Decentralized Microgrid Protection Through Relative Fault Direction Classification

Preprint

Yue Chen, Ahmed Zamzam, Soham Chakraborty, and Jing Wang

National Renewable Energy Laboratory

Presented at the 2024 IEEE Power & Energy Society General Meeting
Seattle, Washington
July 21-25, 2024

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

Conference Paper
NREL/CP-5D00-88949
September 2024

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Decentralized Microgrid Protection Through Relative Fault Direction Classification

Preprint

Yue Chen, Ahmed Zamzam, Soham Chakraborty, and Jing Wang

National Renewable Energy Laboratory

Suggested Citation
Chen, Yue, Ahmed Zamzam, Soham Chakraborty, and Jing Wang. 2024. *Decentralized Microgrid Protection Through Relative Fault Direction Classification: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-88949. https://www.nrel.gov/docs/fy24osti/88949.pdf.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00-88949
September 2024

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. This work was supported by the Laboratory Directed Research and Development (LDRD) Program at NREL and the U.S Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office Agreement Number 41215. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

Decentralized Microgrid Protection Through Relative Fault Direction Classification

Yue Chen, Ahmed Zamzam, Soham Chakraborty, and Jing Wang
Power Systems Engineering Center, National Renewable Energy Laboratory, Golden, Colorado 80401, USA.
{yue.chen, ahmed.zamzam, soham.chakraborty, jing.wang}@nrel.gov

***Abstract*—Protection in inverter-based resources (IBRs) dominated microgrids generally face significant challenges due to the low fault current and inconsistent fault behaviors from IBRs. Recently, machine learning-based approaches have attracted considerable attention to address these challenges. This paper introduces a novel decentralized protection strategy for microgrids. The proposed method decomposes the protection challenge into several distributed learning tasks, enabling individual relays to autonomously determine the direction of faults using a binary classification framework based on support vector machine (SVM) algorithms. Following the distributed fault direction estimation, classifier outcomes are shared among neighboring relays, facilitating a local decision-making process to ascertain the presence of faults within the neighborhood. Finally, a tripping signal is generated based on the classifier results of each relay to operate the circuit breaker. To test and validate this approach, a 100% renewable microgrid model is simulated in MATLAB/Simulink. In the numerical analysis, the application of SVM classifiers in our approach yields impressive results: an average relay classification accuracy of 98%, and a 96% accuracy in circuit breaker control. These findings highlight the potential of machine-learning-based approaches in enhancing the efficiency and reliability of microgrid protection systems.**

***Index Terms*—Decentralized approach, fault localization, microgrid protection, support vector machine.**

I. Introduction

In a power system, promptly localizing and isolating faults are crucial for maintaining system reliability and safety. Traditional protection schemes achieve this by using relay devices, which are configured with pre-defined thresholds for parameters such as voltage and current. Upon detecting and localizing a fault, these relays activate circuit breakers to isolate the impacted area, ensuring uninterrupted operation for the remainder of the system. Designing these thresholds requires an in-depth understanding of power system dynamics and the nature of potential disturbances. Threshold-based protection schemes, while reliable in stable power systems, encounter difficulties in systems dominated by IBRs. The unique characteristics of IBRs, such as low inertia, rapid fluctuations in power flow, and unpredictable generation patterns, challenge the effectiveness of these traditional schemes.

In microgrids with a significant integration of IBRs, traditional protection schemes face amplified challenges [1], [2]. These IBRs, unlike conventional power sources, typically provide limited contributions to fault currents and voltages, challenging relay operations that rely on specific current or voltage magnitudes. Microgrids also feature bidirectional power flows, resulting from their distributed generation sources, adding complexity to fault localization. Additionally, the variability in load and generation dynamics can lead to current and voltage fluctuations, challenging traditional protection schemes. Moreover, microgrids can operate in 'islanded' mode, necessitating a fast adaptation of the protective relays to different operational parameters. These aspects demand advanced protection approaches that are adaptable to the varying operational conditions of microgrids.

In the era of digital transformation, a data-driven approach presents a compelling alternative to traditional power system protection schemes. The data-driven approach capitalizes on the massive volumes of data generated by modern power systems, especially with the integration of smart meters, advanced sensors, and real-time monitoring devices. Potentially, machine learning algorithms can be trained to recognize the unique signatures of system faults, which might remain undetected by conventional protection schemes. As electrical grids undergo transformations, such as the introduction of new energy sources, the implementation of advanced technologies, or shifts in consumption patterns, the inherent adaptability of machine learning algorithms enables them to continuously learn from new data, refining their models and predictions to stay in step with the grid's evolving dynamics.

In recent literature, machine learning algorithms have been employed for power system protection. However, most existing work focuses on centralized computations and learning, e.g., [3], [4], which demands considerable communication and computation resources for a large system. [5] utilizes the gated recurrent unit for localizing faulty sections in a distribution network, under the assumption that measurements are accessible at all nodes. [6] introduces a support vector machine (SVM)-based method for fault location in distribution networks, where it combines feature extraction techniques using wavelet transform, Fourier transform, and the minimum redundancy maximum relevance algorithm. [7] presents a

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. This work was supported by the Laboratory Directed Research and Development (LDRD) Program at NREL and the U.S Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office Agreement Number 41215. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

zonal machine-learning-based fault localization algorithm utilizing local measurements; however, it is limited to considering only two fault zones, highlighting a potential area for further expansion. Our previous work [8] introduces a hierarchical data-driven protection for microgrids but the performance is not consistently satisfactory at some relays.

This paper introduces an innovative data-driven protection approach for microgrids, which is decentralized, coordinated and fast in decision-making. In our proposed approach, each relay serves as a distributed decision-making unit, responsible for data collection, fault localization, and circuit breaker tripping. To enable effective fault localization, each relay communicates locally with neighboring relays whenever cooperation is needed. Compared to centralized approaches, distributing the decision-making process across multiple relays significantly reduces the problem complexity and alleviates computational burden, enabling a fast and reliable real-time response to fault events. Furthermore, the distributed structure offers algorithmic flexibility within each relay, ensuring the robustness of the overall system across a variety of scenarios.

The main contributions of this paper are summarized as follows: 1) The development of SVM-based distributed binary classifiers at each relay, specifically designed to accurately classify the relative direction of faults; 2) The creation of a decentralized decision-making logic that leverages the classification results of neighboring relays, enabling precise determination of fault locations and effective fault isolation; and 3) The validation of the proposed algorithm on a 100% renewable microgrid model, demonstrating reliable protection.

II. Microgrid Model

To demonstrate the proposed data-driven protection approach, we refer to the microgrid model presented in Fig. 1. This example microgrid is based on Feeder 2 from the Banshee distribution benchmark system [9]. In its original form, this distribution network includes a 2.5-MVA battery energy storage system (BESS-1) and a 2-MW photovoltaic unit (PV-1), connected at Bus-1 and Bus-8, respectively. To convert this network to a 100% renewable microgrid, additional energy resources are incorporated: a 1-MVA BESS (BESS-2) at Bus-9, a 0.5-MW PV unit (PV-2) at Bus-6, and a 1-MW PV unit (PV-3) at Bus-7. The BESS units operate with grid-forming (GFM) control, which includes power tracking in grid-connected mode and V-f power sharing control when islanded. The PV units, under Grid-following (GFL) control, operate in three modes: fixed power factor, P-Q dispatch, and volt-volt ampere reactive control. Both BESS and PV responses to abnormal voltages and their voltage ride-through capabilities are in compliance with IEEE 1547-2018 Category III [10]. In addition, the model includes 13 potential fault locations and 12 protective relays, which are labeled as ‘F#’ and ‘R#’, respectively, in Fig. 1.

III. Decentralized Protection Algorithm

Given the potential fault locations within a microgrid, the task of fault localization is a multi-class classification problem,

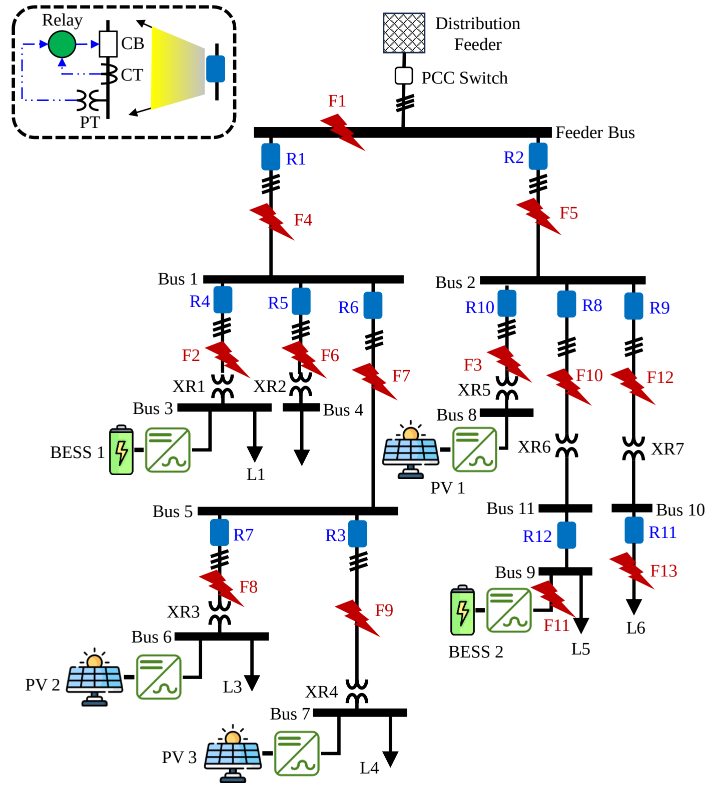

Fig. 1. The 100% renewable microgrid test system.

where each class corresponds to a specific fault location. Solving the multi-class classification problem often relies on a centralized approach that necessitates the collection and analysis of all (or most) relay data within the microgrid. However, such centralized approaches require significant computational and communication resources at the central decision unit. This often leads to potentially compromised accuracy due to the necessity for problem relaxation or simplification. Additionally, in large systems, the issue of asynchronous communication further exacerbates the challenge, potentially impacting the effectiveness and of the centralized approach.

To address these challenges, we propose a decentralized fault localization approach with minimal communication requirements. The fault localization problem is generally challenging for distributed algorithms, where each relay has access only to its own measurements. Specifically, while observing from a single relay, system fault responses for different locations may appear indistinguishable. To circumvent this issue, we solve the fault localization problem using the following two processes: 1) distributed relay classification, which produces a binary output indicating whether the fault location is upstream or downstream relative to the relay’s position in the network; and 2) local relay cooperation, where each relay shares its binary classification decision solely with neighboring relays to collaboratively determine the presence of a fault in the neighborhood. The first process simplifies the multi-class problem to a relatively simple two-class problem; more importantly, it improves the relay’s observability on the two-class problem

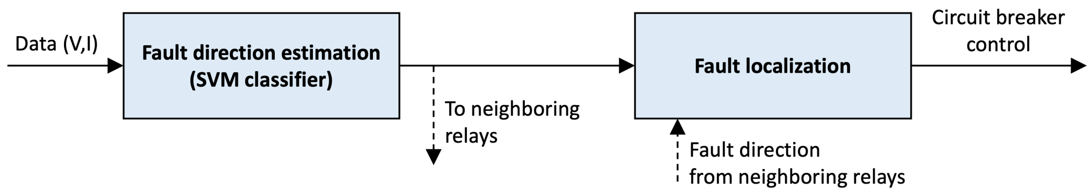

Fig. 2. Decentralized fault localization utilizing neighboring relay decisions.

TABLE I
RELATIVE FAULT DIRECTION WITH RESPECT TO EACH RELAY (0: UPSTREAM; 1: DOWNSTREAM)

Fault Location \ Relative Direction	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
F1	0	0	0	0	0	0	0	0	0	0	0	0
F2	1	0	0	1	0	0	0	0	0	0	0	0
F3	0	1	0	0	0	0	0	0	0	1	0	0
F4	1	0	0	0	0	0	0	0	0	0	0	0
F5	0	1	0	0	0	0	0	0	0	0	0	0
F6	1	0	0	0	1	0	0	0	0	0	0	0
F7	1	0	0	0	0	1	0	0	0	0	0	0
F8	1	0	0	0	0	1	1	0	0	0	0	0
F9	1	0	1	0	0	1	0	0	0	0	0	0
F10	0	1	0	0	0	0	0	1	0	0	0	0
F11	0	1	0	0	0	0	0	1	0	0	0	1
F12	0	1	0	0	0	0	0	0	1	0	0	0
F13	0	1	0	0	0	0	0	0	1	0	1	0

TABLE II
FAULT LOCALIZATION USING THE LOCAL FAULT DIRECTION ESTIMATION (0: UPSTREAM; 1: DOWNSTREAM)

Fault Location \ Relative Direction	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
F1	0	0	-	-	-	-	-	-	-	-	-	-
F2	-	-	-	1	-	-	-	-	-	-	-	-
F3	-	-	-	-	-	-	-	-	-	1	-	-
F4	1	-	-	0	0	0	-	-	-	-	-	-
F5	-	1	-	-	-	-	-	0	0	0	-	-
F6	-	-	-	-	1	-	-	-	-	-	-	-
F7	-	-	0	-	-	1	0	-	-	-	-	-
F8	-	-	-	-	-	-	1	-	-	-	-	-
F9	-	-	1	-	-	-	-	-	-	-	-	-
F10	-	-	-	-	-	-	-	1	-	-	-	0
F11	-	-	-	-	-	-	-	-	-	-	-	1
F12	-	-	-	-	-	-	-	-	1	-	0	-
F13	-	-	-	-	-	-	-	-	-	-	1	-

over the potentially indistinguishable multi-class problem. The second process serves as a complementary step, combing the distributed decisions for precise fault location.

The complete fault localization process is depicted in Fig. 2. Once there is a system fault, the relative-fault-direction classifier that embedded in each relay is triggered. Upon determining the relative fault direction using the collected data, the relay exchanges its classification decision with neighboring relays. Subsequently, the relay assesses if a fault has occurred within its neighborhood and accordingly produces the circuit breaker control signal. Detailed descriptions are presented in the following subsections.

A. *Distributed Relative Fault Direction Classification*

To find the relative fault direction, it is necessary to understand the relationship between the fault location and the relative fault direction from a relay's perspective. Such information is contingent upon the specific system network topology. According to the microgrid example in Fig. 1, Table I provides the conversion from specific fault locations to their corresponding relative fault direction for each relay. In the table, a fault's relative direction viewed from a relay is labelled as either '1' (downstream) or '0' (upstream), according to the fault location and the microgrid topology. In this way, for each fault location, there is a unique combination of relay's relative fault directions. In other words, we can determine the fault location by looking at relays' relative fault direction results. This converts the multi-class classification problem to distributed binary classification problems, where each relay only have to classify whether the fault is upstream or downstream.

B. *Fault Localization*

As described above, fault localization requires a combination on relative fault directions from all relays. However, such decision-making process is notably sensitive to the accuracy of each individual relay's classification result, rendering it susceptible to vulnerabilities. This is extremely challenging for a large system with numerous relays. Consequently, our proposed decentralized approach emphasizes the local relay decisions for fault localization. For instance, within the microgrid shown in Fig. 1, the fault F4 is validated by the combined decisions of its neighboring relays: R1 (downstream), R4 (upstream), R5 (upstream), and R6 (upstream). A comprehensive summary of fault locations and their corresponding local relay decisions is given in Table II.

For distributed implementation, each relay exchanges the fault direction result with its neighboring relays. Fig. 3 provides the relay communication diagram for the microgrid example in Fig. 1. With neighboring relays' fault direction information, a relay can identify whether there is a fault within its neighborhood.

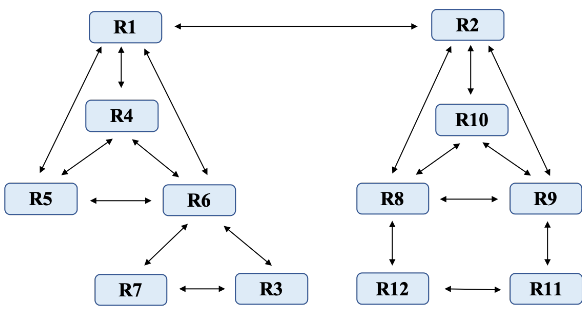

Fig. 3. Local communication diagram for fault localization.

C. Fault Isolation

To effectively isolate a fault, a relay must trip its circuit breaker upon the detection of a fault within its neighborhood. For instance, as shown in Fig. 1 (or Table II), relay R1 is responsible for monitoring faults F1 and F4. Using the fault direction results from itself and its neighboring relays R2, R4, R5, and R6, it can determine if there is fault at F1 or F4. Detection of either fault prompts the relay to dispatch a control signal, tripping the circuit breaker to isolate the fault from the system.

IV. Numerical Study

In this section, we demonstrate the efficacy of the decentralized microgrid protection approach. Numerical simulations of the microgrid model (Fig. 1) were performed on MATLAB/Simulink. To represent comprehensive microgrid fault scenarios, simulations were conducted using various parameters, such as fault type, fault location, fault impedance, load condition, solar irradiance, and inverter type. The load profiles and PV generation were generated from the measured data in [9]. During the simulation, each relay continuously measured three-phase voltage and current at a sampling frequency of 6 kHz. For every fault scenario encountered, each relay collected four cycles of three-phase voltage and current magnitudes, where the first cycle data was collected before the fault event, and the remaining three-cycle data (corresponding to 0.05 seconds) captured the post-fault response. In total, we collected data from 1000 fault scenarios, of which 800 scenarios were used for learning algorithm training and the rest 200 scenarios were used for testing.

In this work, we employed the SVM classifier [11] for the relative fault direction classification. SVM is a supervised learning algorithm commonly used for classification tasks. The algorithm objective is to determine an optimal separating hyperplane that divides a given dataset into distinct classes. This is accomplished by maximizing the margin between the closest data points of different classes. SVM can handle non-linearly separable data through the use of kernel functions, which maps the data into a higher-dimensional feature space where the classes are linearly separable. Popular kernel functions include polynomial functions, radial basis functions, and sigmoid functions. One big advantage of SVM is its ability to handle high-dimensional data effectively, allowing for accurate classification even when the number of features exceeds the number of observations.

In our distributed setting, 12 relays perform the SVM training process independently using their local measurement data. The training process for each SVM classifier follows the flowchart in Fig. 4. First, the dataset is standardized to ensure consistent scaling among features. To reduce the computational complexity and mitigate the risk of overfitting, dimensionality reduction is performed using the principal component analysis (PCA) technique. Thereafter, we initialize the hyperparameters for the SVM model, including the misclassification parameter and the kernel function selection. As evidenced by Table I, the data exhibit a greater number of upstream samples than downstream samples. To address this unbalanced data issue, we allocate a larger weight to the downstream class, allowing the model to balance the importance between the downstream and upstream classes. To enhance the model generalizability, we employ the 5-fold

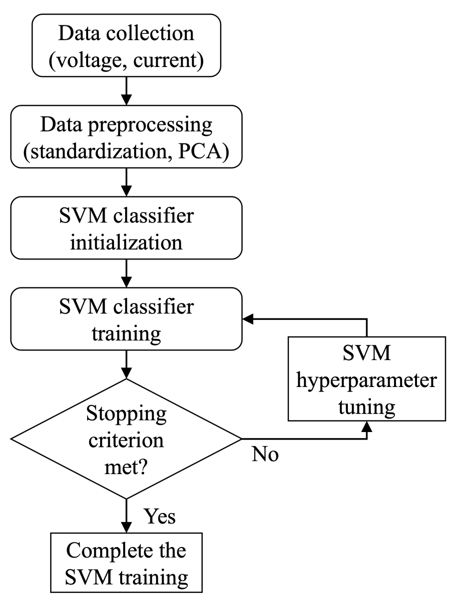

Fig. 4. Flowchart for SVM classifier training.

cross-validation method to reduce the model sensitivity to the partitioning between training and test data. An iterative process of hyperparameter tuning and model training is repeated if the model fails to meet required performance metrics, such as accuracy, precision, and recall.

Table III summarizes the testing performance for both the relay SVM classifiers and circuit breaker control. All SVM classifiers can effectively classify the relative fault direction and the average accuracy is 98.29%. In general, the accuracy of circuit breaker operation is lower than that of the corresponding SVM classifier. This is mainly because correct fault localization relies on the combination of correct classification results from multiple relays. However, there are exceptional cases where the circuit breaker may trip correctly even if the classification result is incorrect. For instance, in the scenario involving fault F7, relay R7 incorrectly classifies the fault direction (upstream misclassified as downstream), leading to a failure in detecting F7. Interestingly, this misclassification inadvertently causes the detection of fault F8, resulting in the correct tripping of the R7 circuit breaker. This particular situation explains the row R7 in Table III where the accuracy of circuit breaker control for R7 is noted to be higher than its classification accuracy. In addition, we found that our algorithm is robust in both grid-connected and islanded scenarios, each has consistent accuracy as detailed in Table III.

TABLE III
PERFORMANCE OF RELAY CLASSIFIERS AND CIRCUIT BREAKER CONTROL.

Accuracy	Classifier	Circuit Breaker
R1	0.915	0.915
R2	0.890	0.860
R3	1	0.995
R4	1	0.990
R5	1	0.990
R6	1	0.985
R7	0.995	1
R8	1	0.935
R9	0.995	0.94
R10	1	0.935
R11	1	0.995
R12	1	1
Average	0.9829	0.9617

One interesting numerical result worth mentioning is that the algorithm's comparable performance for both high-impedance and low-impedance faults. This outcome is particularly encouraging for high-impedance fault protection, which is typically more challenging to address effectively. We attribute this success, at least in part, to the data standardization process implemented in our approach. By normalizing the data, this process effectively minimizes the impact of varying data magnitudes, allowing the algorithm to more accurately recognize the characteristic patterns for different fault locations.

V. CONCLUSIONS

This paper presented a decentralized, data-driven approach for microgrid protection, effectively addressing the challenges introduced by a high integration of IBRs. Our approach overcomes the limitations of traditional protection schemes by employing a decentralized framework where each relay operates as a data-driven decision-making unit. This setup not only ensures effective fault localization and isolation but also significantly reduces the computational and communication burdens associated with centralized protection schemes. The implementation of SVM-based decentralized protection at each relay demonstrated a high accuracy of circuit breaker operations in response to microgrid faults.

Moving forward, the exploration of this research can be extended in several directions. One direction could be the consideration of the asynchronization issue in the relay communication. Additionally, exploring the application of this approach in larger-scale grid systems, and assessing its interoperability with existing grid infrastructure, would be valuable for understanding its scalability and practicality.

REFERENCES

[1] V. Telukunta, J. Pradhan, A. Agrawal, M. Singh, and S. G. Srivani, "Protection challenges under bulk penetration of renewable energy resources in power systems: A review," *CSEE Journal of Power and Energy Systems*, vol. 3, no. 4, pp. 365–379, 2017.

[2] P. Denholm and B. Kroposki, "Understanding power systems protection in the clean energy future," *NREL technical report*, May 2022.

[3] Y. D. Mamuya, Y.-D. Lee, J.-W. Shen, M. Shafiullah, and C.-C. Kuo, "Application of machine learning for fault classification and location in a radial distribution grid," *Applied Sciences*, vol. 10, no. 14, 2020.

[4] M. J. Aparicio, M. J. Reno, P. Barba, and A. Bidram, "Multi-resolution analysis algorithm for fast fault classification and location in distribution systems," *2021 IEEE 9th International Conference on Smart Energy Grid Engineering (SEGE)*, pp. 134–140, 2021.

[5] M. R. Shadi, H. Mirshekali, R. Dashti, M.-T. Ameli, and H. R. Shaker, "A parameter-free approach for fault section detection on distribution networks employing gated recurrent unit," *Energies*, vol. 14, no. 19, 2021.

[6] A. Keshavarz, R. Dashti, M. Deljoo, and H. Shaker, "Fault location in distribution networks based on svm and impedance-based method using online databank generation," *Neural Comput. Applic.*, p. 2375–2391, 2022.

[7] B. P. Poudel, A. Bidram, M. J. Reno, and A. Summers, "Zonal machine learning-based protection for distribution systems," *IEEE Access*, vol. 10, pp. 66634–66645, 2022.

[8] A. Zamzam and J. Wang, "Hierarchical data-driven protection for microgrid with 100% renewable," *2023 IEEE Energy Conversion Congress and Exposition (ECCE)*, 2023.

[9] R. Salcedo, E. Corbett, C. Smith, E. Limpaecher, R. Rekha, J. Nowocin, G. Lauss, E. Fonkwe, M. Almeida, P. Gartner, *et al.*, "Banshee distribution network benchmark and prototyping platform for hardware-in-the-loop integration of microgrid and device controllers," *The Journal of Engineering*, vol. 2019, no. 8, pp. 5365–5373, 2019.

[10] "IEEE standard for interconnection and interoperability of distributed energy resources with associated electric power systems interfaces," *IEEE Std 1547-2018 (Revision of IEEE Std 1547-2003)*, pp. 1–138, 2018.

[11] C. M. Bishop and N. M. Nasrabadi, *Pattern recognition and machine learning*, vol. 4. Springer, 2006.