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Enhanced fault identification in grid-connected microgrid with SVM-based control algorithm

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ABSTRACT

The penetration of renewable energy sources, electric vehicles (EVs) and load dynamics, and network complexities often lead to nuisance tripping in grid-connected microgrids. Traditional protection methods fail to discriminate fault and other dynamic volatilities in the system. The paper presents a novel two-level adaptive relay algorithm to avoid nuisance tripping in a grid-connected microgrid under varying grid dynamics. The novelty of the adaptive relay algorithm is that nuisance tripping is eliminated by precisely determining normal system-level dynamics at the first level using a phase deviation reference block. The first level determines the necessity for activating the second level, which consists of a detection scheme combining a multiclass support vector machine (SVM) and discrete wavelet transform (DWT). The hybrid DWT-SVM methodology ensures effective fault diagnosis, adapting to variations in energy sources, load fluctuations, and fault scenarios. Real-time hardware-in-the-loop (HIL) simulation validates the system's effectiveness in dynamic microgrid environments. Extensive experiments on scenarios, including faults, fluctuations in renewable energy generation, and intermittent simulations of EV charging and capacitor switching, were conducted to test the efficacy of the adaptive relay algorithm. Finally, experiments using OPAL-RT HIL real-time simulator and the Raspberry Pi microcontroller validated the adaptive relay algorithm in a grid-connected microgrid under varying grid dynamics.

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1. INTRODUCTION

The era of profound change for power systems has begun with the extensive integration of renewable energy sources, electric vehicle (EV) proliferation, and dynamic load changes. This integration led to the microgrid concept, an interconnected system of sources and loads with controllable attributes. Microgrids exhibit the flexibility to operate in both grid-connected and isolated modes. However, when operating in grid-connected modes, microgrids are vulnerable to faults occurring on the grid side [1]. In such instances, immediate disconnection becomes imperative due to the limited capacity of low-rating distributed energy resources (DER) to withstand high fault currents, particularly true for inverter-based DERs [2], which have a lower current-carrying capacity compared to conventional synchronous-based units [3]. Furthermore, the fault current level in an microgrid is highly reliant on the network layout and changes dramatically across operation modes (grid-connected/islanded) [4], [5]. Hence, an adequate protection strategy is essential for microgrids, considering the distinctive characteristics of their sources, dynamic operating conditions, and the need to accommodate renewable energy sources [6], [7]. EVs are gaining popularity as fossil fuel prices keep rising and environmental concerns about greenhouse gas emissions from the transportation sector increase. However, there are more security and protection issues due to the extensive EV integration into the grid [8].

The traditional protection strategies used in distribution systems become ineffective due to bidirectional fault currents in microgrids. Furthermore, the participation of DERs in fault currents interferes with protection device trip times [9], which deteriorates the coordination [10]. Immediately disconnecting the DERs in case of a problem is a simple way to deal with these issues. This strategy guards against problems like sympathetic tripping and blinding protection while maintaining the efficacy of legacy protection programmes [11]. However, when there is a significant penetration of DERs, disconnection of DERs may cause a decrease in grid voltage during fault conditions, resulting in instability [12]. Developing protection strategies that consider the impact of DERs and variations in grid topology becomes imperative to address the difficulties above. In order to do this, a variety of machine learning and computational intelligence techniques, including fuzzy systems, multi-agent systems, artificial neural networks (ANNs) [13], and metaheuristics, have been proposed as microgrid protection mechanisms [14].

The integration of renewable energy, coupled with variations in load patterns, poses significant challenges for microgrid protection [15]. Centralized protection schemes used in conventional power systems are deemed insufficient for dynamic microgrids [16]. The widespread adoption of renewable energy alters protection characteristics, requiring a robust fault prediction scheme that considers dynamic variations in the system [17]. A real-time fault detection and isolation protection system is crucial to prevent cascading failures and sympathetic tripping. Numerous ongoing research efforts are dedicated to developing comprehensive protection systems that address the unique challenges grid-connected microgrids face [18]. The critical component in these protection systems is the relay, but traditional relays with single-threshold and current-dependent functions are unsuitable for dynamic microgrids. Thus, there is a pressing need to develop new dynamic protection schemes [19].

Various schemes have been proposed in the literature to address microgrid challenges, including data mining-based differential protection, time-frequency-based differential schemes, fault clearing methods for converter-dominant microgrids [20], and machine learning approaches [21]. Recent studies have explored the application of convolutional neural networks (CNN) [22], random forest, k-nearest neighbour algorithms, and ANN for fault identification. Among these classifiers, support vector machine (SVM)-based classifiers have demonstrated superior performance [23].

Vijayachandran and Shenoy [24], a relay coordination scheme utilizing SVM for distribution systems with renewable energy sources is introduced. Li *et al.* [25] discusses a learning approach that incorporates fault detection and diagnosis, considering variations in irradiance. Aiswarya *et al.* [26] presents a unique adaptive scheme based on SVM for precise fault identification in microgrids. SVM yield several benefits: reduced outlier impact, faster prediction, higher accuracy, shorter execution time, and avoided over-fitting. The discrete wavelet transform (DWT) is utilized for feature extraction to improve prediction speed and accuracy while reducing the amount of data the machine learning model must handle [27].

Numerous studies have made a substantial contribution to diagnosing faults in grid-connected microgrids; however, considerable research gaps still open up possibilities for further investigation. When it comes to selecting and representing data for analysis, there remains a crucial gap. The dependability and quality of the data will influence how well the protection mechanism functions. More research on different fault scenarios, load patterns, and fluctuations in renewable energy sources should be conducted methodically to improve the flexibility of the fault diagnosis system. Uncovering the complex dynamics of DERs and dynamic demand changes is also necessary. In order to close these research gaps, it is recommended that DWT be used for feature extraction from the current and voltage signals in fault identification methodologies. Extracting significant features from the input signal-based approaches simplifies the SVM classification process and reduces the data training requirements. The approach precisely differentiates the fault cases from system-level dynamics. The approach will reduce the data handled by the machine learning model and improve prediction speed and accuracy.

This paper proposes a two-level adaptive relay algorithm to avoid nuisance tripping in a grid-connected microgrid under varying grid dynamics. The relay uses multiclass SVM in conjunction with DWT feature extraction for fault-type detection. Real-time experiments using the prototype relay significantly improved microgrid resilience and overall performance. A grid-connected microgrid fault prediction and identification method based on sequential multiclass machine learning is developed. The relay was trained using a hybrid DWT and SVM-based approach, which provided quick and precise training information for fault diagnosis. The major contributions of this paper are outlined below:

– The novel two-level adaptive fault identification scheme is tailored for grid-connected microgrids, addressing challenges like bidirectional fault currents, dynamic load variations, and DER participation. The proposed approach combines the DWT and multiclass SVM to enhance fault diagnosis efficiency.
– An adaptive relay system based on DWT and multiclass SVM ensures quick, accurate, and reliable protection, enhancing microgrid resilience under diverse operating conditions. A key development is the hybrid DWT and SVM methodology, which improves fault diagnosis speed and accuracy even with limited training data.
– Real-time HIL simulations validate the proposed scheme, utilizing a Raspberry Pi microcontroller interfaced with the OPAL-RT simulator. This experimental validation demonstrates the practical implementation and real-time prediction capabilities, ensuring reliability and precision in dynamic microgrid scenarios.

This paper is structured as follows: section 2 discusses the development of a fault identification scheme with multiclass SVM and DWT. Section 3 describes the analysis and outcomes of the simulation. The experimental validation of the approach utilising real-time HIL simulation is covered in section 4.

2. DEVELOPMENT OF A FAULT DETECTION ALGORITHM UTILIZING MULTICLASS SVM AND DWT TECHNIQUES

The microgrid promotes renewable energy with DERs but faces challenges from source variability and load changes like EV charging, causing voltage instability and power quality issues. Existing protective relays struggle, risking islanding and safety hazards. The proposed adaptive relaying method incorporates a two-tier adaptive relay algorithm to prevent nuisance tripping. The first level is a phase deviation reference block, which uses a PLL-based control strategy to continuously monitor the phase angle between the main grid and the microgrid. If the main grid and microgrid lose synchronization, the phase deviation reference block sends a initiating signal to the second level, which is a hybrid detection scheme that combines SVM and DWT techniques. This hybrid detection scheme is responsible for detecting any anomalies in the system. Therefore, the phase deviation reference block determines whether the hybrid detection scheme needs to be activated, allowing the system to avoid unnecessary disconnections and unintentional islanding while maintaining operational speed. Figure 1 depicts a two level hybrid SVM and DWT method to detect system issues efficiently. With minimal data, it identifies faults, source dynamics, and load fluctuations reliably. Multiclass SVM distinguishes faults using voltage and current measurements processed through DWT.DWT-based feature extraction captures fine signal details, enabling fast and accurate SVM decisions with minimal data. Signal undergoes two-level decomposition via low-pass and high-pass filters. SVM classifier is trained on four essential features per scenario.

2.1. Discrete wavelet transform

The process of DWT involves dividing a signal into wavelets that are localized in both time and frequency domains. This division is achieved through a combination of filtering and downsampling techniques. To establish a hierarchical representation, the signal is systematically decomposed into high-frequency detail coefficients and low-frequency approximation coefficients. Features that capture various aspects of the signal are then extracted from these coefficients at different levels. The Daubechies wavelet, specifically the db4 wavelet, is selected as the mother wavelet for its advantageous properties such as good time-frequency localization, similarity to signals observed during fault conditions, and its ability to effectively capture both low and high-frequency components of the signal. In this context, a two-level decomposition in DWT is chosen for feature extraction. This decision is made because the initial two levels typically contain the most critical information, leading to reduced noise and computational complexity. By examining both the approximation and detail coefficients obtained through DWT, relevant features are extracted to facilitate fault detection within the signal. This methodology enables the identification of key characteristics that can indicate the presence of faults or anomalies, thereby enhancing the effectiveness of fault detection and diagnosis processes. The features selected for the DWT analysis are the mean of detailed voltage coefficients, the mean of approximate voltage coefficients, the mean of detailed current coefficients, and the L1 norm.

$$\bar{V}_{approx} = \frac{\sum_{i=1}^{n} V_i^{approx}}{n} \tag{1}$$

$$\bar{V}_{det} = \frac{\sum_{i=1}^{n} V_i^{det}}{n} \tag{2}$$

$$\bar{I}_{det} = \sum_{i=1}^{n} I_i^{det} \tag{3}$$

$$\|V\|_1^{det} = \sum_{i=1}^{n} V_i^{det} \tag{4}$$

For every microgrid event in this work, four features are gathered from thirteen buses, for a total of fifty-two DWT features. The total number of data points collected is calculated as 52 (selected DWT features) multiplied by the sum of 556 data points from 245 fault cases and 311 normal cases, resulting in a total of 28,912 data points. The gathered data undergo preprocessing and are classified with suitable labels to train the supervised learning model. For this training, 80% of the data is utilized, while the remaining 20% is allocated for evaluating the model's effectiveness.

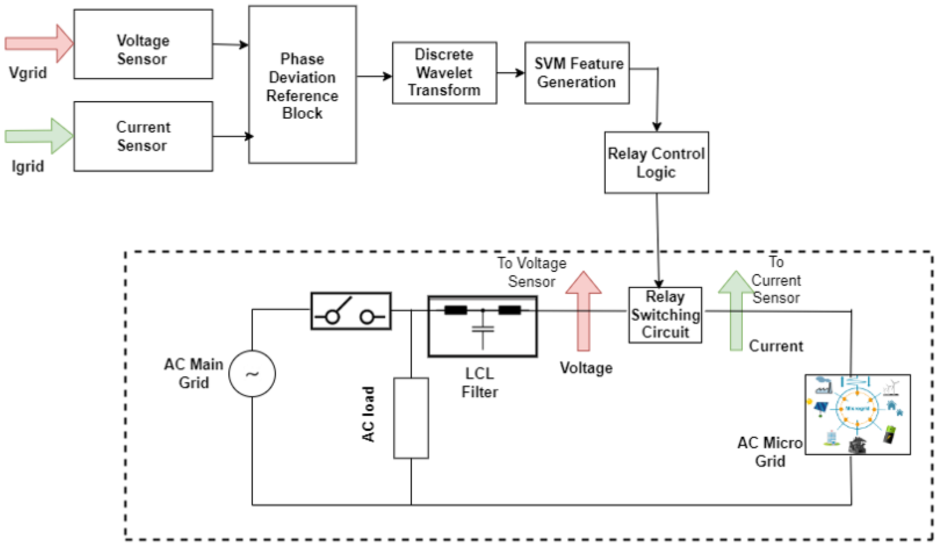


Figure 1. Fault identification scheme with DWT and SVM

2.2. Multiclass SVM classifier

SVM present a practical option for fault diagnosis in complex data environments where traditional machine learning and deep learning methods may fall short. Their sound theoretical base makes it possible to manage high-dimensional data effectively, which is a common feature of fault identification tasks involving many measurements and indicators. SVM's resilience to overfitting is one of its main advantages in fault detection, helping to avoid costly errors. This resilience results from its statistical learning principles, which are particularly helpful when the number of dimensions exceeds the number of samples. The kernel trick enables SVM to navigate and classify a wide range of complex and variable data structures by converting them into spaces where they become separable. SVM provides transparency in its decision-making process, differentiating it from the frequently opaque deep learning models. The process is a crucial aspect of a fault diagnosis, where it is crucial to comprehend the reasoning behind predictions. SVM may also offer computational efficiency for smaller to medium-sized datasets, offering a faster solution without compromising performance in comparison to its deep learning peers. Furthermore, SVM's skill in managing imbalanced datasets, which are prevalent in fault identification, ensures its sensitivity to minority classes, such as faults, due to its thoughtful kernel and parameter selection. As a result, SVM are a standout option for problem diagnosis, supported by their capacity to handle complicated and high-dimensional data as well as their open and theoretically sound decision-making process.

The multiclass SVM classifier is practical for tasks with multiple classes. Originally for binary classification, SVM has been adapted for multiclass tasks. SVMs efficiently categorize occurrences into multiple classes, utilizing support vectors near the decision boundary. For multiclass SVMs, there are two approaches: one-vs-one (OvO) and one-vs-rest (OvR). For each pair of classes, OvO trains a binary classifier, producing $K.(K-1)/2$ classifiers for K classes. OvR produces K classifiers by training a binary classifier for each class against all others. Computationally, OvR usually performs better, especially when dealing with several classes.The radial basis function (RBF) kernel adopted demonstrates exceptional performance when dealing with overlapping data. Specifically, the most influential factors in classifying new observations are the closest data points, while those situated at a greater distance have minimal impact on the classification process.

With a set of training samples $(x_1, y_1), (x_2, y_2)\ldots.(x_m, y_m)$, where y_i represents the associated class label and x_i represents the feature set of the i^{th} sample, the decision-making function $f(x)$ for a binary SVM with labels +1 and -1 is as follows:

$$f(x) = sign\left(\sum_{i=1}^{n} w_i.x_i + b\right) \tag{5}$$

in this case, the maximum number of features is n, the bias term is b, the input features are x_i, and the weight parameters are w_i.

The decision function for class k in a multiclass SVM is represented by $f_k(X)$, where K is the total number of classes.An SVM that is binary and trained to differentiate class k from the others is represented by each $f_k(X)$. The predicted class y for a data point x is the one with the maximum decision function value:

$$\hat{y} = argmax_k\left(\sum_{i=1}^{n} w_{ki}.x_i + b_k\right) \tag{6}$$

Figure 2 shows the multiclass SVM training and prediction flowchart using a OVR strategy. Fault states are classified, while normal conditions and dynamic fluctuations are grouped together. This aids in distinguishing when relay operation is required. It also enables fault detection and identification.

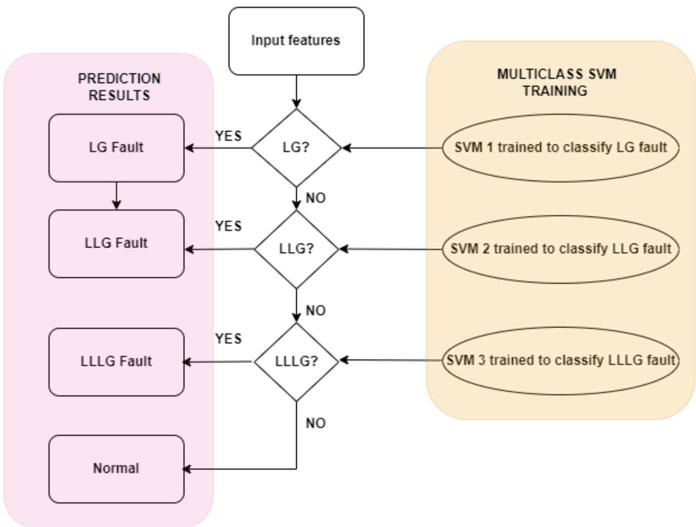


Figure 2. Multiclass SVM training and prediction

3. IMPLEMENTATION OF FAULT DIAGNOSIS METHODOLOGY USING MULTICLASS SVM AND DWT

3.1. Modelling of system under study

A radial microgrid with 13 buses, operating at 13.8 kV and 50 Hz, is simulated using the MATLAB/Simulink platform. Three distributed generation (DG) sources are part of the microgrid configuration: two diesel generators and photovoltaic (PV) units at buses 1, 2, and 10. Furthermore, buses 1, 2, 7, and 8 have a dynamic EV charging load. Table 1 contains the microgrid's comprehensive specifications.

Table 1. Microgrid parameters

Component	Parameter
Three phase grid supply	Voltage = 13.8 kV (transformer 69/13.8 kV)
Photo voltaic system	70 kW each at bus 1,2 and 10
Generator (diesel)	500 MVA ,440 V, at bus 8,13
EV station	22 kW each at Bus 1,2,7,8
Load	20 kW load at 1, 2, 7, 8, 9, 11, 12, 13
	10 kW load at bus 7 and 10

3.2. Design of prediction scheme

An adaptive protection scheme is developed for fault identification in a grid-connected microgrid, particularly when integrating dynamic sources like PV and loads like EV. As the system behavior becomes dynamic, a reliable fault detection technique is crucial to minimize energy loss and monitoring costs in a growing microgrid. This section introduces a fault detection system based on DWT and multiclass SVM . The flowchart depicting offline training and online prediction processes is shown in Figure 3.

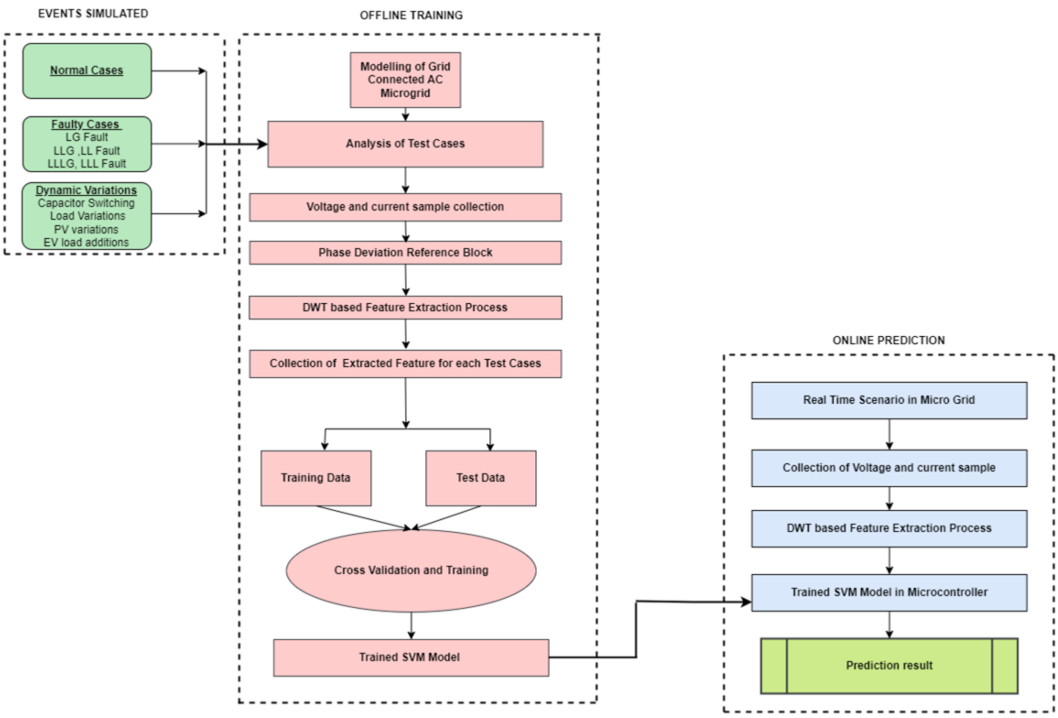


Figure 3. Multiclass SVM and DWT scheme

A Simulink model of a 13-bus system is constructed for this objective. Sensing devices gather the voltage and current signals, which are then supplied to the phase deviation reference block-basically a PLL. The DWT and SVM module will receive an initiating signal when the reference value above a predetermined limit. In this scenario, a pretrained SVM classifier receives the data. Voltage and current readings from every bus under a variety of conditions, such as faults, load variations, and regular grid operations, are included in the training dataset. These measurements are used to extract features using the DWT, which is then input into SVM models. In the course of testing, bus data is sent in real-time communication to the transformation block, which uses it to extract features for the SVM models that are executed in microcontrollers. These models forecast microgrid problems and show them to operators through a graphical user interface (GUI). This organized process ensures systematic defect detection in dynamic microgrid settings, aiding quick and effective decision-making.

3.2.1. Data collection and classifier modelling

The IEEE 13-bus system is modified and modeled in MATLAB to simulate the microgrid under study. The DWT is used to extract features from the three-phase voltages and currents from each of the thirteen buses. With Google Colab's assistance, SVM models are built and trained using Python's sci-kit learn module. The svc function is utilized for training. Each microgrid event gathers four features from each of the 13 buses, resulting in a total of 52 DWT features. This comprehensive dataset comprises 28,912 data points covering various fault and normal scenarios, enabling a thorough examination of microgrid behavior. Table 2 displays the obtained DWT characteristics for the bus at the point of common coupling, along with the decision made by the SVM classifier, feature values, and corresponding label for each scenario.

Table 2. Extracted DWT-based features

Sl no	Event	Feature 1	Feature 2	Feature 3	Feature 4	Label	Decision
1	LG fault at 0.2 sec	19,854	6.4732	-0.0086	647.32	LG fault	-1
2	LLG fault at 0.2 sec	11,928	19.28	-0.0183	1,928	LLG fault	-1
3	LLLG fault at 0.2 sec	150.18	56.904	-0.1286	5,690.4	LLLG fault	-1
4	Normal	20,701	13.587	0.0014	1,358.7	Normal	1
5	EV1 and EV2 charging at 0.2 sec	20,556	13.575	-0.0115	1,357.5	Normal	1
6	Transformer energisation at 0.2 sec	20,695	13.593	0.0017	1,359.3	Normal	1
7	Capacitor switching at 0.2 sec	20,855	-29.325	0.2759	-2932.5	Normal	1
8	Irradiation variation in PV unit 1 (1,000 W/m^2 to 100 W/m^2)	20,700	13.588	0.0014	1358.8	Normal	1
9	Load variation of 10% at 0.2 sec	20,688	13.573	-0.0008	1,357.3	Normal	1
10	Load variation of 20% at 0.2 sec	20,629	13.327	0.0066	1,332.7	Normal	1

4. RESULTS AND DISCUSSION

4.1. Simulation results

The microgrid model is tested under various scenarios, including faults, fluctuations in renewable energy generation, and intermittent simulations of EV charging and capacitor switching. These simulations aim to enhance the machine learning model's understanding of microgrid dynamics. Fault scenarios such as three-phase to ground (LLLG), double line to ground (ABG, BCG, ACG), and single line to ground faults in three-phase lines (AG, BG, CG) are incorporated into both islanded and grid-connected modes. Below are examples of simulated test scenarios used for data collection.

- Fault in line: single line to ground (LG), double line, and triple line faults are simulated on Line 1 in both grid-connected and islanded modes of the microgrid. Faults start at 0.4 seconds and end by 0.8 seconds, causing a tenfold increase in fault current. Voltage and current waveforms during the LLLG fault are depicted in Figure 4, reflecting changes in output, which will serve as features for SVM analysis.
- PV irradiation variations and PV outages: PV units are disconnected sequentially at 0.2 seconds, with voltage and current measurements recorded. Irradiation decreases abruptly from 1,000W/m^2 to 100W/m^2 for 0.2 seconds during each disconnection. Significant power and current variations are observed at bus 1. Figure 5 shows voltage and current waveforms during PV irradiation fluctuation, reflecting changes in output. These variations serve as features for SVM analysis.
- Dynamic variations in system: dynamic simulations induce variations such as load fluctuations, fast EV charging, and transformer/capacitor switching. Data is collected, with loads arbitrarily altered by +/- 10% to simulate fluctuations. Fast-charging EVs are activated at buses 1, 2, 7, and 8 for 0.2 seconds, noting resulting changes. Adding EV load causes voltage drop and increased current. Transformer energization and capacitor switching simulations illustrate system dynamics further. Switching events occur at 0.2 seconds,

observing voltage and current fluctuations. Relay operation is unnecessary as it produces transient changes considered a natural part of operation.

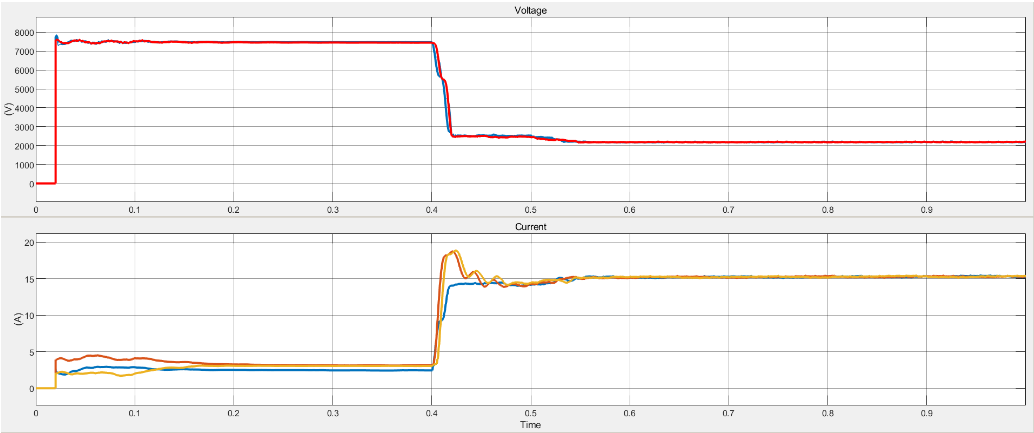


Figure 4. Voltage, current and power output at bus 1 during LLLG fault

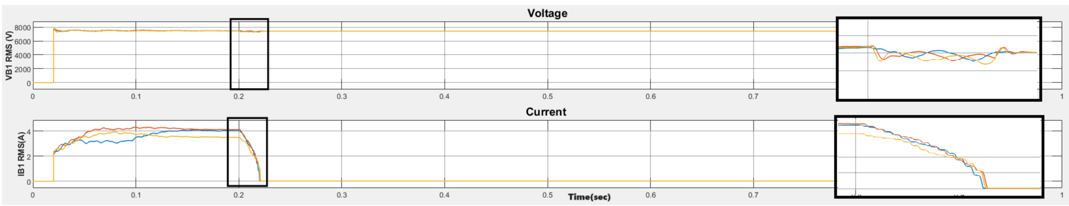


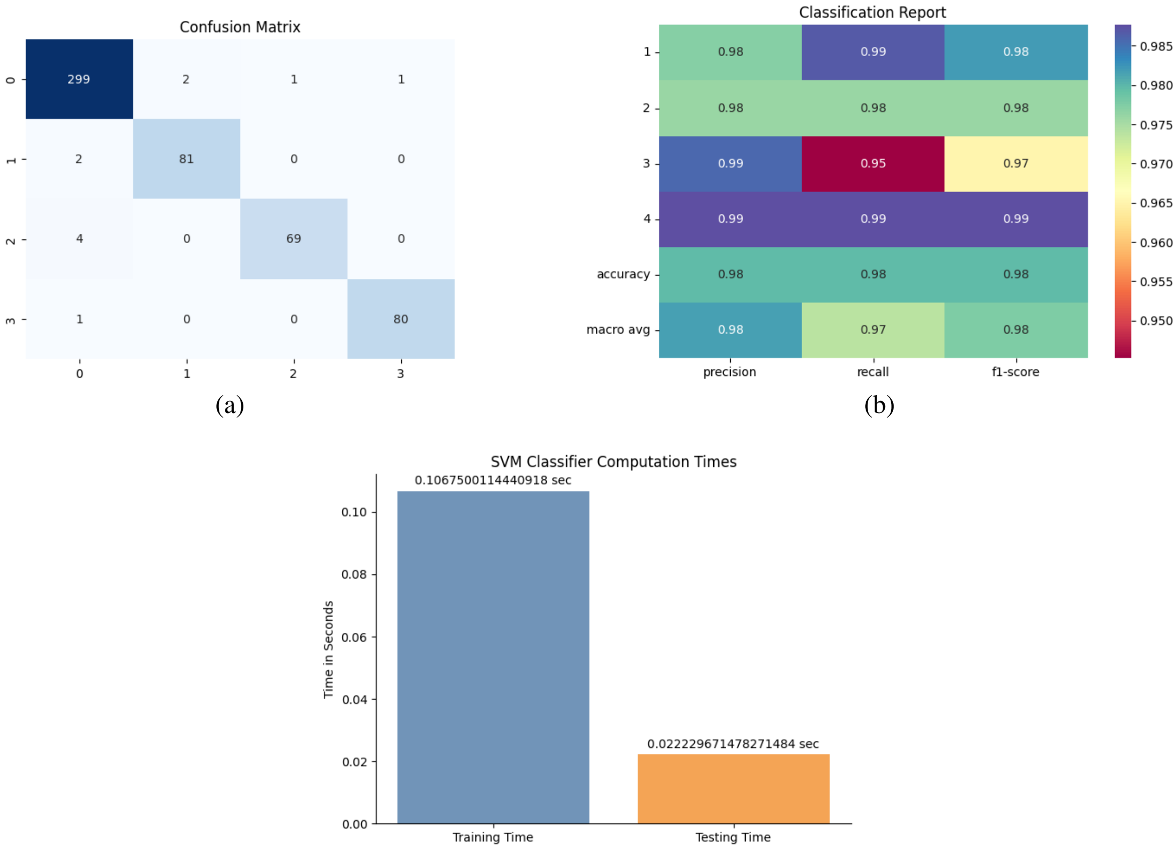
Figure 5. Voltage and current output at bus 1 during irradiation variation at PV1

Simulations conducted for various events present prediction outcomes in Table 3. The multiclass SVM DWT model's performance summary and evaluation metrics is illustrated in Figure 6. Within the confusion matrices illustrated in Figure 6(a), the diagonal entries represent the count of accurately predicted observations, known as true positives (TP), while the off-diagonal entries indicate incorrect predictions, referred to as false positives (FP). The comparison report showing the accuracy, precision and performance matrix components are shown in Figure 6(b). The computation time taken by classifier for both testing and training is illustrated in Figure 6(c).

The proposed multiclass SVM with DWT approach outperforms previous SVM models based on RMS voltage and current values [26], offering higher accuracy as shown in Table 4, which denotes excellent prediction alignment. Moreover, a comparison between the SVM classifier and the Decision Tree (DT) classifier across various events as shown in Table 5 demonstrates SVM's superior performance in predicting microgrid parameter variations.

Table 3. Predictions by the developed SVM based scheme

Event simulated	Specification	Label	Predicted event	No of cases simulated	Prediction accuracy
LG fault	Fault at line 1 and 5	LG fault	LG	85	100%
LLG fault		LLG fault	LLG	75	99.50%
LLLG faults		LLLG Fault	LLLG	85	99.10%
Normal operating condition		Normal	Normal	101	99.50%
PV irradiation Variation and outages	At bus 1, 2 and 10	Normal	Normal	35	99.30%
Load variations	10% and 20% at bus 1, 2, 7, 9	Normal	Normal	70	100%
EV load additions	At bus 1, 2, 7, 8	Normal	Normal	60	99.40%
Transformer energisation	At bus 3	Normal	Normal	25	100%
Capacitor switching	At bus 3	Normal	Normal	20	100%



(a) (b) (c)

Figure 6. Evaluation metrics and performance overview of the multi-class SVM DWT model: (a) confusion matrix displaying classification accuracy and errors; (b) comparison report with precision, recall, and F1-score metrics for each class; and (c) compilation time showing the model's training efficiency

Table 4. Comparison with prior work

Event	No of cases taken	SVM with Vrms and Irms	SVM and DWT
LG fault	85	98.70%	100%
LLG fault	75	98.20%	99.50%
LLLG fault	85	98.20%	99.30%
Normal	311	98.50%	99.10%

Table 5. Comparisons SVM vs DT

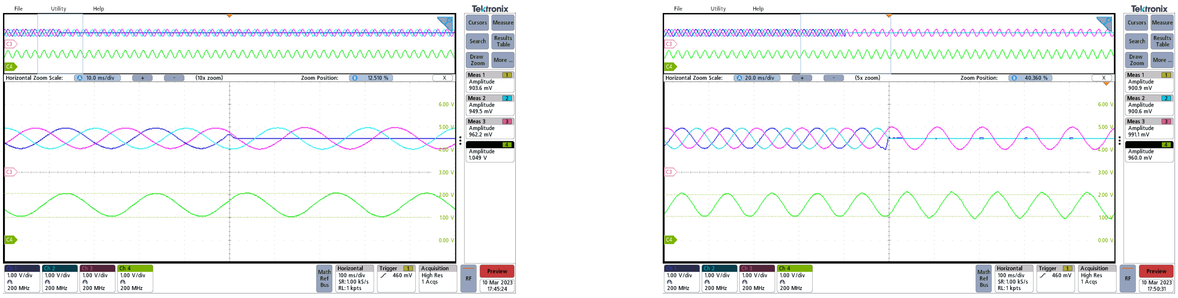
ML model	Accuracy
SVM	99.1
DT	97

5. EXPERIMENT VALIDATION OF DWT BASED SCHEME USING REAL-TIME HARDWARE IN LOOP SIMULATION

The microcontroller and OPAL-RT work together to simulate in real time. The simulated 13 bus microgrid model comprises two main subsystems: SM Master and SC Console. All computational components are integrated into the SM Master, which is inserted into the OPAL-RT simulator OP 4510. Conversely, the SC Console operates within the host system, facilitating user interaction and integrating Simulink blocks for data collection and display.

For real-time operation, the micro grid model in the SM Master subsystem is converted to C and put into the OP 4510 OPAL-RT real-time simulator. The Raspberry Pi model 4 b, known for its large RAM and fast onboard processor, is the optimal choice for machine learning applications, providing efficient tools for running machine learning programs. Trained machine learning models, saved as Python Pickle files (.pkl) from Google Colab, are included in the Python prediction code for seamless integration. This method enables the easy deployment of trained models in the Python environment for accurate and efficient predictions, ultimately installed onto the Raspberry Pi for real-time use.

In real-time simulation outputs are for fault cases are depicted in Figure 7, the voltage and current waveforms under single line to ground fault is shown in Figure 7(a) and double line to ground fault case is shown in Figure 7(b). The faults are created while system is running in real time mode with OPAL RT unit and corresponding variations are observed in the waveforms. The occurence of LLG fault in line 1 is predicted by the in around 11.79 ms and LG fault in line 1 is predicted in around 7.26 ms. The corresponding experimental set up, GUI display, 13 bus voltage and current measurements are displayed in the host PC.

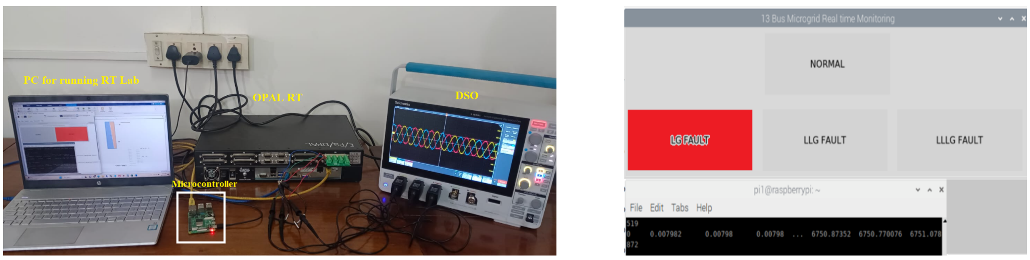


(a) (b)

Figure 7. Real time voltage and current output at bus 1 from PCC for (a) LG fault and (b) LLG fault

The real-time simulator transmits thirteen bus measurements as a 1D array to the Raspberry Pi using the UDP/IP protocol. Tkinter Python library constructs a user-friendly GUI on the Raspberry Pi, displaying SVM model predictions clearly. The microgrid model is loaded into the OPAL-RT OP4510 simulator for HIL simulation. The Raspberry Pi's GUI and control are displayed on the PC for the RT Lab. The Raspberry Pi controller executes the trained SVM models as part of the system implementation.

OPAL-RT and the Raspberry Pi microcontroller communicate via ethernet and UDP/IP. Figure 8 shows the HIL simulation configuration for real-time prediction. Figure 8(a) illustrates the HIL experimental setup, whereas Figure 8(b) shows the output at the GUI interface. OPAL-RT's analog output range is -16 V to +16 V, so the DSO displays scaled voltage and current outputs. Real-time output serves as test data, with classifier output displayed on the Raspberry Pi GUI.



(a) (b)

Figure 8. Hardware in loop simulation of system (a) experimental setup and (b) prediction output at user interface of Raspberry Pi

6. CONCLUSION

Creative protection techniques are crucial in grid-connected microgrids to prevent nuisance tripping amidst dynamic circumstances like transformer energization and capacitor switching, along with source and load dynamics. This article introduces an intelligent adaptive relay system employing DWT and multiclass SVM to address the challenges posed by renewable energy integration, EVs, load dynamics, and microgrid complexities, which often lead to nuisance tripping in grid-connected setups. By combining SVM and DWT, the proposed methodology ensures precise fault identification even amidst severe dynamics, preventing unnecessary disconnections and enhancing microgrid resilience. Real-time HIL simulations validate the system's effectiveness in dynamic microgrid environments. The research highlights the importance of developing intelligent adaptive relays for grid-connected microgrids to enhance fault detection and prevent nuisance tripping. The hybrid DWT-SVM methodology enhances fault diagnosis speed and accuracy, even with limited training data. In conclusion, the paper presents a comprehensive approach to fault identification in grid-connected microgrids, emphasizing the effectiveness of the SVM-based adaptive scheme with an improved control algorithm. The integration of SVM and DWT techniques offers a robust solution for fault diagnosis, contributing to the development of more adaptable and resilient microgrid protection strategies. The proposed methodology's validation through real-time simulations underscores its practical implementation and reliability in dynamic microgrid environments.

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