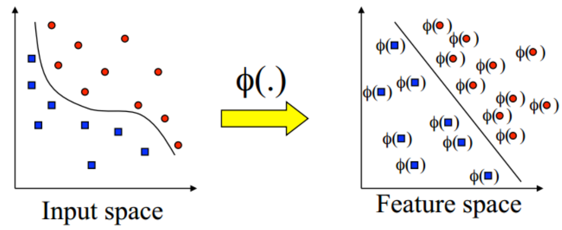

Fig. 4. Typical view of input and feature spaces. Note: feature space is of higher dimension than the input space in practice.

There are some standard common kernels for quadratic optimization problems:

- Linear Kernel: $K_0(x, y) = (x.y)$
- Polynomial Kernel: $K_1(x, y) = \left((x.y) + \varphi\right)^d$, where d is the degree of polynomials.
- Gaussian Kernel: $K_2(x, y) = \exp(-\frac{||x-y||^2}{\gamma})$
- Sigmoidal Kernel: $K_3(x, y) = \tanh((x.y) + \varphi)$

This study used the Gaussian kernel to optimize the quadratic optimization problem using a software implementation. Thus, the optimization equation was written in the form below:

Maximize:

$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i\alpha_j y_i y_j K_2(x, y) \quad (14)$$

subject to: $C \geq \alpha_i \geq 0$ and $\sum_{i=1}^{n} \alpha_i y_i = 0$.

III. RESULTS AND ANALYSIS

Two area power systems were considered for the validation and testing of the proposed method for the prediction of abnormalities in power systems and their devices using data classification. The system consisted of 14 buses and 4 generators, including the slack bus, where a Thyristor-Controlled Series Capacitor (TCSC) was coupled between the areas. The network itself consisted of 11 buses, and the other 3 buses were for TCSC [23]. The Power System Toolbox (PST) was used to obtain the voltage magnitude and machine angle samples of all buses and was run in MATLAB environment. MATLAB R2010a was used for all cases, including the SVM training. The LIBSVM 3.17 library was used for training and testing data classification, which is written in C language and was automatically interfaced with the prescribed version of MATLAB. LIBSVM supports a specific data type format, which was checked using Python 3.4. Classification was performed in MATLAB using the LIBSVM function, but parameter optimization was performed using Python 3.4.

To predict the faulty condition of the system, the angles of the machine in radians, the magnitude of the voltage per unit, and the corresponding time in seconds were considered to be the three features arranged following the prescribed LIBSVM format. The effectiveness of the proposed method was investigated by taking 601 samples for each feature. However, as the system consisted of 14 buses and 4 machines, where time was taken as the first type of feature, there were 19 columns arranged for the dataset according to the LIBSVM format. In this task, both faulty and healthy types of data were taken randomly to organize the dataset in one file to train the SVM and simultaneously classify data to show the system's condition; thus, it consisted of 1202 rows. Therefore, a total of 1202×19 = 22,838 samples were arranged in the file, following the LIBSVM format, where healthy sets were indicated by "+1" and faulty sets were indicated by "-1". Before using the data file, the correction of the data format was performed using Python 3.4. The parameters of the SVM were optimized for use in the classification program written in the MATLAB environment with the LIBSVM function according to the corresponding data using Python.

Five-fold cross-validation was used, and thus five outputs were created for each validation. This cross-validation involved a process of training the network to create a standard model to predict the stability of the system. The results were achieved after training and testing the SVM to predict system abnormalities. The minimized value of the objective function of the dual optimization problem and the optimized bias parameter *b* of the SVM separating hyperplane were 10.392955 and -0.037342, respectively. In this case, the total number of support vectors for classifying the data was 200. In this task, healthy and completely faulty data were used for classification. The classification accuracy was 100%, or 302/302. Less severe faulty data will result in lower accuracy. However, any classification accuracy will indicate that the system has faults because the SVM collects two classes of data; one class for a healthy system and a newly added faulty class of data resulting from the occurrence of faults. This positive classification indicates the system's abnormality. If the system is healthy, the SVM will collect only one class of data for classification, and the SVM will show negative results because it is valid only for two or more classes of data to classify these datasets. Thus, this negative result will assure the system operators of a healthy system with normal operation. In the case of the second mode, MATLAB was used with only the best 2 features out of a total of 18 to reduce the computation burden. The best 2 features were optimally identified among the 18. Meanwhile, the Radial Basis Function (RBF) kernel and Sequential Minimal Optimization (SMO) algorithm were considered to solve the quadratic SVM problem. Considering the box constraint or cost parameter for the case of error data and kernel function, gamma, the estimated objective function was minimized, as shown in Figure 5.

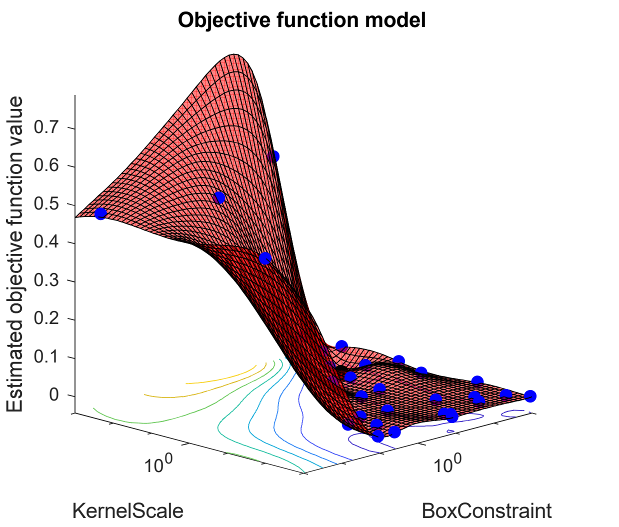

Fig. 5. Estimated objective function, kernel parameter, and box constraint.

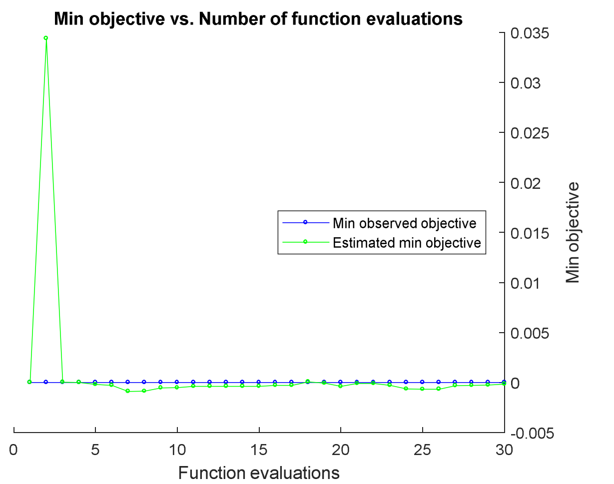

Fig. 6. Minimum estimated and observed objective function vs. the number of iterations.

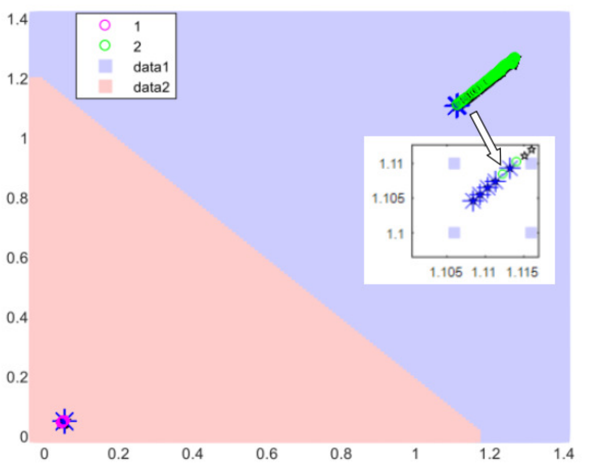

Fig. 7. Optimization hyperplane of healthy or faulty condition for 14-bus 4 areas power system.

In the MATLAB simulation, the optimal kernel parameter and box constraint obtained were 94.082 and 981.16, respectively, for the SVM model after minimizing the estimated objective function value to -0.00015283. For this SVM model, following the best estimated objective function value, the best observed objective function value achieved was "0". The corresponding best kernel and box-constraint parameters were obtained at 0.16154 and 5.5839, respectively. Figure 6 shows the best minimum estimated and observed objective function value, obtained after 30 iterations, and Figure 7 shows the hyperplane for this SVM model.

Following both the health and faulty data provided to construct the SVM model to classify the faulty condition apart from the healthy condition of a power system, the trained SVM model identified two hyperplanes of two colors. Although the data were non-linear, the RBF kernel successfully made it linear to be classified perfectly, which is clear from Figure 8. According to the Figure and the simulation results, the training and testing data were separated with 100% accuracy. Largely, the two classes of data overlapped in the two hyperplanes. The data in the two regions were separated into three colors, considering three types of data points: training, testing, and support vectors. The black star data points represent the training data points, the large blue star points indicate the support vectors, and the green points are the testing data points that can be observed from the zoomed-in picture in the light blue hyperplane area. The same scenario is also present in the light-red hyperplane area, where the testing data are depicted in magenta color.

IV. CONCLUSION

Abnormality detection is a major concerns in the field of power systems, where a fault may introduce an unstable abnormality into the system. In this study, a machine learning-based framework was proposed, using SVM to detect and distinquish a faulty system condition from a healthy condition based on the optimization of the cost parameter C and the Gaussian parameter γ. To ensure the robustness of the SVM models in classifying the data of healthy and faulty systems, two modes of optimization were conducted. In the first mode, the data were arranged according to the LIBSVM format in the MATLAB environment considering the maximum number of possible features and using Python to render the mode of optimization in a usable format. On the other hand, for the second mode of optimization, MATLAB was used directly to classify the condition of the power system. In this case, the combination of healthy and faulty data from 1202 samples was randomly separated for training and testing purposes in a ratio of 902/300. Five-fold cross-validation was performed during the training period of the SVM. The kernel trick was used for both modes to render the system linear for SVM classification, which is required for high-dimensional feature spaces and large samples of features. Compared to similar studies, the results obtained in both optimization modes demonstrated the robustness of SVM in classifying the healthy or faulty condition of the power system. In future work, the proposed method can be modified to analyze power systems with distributed generation and more integrated smart grid information and communication technologies.

ACKNOWLEDGMENT

The authors acknowledge the support of King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia.

REFERENCES

[1] X. Mou, W. Li, and Z. Li, "PMU placement for voltage stability assessment and monitoring of power systems," in *Proceedings of The 7th International Power Electronics and Motion Control Conference*, Harbin, China, Jun. 2012, vol. 2, pp. 1488–1491, https://doi.org/10.1109/IPEMC.2012.6259045.

[2] H. R. Ali and N. Hoonchareon, "Real-time monitoring of inter-area power oscillation using Phasor Measurement Unit," in *2013 10th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, Krabi, Thailand, Feb. 2013, pp. 1–6, https://doi.org/10.1109/ECTICon.2013.6559496.

[3] J. Zhang and D. Chen, "On the application of Phasor Measurement Units to power system stability monitoring and analysis," in *2012 IEEE Power and Energy Conference at Illinois*, Champaign, IL, USA, Oct. 2012, pp. 1–6, https://doi.org/10.1109/PECI.2012.6184607.

[4] D. Q. Zhou, U. D. Annakkage, and A. D. Rajapakse, "Online Monitoring of Voltage Stability Margin Using an Artificial Neural Network," *IEEE Transactions on Power Systems*, vol. 25, no. 3, pp. 1566–1574, Dec. 2010, https://doi.org/10.1109/TPWRS.2009.2038059.

[5] W. Nakawiro and I. Erlich, "Online voltage stability monitoring using Artificial Neural Network," in *2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, Apr. 2008, pp. 941–947, https://doi.org/10.1109/DRPT.2008.4523542.

[6] T. Hiyama, N. Suzuki, T. Kita, and T. Funakoshi, "Development of real time stability monitoring system for power system operation," in *IEEE Power Engineering Society. 1999 Winter Meeting (Cat. No.99CH36233)*, New York, NY, USA, Jan. 1999, vol. 1, pp. 525–530 vol.1, https://doi.org/10.1109/PESW.1999.747509.

[7] Y. Nguegan, A. Claudi, and C. Strunge, "Online Monitoring of the Electrical Power Transfer Stability and Voltage Profile Stability Margins in Electric Power Transmission Systems Using Phasor Measurement Units Data Sets," in *2009 Asia-Pacific Power and Energy Engineering Conference*, Wuhan, China, Mar. 2009, pp. 1–9, https://doi.org/10.1109/APPEEC.2009.4918561.

[8] H. Kang, B. Cvorovic, C. Mycock, D. Tholomier, and R. Mai, "PMU simulation and application for power system stability monitoring," in *2009 IEEE/PES Power Systems Conference and Exposition*, Seattle, WA, USA, Mar. 2009, pp. 1–7, https://doi.org/10.1109/PSCE.2009.4840125.

[9] Y. Yuan, P. Ju, Q. Li, Y. Wang, H. Hu, and H. Sasaki, "A real-time monitoring method for power system steady state angle stability based on WAMS," in *2005 International Power Engineering Conference*, Singapore, Aug. 2005, pp. 761-764 Vol. 2, https://doi.org/10.1109/IPEC.2005.207010.

[10] B. Bhargava and A. Salazar, "Use of Synchronized Phasor Measurement system for monitoring power system stability and system dynamics in real-time," in *2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, Pittsburgh, PA, USA, Jul. 2008, pp. 1–8, https://doi.org/10.1109/PES.2008.4596963.

[11] B. Bhargava and A. Salazar, "Use of Synchronized Phasor Measurement system for monitoring power system stability and system dynamics in real-time," in *2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, Pittsburgh, PA, USA, Jul. 2008, pp. 1–8, https://doi.org/10.1109/PES.2008.4596963.

[12] S. S. Biswas, Tushar, and A. K. Srivastava, "Performance analysis of a new synchrophasor based real time voltage stability monitoring (RT-VSM) tool," in *2014 North American Power Symposium (NAPS)*, Pullman, WA, USA, Sep. 2014, pp. 1–6, https://doi.org/10.1109/NAPS.2014.6965482.

[13] C. Bulac, I. Triştiu, A. Mandiş, and L. Toma, "On-line power systems voltage stability monitoring using artificial neural networks," in *2015 9th International Symposium on Advanced Topics in Electrical Engineering (ATEE)*, Bucharest, Romania, Feb. 2015, pp. 622–625, https://doi.org/10.1109/ATEE.2015.7133884.

[14] A. C. Z. de Souza, J. C. S. de Souza, and A. M. L. da Silva, "On-line voltage stability monitoring," *IEEE Transactions on Power Systems*, vol. 15, no. 4, pp. 1300–1305, Aug. 2000, https://doi.org/10.1109/59.898105.

[15] S. Chakrabarti and B. Jeyasurya, "Multicontingency voltage stability monitoring of power systems using radial basis function network," in *Proceedings of the 13th International Conference on, Intelligent Systems Application to Power Systems*, Arlington, VA, USA, Aug. 2005, https://doi.org/10.1109/ISAP.2005.1599282.

[16] S. S. Mehta and N. S. Lingayat, "Comparative Study of QRS Detection in Single Lead and 12-Lead Electrocardiogram using Support Vector Machine," *Engineering Letters*, vol. 15, no. 2, 2007.

[17] M. F. Hashmi, A. R. Hambarde, and A. G. Keskar, "Robust Image Authentication Based on HMM and SVM Classifiers.," *Engineering Letters*, vol. 22, no. 4, pp. 183–193, 2014.

[18] R. Eslami, S. H. H. Sadeghi, and H. A. Abyaneh, "A Probabilistic Approach for the Evaluation of Fault Detection Schemes in Microgrids," *Engineering, Technology & Applied Science Research*, vol. 7, no. 5, pp. 1967–1973, Oct. 2017, https://doi.org/10.48084/etasr.1472.

[19] B. K. Ponukumati, P. Sinha, M. K. Maharana, A. V. P. Kumar, and A. Karthik, "An Intelligent Fault Detection and Classification Scheme for Distribution Lines Using Machine Learning," *Engineering, Technology & Applied Science Research*, vol. 12, no. 4, pp. 8972–8977, Aug. 2022, https://doi.org/10.48084/etasr.5107.

[20] L. B. Raju and K. S. Rao, "Evaluation of Passive Islanding Detection Methods for Line to Ground Unsymmetrical Fault in Three Phase Microgrid Systems: Microgrid Islanding Detection Method," *Engineering, Technology & Applied Science Research*, vol. 11, no. 5, pp. 7591–7597, Oct. 2021, https://doi.org/10.48084/etasr.4310.

[21] C. Campbell and Y. Ying, *Learning with Support Vector Machines*. Cham, Switzerland: Springer International Publishing, 2011.

[22] L. H. Hamel, Knowledge Discovery with Support Vector Machines. Hoboken, NJ, USA: Wiley, 2009.

[23] P. S. Kundur, *Power System Stability and Control*, 1st Ed. New York, NY, USA: McGraw Hill, 1994.