

Fault Current Directionality in Islanded Microgrids Using SVM and Synthetic Harmonic Injection

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Abstract—Determining fault current direction in islanded inverter-based microgrids is highly challenging due to the unconventional and limited fault current contribution of inverters. This paper explores the application of a combined support vector machine (SVM) and synthetic harmonic injection method for determining fault current direction in such microgrids under balanced faults. A training set is created and an SVM is trained for each relay by applying forward and reverse faults in PSCAD/EMTDC and using MATLAB. The trained SVM is then used to predict fault current direction for a balanced fault at a different location. Simulation results are provided to analyze the performance of the proposed method.

Index Terms—Inverter-based generation, machine learning, microgrids, power system protection, support vector machines.

I. INTRODUCTION

Advances in renewable energy generation and power electronics have enabled the proliferation of inverter-based resources (IBR) in power distribution systems in the form of microgrids. Microgrids can operate in islanded or grid-connected modes. Microgrids have enough generation capacity to supply loads. Thus, they can maintain power supply in case of grid faults. In addition, in case of having excess generation, they can supply power to the grid to assist with its recovery and reduce the frequency and duration of outages. Therefore, microgrids are an important asset for improving the reliability and resiliency of the grid [1].

In order to maintain the advantageous features provided by microgrids, they should be protected from internal short-circuit faults. This issue is challenging because of very small fault current contribution of IBRs in the islanded mode [2] and failure of directionality detection by conventional torque- and impedance-based relays due to corrupted voltage and current phasor estimations [3]. A multi-setting adaptive microgrid protection scheme based on directional overcurrent relays is proposed in [4]. However, this method is designed for microgrids with synchronous generation, and it is rendered

infeasible in inverter-based microgrids because it cannot operate with small fault current magnitudes during islanded mode. Distance protection is not recommended either due to the presence of short lines and compromised phasor estimation [1]. Differential relaying is immune to the aforementioned challenges. However, employing differential relays for every line is uneconomical, and they cannot operate on branched lines because the sum of currents is no longer zero and the bidirectional power flow caused by the IBRs makes the relay setting to be very complex [5]. In order to overcome these problems, a protection scheme that relies on the capabilities of the existing IBRs and commercially available digital relays is proposed in [6]. In this method, IBRs inject a pattern (IP) of 3rd, 5th, and 7th harmonics when the voltage drops below a certain threshold during a fault. IPs are measured at each relay station (MP), and fault current direction is determined by measuring the alignment percentage between MP and the characteristic pattern (CP) of the relay. This method utilizes the cosine similarity (CS) function to determine the degree of alignment between the two patterns. However, CS is not always reliable because the alignment threshold varies with different conditions such as microgrid topology, IBR locations, and ratings. The same issue exists with calculating the CPs as nodal analysis is required for this purpose. Additionally, fault current directionality is more reliable if it can be performed based on local measurements and without communication. Determining fault current direction can be formed into a classification problem within the realm of machine learning with two classes: forward and reverse. Support vector machines (SVM) are a reliable choice for solving this classification problem [7], [8]. SVMs are preferred over artificial neural networks (ANN) because they offer larger generalization capability. Moreover, ANNs are difficult to execute during the sampling interval. SVMs are used in [9]–[15] to solve power system protection problems. References [16], [17] investigate the application of machine learning for microgrid protection. However, both of these methods are designed for microgrids with synchronous generators and are not applicable to inverter-based microgrids.

In this paper, SVM is used alongside the synthetic harmonic injection method proposed in [6] to detect fault current direction in an islanded inverter-based microgrid under balanced faults. SVM replaces the CS function to eliminate the need for calculating an alignment threshold and CPs for the protective

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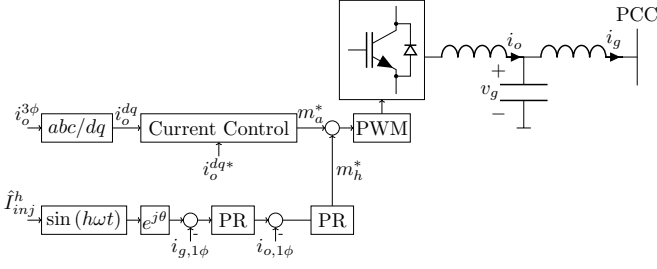


Fig. 1. Block diagram demonstration of the modified IBR controller for implementing the method proposed in [6].

relays. The harmonic patterns measured at each relay are unique and linearly-separable under forward and reverse faults. This makes SVM a reliable tool and enables its simple implementation. Studies are performed in PSCAD/EMTDC software to create a dataset for training the SVM. The `fitcsvm` function in MATLAB is used to train the SVM. Simulation results are provided to demonstrate the effectiveness of the proposed method.

The rest of this paper is structured as follows. Section II provides an overview of the method proposed in [6]. An overview of SVM theory is presented in Section III. Section IV discusses the problem setup. Section V analyzes the performance of the proposed method. Finally, conclusions are presented in Section VI.

II. OVERVIEW OF SYNTHETIC HARMONIC INJECTION-BASED PROTECTION

Fig. 1 shows the modified per-phase IBR controller for implementing the method proposed in [6]. The upper control loop is the conventional IBR controller. The output current of the IBR i_o is measured, converted into dq values, and fed to the current control loop. Based on the reference output current, which is either determined by PQ control or droop control, the reference fundamental modulation signal m_a^* is generated by this loop and fed to the PWM block to control the inverter. The lower loop is designed for injecting synthetic harmonics during faults in the microgrid. The relationship for each synthetic harmonic i_{inj}^h is designed as:

$$i_{inj}^h = \hat{I}_{inj}^h \sin(h\omega t + \theta) \quad (1)$$

$$h = 3, 5, 7,$$

where $\hat{I}_{inj}^h$ is the magnitude of the h th synthetic harmonic, ω is the fundamental angular frequency, and θ is the phase shift of each synthetic harmonic. The magnitude of the injected harmonics $\hat{I}_{inj}^h$ is calculated using (2) to limit the total rms current of the IBR to 120% of its rated current I_{DG}^{rated} :

$$\hat{I}_{inj}^h = 0.38 I_{DG}^{\text{rated}}. \quad (2)$$

The phase shift of the synthetic harmonics are set to θ instead of $h\theta$ to convert the 3rd and 5th harmonics into positive-sequence components rather than zero- and negative-sequence components. Thus, the low-order harmonics can be utilized with the help of this manipulation.

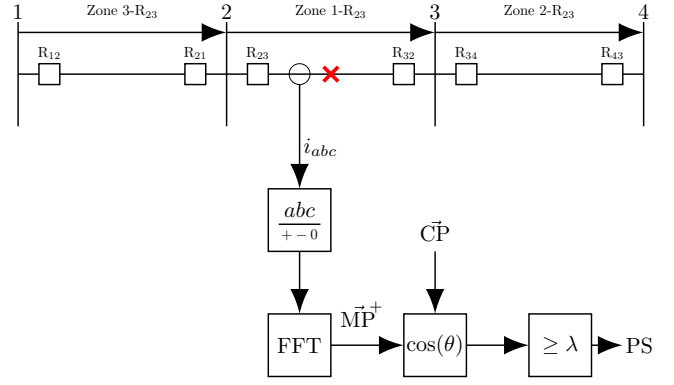


Fig. 2. Directional element logic proposed in [6].

A per-phase voltage threshold is considered for triggering the synthetic harmonic current injection in the faulted phases. Based on the IBR LVRT standard defined in IEEE Std 1547-2018 [18], this threshold is set to 0.88 pu. As soon as the filtered terminal voltage of the IBR v_g drops below 0.88 pu, a modified modulation signal m_h^* is added to the reference fundamental modulation signal m_a^* to enable the injection of synthetic harmonics by the IBR.

The control loop for injecting synthetic harmonics is designed in the abc frame. It includes a low-bandwidth controller to regulate the grid current i_g and a high-bandwidth controller to regulate IBR current i_o . The controllers are of proportional-resonant type with the following transfer function

$$F(s) = K_p + \frac{K_r s}{s^2 + \omega_o^2}, \quad (3)$$

where K_p is the proportional gain, K_r is the resonant gain, and ω_o is the resonant frequency which is set to the frequency of the injected harmonic current.

Fig. 2 shows the directional element logic used in [6]. In this logic, the three-phase currents are measured and converted into sequence components. The FFT function is applied to the positive sequence current to measure the three injected harmonics. Therefore, a three-element vector of three measured harmonics $\vec{M}\vec{P}$ is constructed. Each relay also has a predefined characteristic pattern $\vec{C}\vec{P}$. When $v_g < 0.88$ pu, the alignment percentage of the two vectors is measured using the CS function:

$$\cos(\theta) = \frac{\langle \vec{M}\vec{P}, \vec{C}\vec{P} \rangle}{\|\vec{M}\vec{P}\| \|\vec{C}\vec{P}\|}, \quad (4)$$

where $\langle \cdot, \cdot \rangle$ denotes inner product, $\|\cdot\|$ is the norm function, and θ is the angle between the two vectors. If the result of (4) is 1, the two vectors are completely aligned. However, in the method proposed in [6], the two vectors are said to be aligned if $\cos(\theta)$ is larger than $\lambda = 0.85$. This method uses the permissive overreaching transfer trip (POTT) and direction zone-interlocking (DZI) methods for primary and backup protection, respectively. Fig. 2 shows an example system to illustrate these two methods. In this system, the relay R_{23} has three zones of operation. Primary protection is set for

faults in Zone 1, backup protection is set for faults in Zone 2, and the operation is blocked for faults in Zone 3. If both R_{23} and R_{32} detect a forward fault, the primary POTT is activated for R_{23} . However, if one relay detects a reverse fault and the other detects a forward fault, an external fault is detected. A communication system is required for implementing DZI for backup protection. R_{23} sends its POTT signal to R_{12} and receives the POTT signal from R_{34} . Hence, R_{12} can operate if R_{23} fails, and R_{23} can act as the backup protection device if R_{34} fails.

This method uses the undervoltage tripping function of IBRs to de-energize the entire microgrid if both primary and backup protection devices fail to operate. Thus, all IBRs trip if the fault is not cleared within 15 cycles.

III. PROPOSED SVM-BASED APPROACH

The CS function used in [6] is not a generally reliable method. The value of λ in this function is determined by calculating all possible combinations of $\bar{M}\bar{P}$ s. Due to different IBR ratings and locations, acquiring binary $\bar{M}\bar{P}$ s is almost impossible, making the estimation of λ quite complicated. In addition, an optimization problem is solved and nodal analysis is performed for determining $\bar{C}\bar{P}$ s, which should be rerun each time a change occurs in its input information, including microgrid topology, IBR ratings, and locations. Moreover, the method proposed in [6] relies on communication between relays, which reduces its reliability. In this paper, the CS function is replaced with an SVM to detect fault current direction for balanced faults in an islanded inverter-based microgrid. Therefore, calculating λ is no longer required, and the relay stations do not need to be set to specific $\bar{C}\bar{P}$ s. Additionally, the proposed approach relies on local measurements at each relay to determine fault current direction. Hence, no communication is required. SVM is a branch of machine learning algorithms that can be used to solve classification, regression, and density estimation problems. The main logic behind SVM is to find the optimal support vectors (SV) to construct the optimal hyperplane for pattern recognition. Maximizing margins and minimizing the error becomes the main goal of SVM if no optimal hyperplane exists. This hyperplane is calculated by solving the following optimization problem:

$$\min_w \frac{1}{2} \|w\|^2 + C \left(\sum_{i=1}^l \zeta_i \right) \quad (5)$$

$$\text{subject to } y_i (w \cdot x_i + b) \geq 1 - \zeta_i, \quad \zeta_i \geq 0 \quad \forall i,$$

where x_i is the i th feature sample in the training set, and y_i is the i th class label which can take +1 or -1. This problem is usually solved through its dual form:

$$\begin{aligned} \max L_D &= \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j (x_i^T x_j) \\ \text{subject to } 0 &\leq \alpha_i \leq C \quad \forall i, \quad \sum_i \alpha_i y_i = 0. \end{aligned} \quad (6)$$

In case the input data is nonseparable, a kernel function $K(\cdot, \cdot)$ is found such that $K(x_i, x_j) = x_i^T \cdot x_j$. Utilization of kernels allows to obtain a nonlinear SVM capable

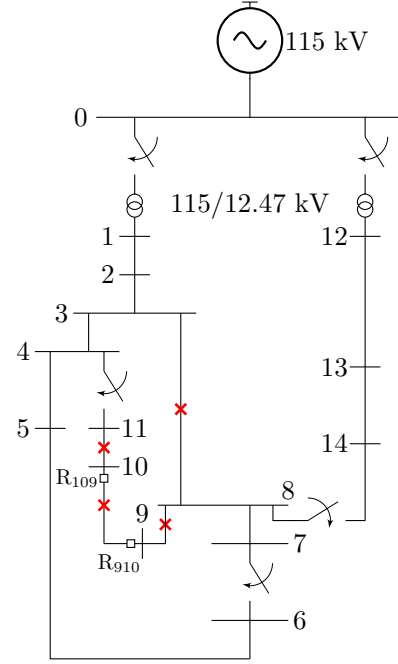


Fig. 3. CIGRE 12.47 kV benchmark system.

of handling nonseparable data in the training set. There are three general types of kernel choices: the linear kernel $Q_{ij} = K(x_i, x_j) = x_i^T \cdot x_j$, the polynomial kernel $Q_{ij} = K(x_i, x_j) = (\gamma(x_i \cdot x_j) + r)^d$, and the radial basis function (RBF) kernel $Q_{ij} = K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$. After the proper kernel is selected, the nonlinear decision function is built as below:

$$f(x) = \text{sign} \left(\sum_{i=1}^l \alpha_i y_i K(x, x_i) + b \right), \quad (7)$$

where b is calculated by $\alpha_i (y_i (w \cdot x_i + b) - 1) = 0, i = 1, \dots, l$, such that α_i is not zero.

IV. PERFORMANCE ANALYSIS

A. Training the SVM

In this paper, the 12.47 kV CIGRE benchmark distribution network shown in Fig. 3 is modeled in PSCAD/EMTDC software as the study system. The two upper switches are opened so that the microgrid operates in the islanded mode. The three bottom switches are closed to create a meshed network. Based on the optimization carried out in [6], some IBRs inject only one harmonic while others do not inject any harmonics. The harmonics injected by the IBRs are listed in Table I. An SVM is trained for each relay in Fig. 3 by applying forward and reverse balanced faults. For training each SVM, the magnitudes of the three current harmonics are sampled with a period of $30 \mu s$ for one cycle after the fault is detected by the method in [6]. With a nominal frequency of 60 Hz, the number of samples is $10^6 / (30 \times 60) = 556$. In this paper, relays R910 and R109 are selected as examples for analyzing

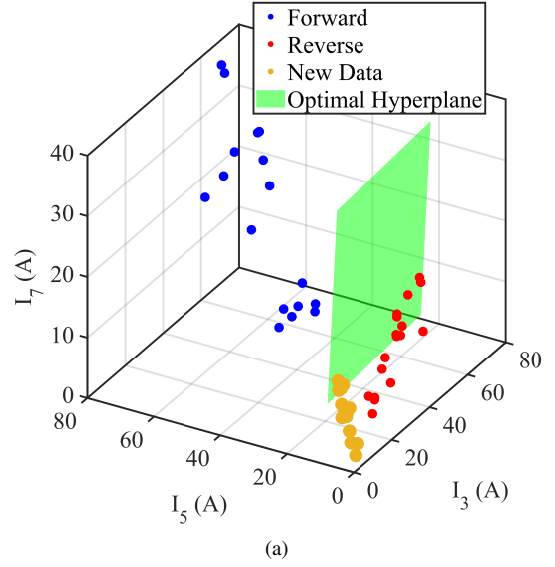
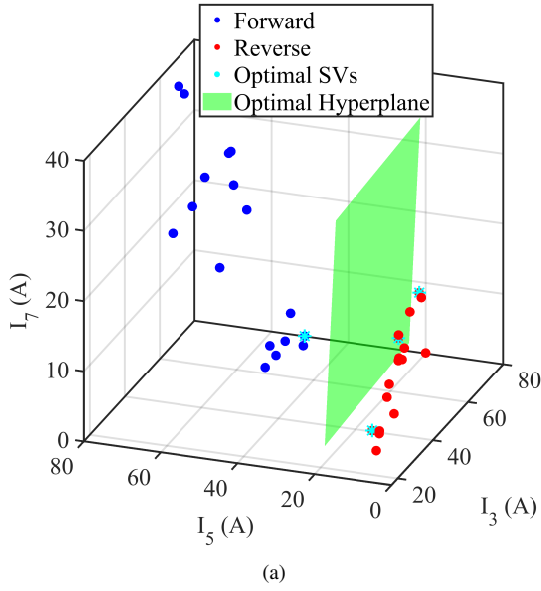


Fig. 4. SVM training results including optimal SVs and hyperplanes for (a) R910 and (b) R109.

the performance of the proposed method. A bolted three-phase fault is applied at the midpoint of line 9-10, and the measurements are recorded as the forward direction samples for both relays. Two other three-phase faults are also applied at the midpoints of line 9-8 and 11-10, and the measurements are recorded as reverse direction samples for R910 and R109, respectively. Thus, there is a $X^{1121 \times 3}$ input space and a $Y^{1121 \times 1}$ output vector for each relay. An SVM model is trained for each relay using the `fitcsvm` function in MATLAB. Figs. 4(a) and (b) show the input space, optimal SVs, and the optimal hyperplane found using `fitcsvm` for R910 and R109. The data for forward and reverse faults are linearly separable. Therefore, `fitcsvm` is able to find the optimal hyperplane in three-dimensional space for implementing large-

Fig. 5. SVM prediction results for a fault at the midpoint of line 8-3 for (a) R910 and (b) R109.

margin classification. Table II summarizes the linear kernel parameters for R910 and R109.

B. SVM Validation

To validate the performance of the trained SVMs, a bolted balanced fault is applied at the midpoint of line 8-3. For this fault, R910 should detect reverse direction while R109 should detect forward direction. Fig. 5(a) shows the new harmonic pattern along with the input space and the optimal hyperplane of R910. This figure shows that the SVM model is successfully able to detect the reverse direction for R910. The accuracy of the trained model for this relay is 100%. This means that the trained SVM is able to predict the correct direction for all of the new samples. Fig. 5(b) shows the harmonic pattern measured at R109 against its input space and

TABLE I
OPTIMAL HARMONIC INJECTION PATTERN FOR IBRS IN THE STUDY SYSTEM

IBR Bus	Injected Harmonic	IBR Bus	Injected Harmonic
1	I_3	8	0
2	0	9	I_5
3	0	10	0
4	I_3	11	I_7
5	0	12	I_5
6	0	13	0
7	I_7	14	0

TABLE II
TRAINED SVM MODEL PARAMETERS

Relay	β_1	β_2	β_3	b
R910	-0.0845	2.4394	0.1618	-1.4340
R109	0.0793	-0.1904	0.0146	1.0172

hyperplane. This figure shows that the R109 SVM model can determine the forward direction for this relay. The accuracy for this SVM is 88%, which means the SVM is able to predict the correct direction for 88% of the new samples. Table III summarizes the results from the conventional method in [6] and the proposed method for the same fault. This table shows that the conventional method detects forward direction at relay 910 while it should have detected reverse direction. However, the proposed method correctly detects the direction as reverse. This is because the result of the CS function in the conventional method for this relay is 91%, which is above the threshold $\lambda = 0.85$. This originates from the fact that designing $\vec{C}_P$ s and λ without having binary $\vec{M}_P$ s is quite complicated and not generally reliable. However, the proposed method does not rely on the CS function. Therefore, it is able to correctly determine the fault current direction.

V. CONCLUSIONS

This paper proposes a method to detect fault current direction for balanced faults in islanded inverter-based microgrids using SVM and synthetic harmonic injection via IBRs. The proposed method replaces the CS function with an SVM to detect fault current direction. Therefore, it increases the reliability of the protection system and simplifies its design. The performance of the proposed method is analyzed on two relays protecting the same line. A training set is created by simulating balanced faults in forward and reverse directions in PSCAD/EMTDC software, and an SVM model is trained for each relay using the `fitcsvm` function in MATLAB. Simulation results demonstrate that the proposed method successfully detects the direction of the fault current.

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TABLE III
PERFORMANCE COMPARISON OF THE CONVENTIONAL AND PROPOSED METHODS

Relay	Conventional Method		Proposed Method	
	Direction	CS Result	Direction	Accuracy
R910	Forward	91%	Reverse	100%
R109	Forward	98%	Forward	88%

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