Abnormal Voltage Regulation Detection in on-Grid PV-ESS System by Support Vector Machine with Principal Component Analysis

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***Abstract*—This paper describes an abnormal voltage regulation detection approach based on machine learning algorithm in a on-Grid photovoltaic (PV) system. The three-phase AC voltage of the power conversion system is measured using a voltage transformer and used as a feature of the proposed detection scheme. We integrated the principle component analysis (PCA) technique and the support vector machine to improve the algorithm's accuracy and reliability (SVM). Before applying the real-time data to the SVM model, the PCA analysis is performed. The proposed system's implementation results demonstrate its efficacy and robustness in the intelligent PV-ESS energy farm.**

***Index Terms*—Abnormality detection, voltage regulation, energy storage system, support vector machine, principal component analysis.**

I. Introduction

PHOTOVOLTAIC (PV) power generation is becoming more popular [1] and its integration into a power distribution network might cause substantial voltage regulation issues. Voltage imbalance between phases and over-voltage at nodes are two critical issues [2]. Existing voltage control devices, such as switched capacitors and on-load tap changers, are unable to offer accurate temporal responses to PV generation fluctuations. As a result, significant investments have been made to strengthen the power distribution system [3], including specific equipment such as static synchronous compensators and energy storage systems to adjust voltage [4]. Several centralized-based control approaches have also been presented [5,6] and have demonstrated superior performance.

Support vector machines (SVM) are widely used classifiers that are increasingly being applied in real-world issues because of their superior performance. SVMs [7][8], k-Nearest Neighbor [9], Decision Tree [10], and other classifiers can accomplish defect detection tasks. SVM offers anti-interference performance, outstanding stability, and a positive effect on the binary classification issue. In [11], the authors present SVM based defect diagnostics algorithm by using multi-sensory data from the wind turbines. Using stator currents and their related voltages data, the SVM is used to detect inter-turn short-circuit defects in a three-phase induction motor[12]. Moreover, The extended Kalman filter is employed to estimate three-phase currents in the transformer's primary wingdings, resulting in a hybrid SVM algorithm for successful diagnostics of power transformers [13]. By combining the principal component analysis (PCA) and kernel PCA with the deep structure, a method called deep extended principal component analysis - support vector machine was presented to make full use of the linear and non-linear information for fault identification [14]. Gaussian kernel-based SVM is applied for classifying various fault conditions of electromagnetic pumps by using vibration signals [15]. Furthermore, based on Pearson's correlation coefficient and the SVM technique, wireless sensor measurement fault is detected by using the highly co-related features [16].

Despite the recent increase in interest in data-driven techniques for fault detection and identification in the electric field, there are still gaps in current research in areas such as voltage regulation fault identification, over current fault detection, leakage current fault detection, fault detection in multi-sensor systems, and condition-based predictive fault detection. Considering the gaps in those areas, this paper proposes PCA-SVM based real-time fault detection scheme with multi-features to bridge the present research gap.

The main contribution of this article is to design an abnormality detection model for an integrated PV-ESS energy farm to detect abnormal voltage regulation during PV generation. Therefore, we implement this scheme for real-time detection. This paper organizes as follows: Section II describes the mathematical model for the proposed system. Simulation results and the corresponding discussion are illustrated in section III. Finally, the conclusion of this work is presented in section IV.

II. Methodology

In this section, the methodology of the proposed system is described. Since the PV-ESS is connected to the utility power grid, voltage regulation is a considerable issue. After installing a PV system into a power distribution network, the direction of power flow will change, causing voltage regulation at nodes that cross the acceptable limits. The voltage regulation can also occur due to leading and lagging power factors in the system. Consequently, the system needs to detect voltage regulation in

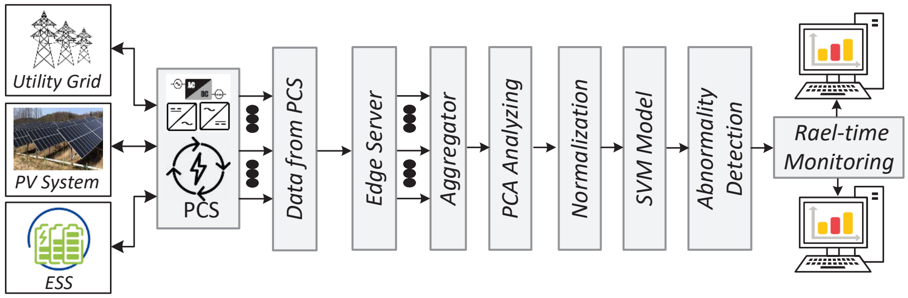

Fig. 1. Overall architecture of the system.

TABLE I
PERFORMANCE ANALYSIS FOR THE PROPOSED SYSTEM

Phase name	Data Sample	Average $V_{NL}(V)$	Regulation limit
R	10000	400.96	±1%
S	10000	397.70	±1%
T	10000	399.75	±1%

the system to know the system condition due to installing PV system. The Fig.1 shows the overall process of the proposed scheme.

The phase transformer is used to measure the three-phase voltage of the power conversion system (PCS). The voltage is measured and sent it to the edge server which is connected central cloud server. The cloud server is used to store the historic data three-phase voltages of the PCS system along with the power generation. The voltage regulation is calculated as follows:

$$VR^{ph}\%) = \frac{V^{ph}_{no-load}(t) - V^{ph}_{fullload}(t)}{V^{ph}_{no-load}(t)} * 100\% \tag{1}$$

where VR^{ph}, $V^{ph}_{no-load}$, and $V^{ph}_{full-load}$ are defined as voltage regulation, no load voltage and full load voltage.

Since the proposed algorithm is supervised learning, the data should be prepared based on the requirements of the algorithm. According to the acceptable range of voltage regulation, we have categorized the system condition. Above the acceptable range of the regulations, the system will be considered as abnormal system. In the proposed system, we have considered the acceptable range of voltage regulation which is presented in Table I. The most significant phase in the effectiveness of machine learning algorithms is generally the selection and extraction of good features.

The statistical learning theory and the Vapnik–Chervonenkis dimension are the foundations of the SVM algorithm [17], [18]. SVM analysis aims to determine an appropriate separating hyperplane by maximizing the margin between the separating data. Let's consider the training data sample D which is consist of N group of data [19]. Then the set of data samples can be expressed as follows:

$$D = (x_i, y_i)^N_{i=1}, \tag{2}$$

where $x_i \in R^M$ is the i^{th} data sample, and $y_i \in 1, -1$ is the sample label. The classification hyperplane is the SVM's optimization objectives which is defined by the following equation:

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

where $w = [w_1, ..., w_n]$ and $x_i = [x_1, x_2, ..., x_n]$ are n-dimensional weights vector and input vector, and b is termed as the biasing unit. According to the Lagrangian Duality Theory, Eq. (2) is turned into an optimization problem that solves for the Lagrangian factor α. The objective function is formulated as follows:

$$\min_{\alpha} \sum_{i=1}^{N}\sum_{j=1}^{N} a_i a_j y_i y_j k(x_i, x_j) s.t. \sum_{i=1}^{N} a_i y_i = 0, 0 \leq a_i \leq C, \tag{4}$$

where C is penalty factor and $k(\cdot)$ is a kernel function that achieves linear separation of samples in a high-dimensional feature space for linearly inseparable data.

$$f(x) = \sum_{i=1}^{N} a_i y_i k(x, x_i) + b \tag{5}$$

In this work, we conducted a classification experiment using Radial basis function (RBF) kernel functions, as shown below:

$$exp\left(\left|-\frac{\|x - x_i\|^2}{2\sigma^2}\right|\right) \tag{6}$$

The performance metrics which are considered to evaluate the proposed algorithm is defined as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{7}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{8}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{9}$$

$$F1 - Score = \frac{TP}{TP + .5(FP + FN)} \tag{10}$$

where, TP= number of true positives, TN= number of true negatives, FP = number of false positives, and FN= number of false negatives.

Fig. 2. Three-phase voltage profile of PCS.

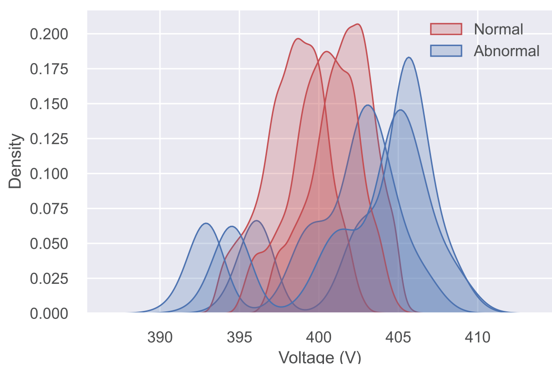

Fig. 3. Normal and abnormal three-phase voltage data distribution.

Fig. 4. Normal and abnormal data distribution of voltage regulations.

III. Result and Discussion

In this study, the three voltage data utilized for state identification and fault diagnosis is acquired from the PV-ESS and utility grid integrated system. The three phase voltage data samples are depicted in Fig. 2. Since the power generation from the PV is DC, the PCS is used to convert the generated DC power to the AC. However, to verify the performance of the proposed algorithm, we have taken into consideration 10000 data samples. The data is split into train and test category. In case of training data set, we have used 80% of total data and rest of the data is used for test purpose. Fig. 3 shows the density of normal and abnormal voltages in the datasets. After calculating the voltage regulation, the density of normal and abnormal data has shown in the Fig. 4. For increasing the performance of the SVM classifier, we have converted 3 features into single features by using PCA. The Fig. 5 shows density of normal and abnormal data distribution. The Table II shows the performance analysis of proposed fault classifier. It can be seen that the PCA-SVM overperform in terms of accuracy, precision, recall, and F1-Score. Table II shows that the SVM models of RBF kernel functions evaluated provided classification accuracy of 94.85%, while PCA-SVM based on

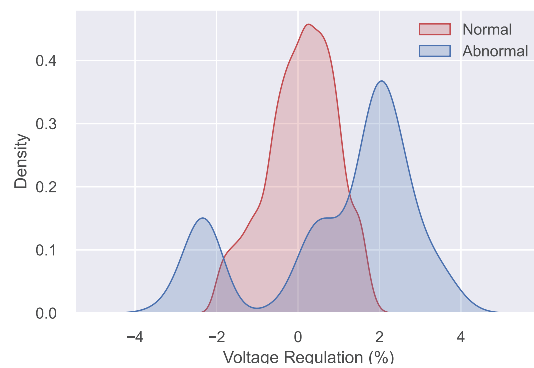

Fig. 5. Normal and abnormal data distribution of voltage regulations after PCA analysis.

TABLE II
PERFORMANCE ANALYSIS FOR THE PROPOSED SYSTEM

Model	Accuracy	Precision	Recall	F1-Score	AUC
SVM	94.85%	94.61%	86.42%	89.86%	0.92
PCA-SVM	95.40%	94.66%	86.73%	90.12%	0.90

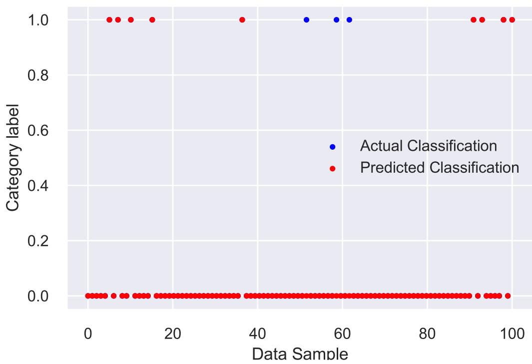

Fig. 6. Abnormal voltage regulations detection results.

rfb kernel functions delivered fault classification accuracy of 95.40%. However, the RBF kernel based SVM show better performance in terms of AUC score which means this classifier is more convinced in its prediction than PCA-SVM classifier. Fig.6 shows the testing results of the PCA-SVM classifiers for voltage regulations faults where normal and abnormal data have labels of 0 and 1, respectively.

IV. Conclusion

Effective abnormal voltage regulation detection in the PV-ESS and grid system can lead to secure and reliable utilization of renewable energy resources. In this study, we have developed machine learning algorithms for detecting abnormal voltage regulation detection. Moreover, the PCA analysis is used for better feature conversion which helps to increase the detection accuracy. The proposed scheme can achieve 95.40% accuracy which is better than the normal SVM algorithm.

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