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Identificación de tipos de falla basada en aprendizaje automático utilizando bosques aleatorios

Machine learning-based fault type identification using random forests

Identificação de tipo de falha baseada em aprendizagem automática usando florestas aleatórias

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Resumen

Este manuscrito presenta un marco avanzado para la clasificación de fallas en redes de distribución eléctrica, utilizando metodologías basadas en Random Forest (RF) junto con conjuntos de datos generados mediante simulación. Se modeló una configuración de prueba IEEE de 6 nodos en MATLAB Simulink para emular distintos tipos de fallas bajo diversas condiciones operativas. Las métricas eléctricas fueron registradas de manera sistemática y, a partir de cada escenario experimental, se extrajeron características estadísticas—principalmente valores de raíz cuadrática media (RMS)—para construir un conjunto de datos estructurado. El clasificador RF fue entrenado con datos etiquetados y evaluado rigurosamente mediante técnicas de validación cruzada estratificada. Se alcanzó una precisión global del 86% en siete clases de fallas distintas, mostrando valores notables de precisión y exhaustividad para la mayoría de los tipos de fallas, especialmente A-G, AB, AC, B-G y C-G. A pesar de una eficacia relativamente reducida en la diferenciación de fallas ABC y BC, el modelo demostró una capacidad de generalización considerable cuando fue aplicado a un caso de prueba externo con una falla AB, la cual fue clasificada correctamente a pesar de no haber estado presente en el conjunto de entrenamiento. Los resultados respaldan la eficacia de la metodología propuesta para el diagnóstico de fallas escalable y basado en datos dentro de redes de distribución. La integración de generación de datos por simulación con técnicas de aprendizaje por ensamble constituye una estrategia sólida para facilitar la supervisión en tiempo real de la red y mecanismos de protección adaptativos. Investigaciones futuras se enfocarán en ampliar el espacio de características, mejorar la clasificación de fallas simétricas e incorporar el marco en arquitecturas de computación en el borde para su implementación en tiempo real.

Palabras clave: Clasificación de fallas eléctricas; Random Forest; protección inteligente; diagnóstico de fallas.

Abstract

This manuscript presents an advanced framework for fault classification in electrical distribution networks, using Random Forest (RF)-based methodologies coupled with simulation-generated datasets. A 6-node IEEE test setup was modeled in MATLAB Simulink to emulate different fault types under diverse operating conditions. Electrical metrics were systematically recorded, and from each experimental scenario, statistical features—mainly root mean square (RMS) values—were extracted to construct a structured dataset. The RF classifier was trained with labeled data and

rigorously evaluated using stratified cross-validation techniques. An overall accuracy of 86% was achieved across seven distinct fault classes, showing remarkable precision and recall values for most fault types, especially A-G, AB, AC, B-G, and C-G. Despite relatively low effectiveness in differentiating ABC and BC faults, the model demonstrated considerable generalization capabilities when applied to an external test case with an AB fault, which was correctly classified despite not being present in the training set. The results support the effectiveness of the proposed methodology for scalable, data-driven fault diagnosis within distribution networks. The integration of simulation-based data generation with ensemble learning techniques constitutes a robust strategy for facilitating real-time network monitoring and adaptive protection mechanisms. Future research will focus on expanding the feature space, improving symmetric fault classification, and incorporating the framework into edge computing architectures for real-time deployment.
Keywords: Electrical fault classification; Random Forest; smart protection; fault diagnosis.

Resumo

Este manuscrito apresenta uma estrutura avançada para a classificação de falhas em redes de distribuição elétrica, utilizando metodologias baseadas em Random Forest (RF) acopladas a conjuntos de dados gerados por simulação. Uma configuração de teste IEEE de 6 nós foi modelada no MATLAB Simulink para emular diferentes tipos de falhas sob diversas condições de funcionamento. As métricas elétricas foram registadas sistematicamente e, de cada cenário experimental, foram extraídas características estatísticas — principalmente valores de raiz quadrada média (RMS) — para construir um conjunto de dados estruturado. O classificador RF foi treinado com dados rotulados e rigorosamente avaliado através de técnicas de validação cruzada estratificada. Foi alcançada uma precisão global de 86% em sete classes distintas de falhas, mostrando valores notáveis de precisão e revocação para a maioria dos tipos de falhas, especialmente A-G, AB, AC, B-G e C-G. Apesar da eficácia relativamente baixa na diferenciação de falhas ABC e BC, o modelo demonstrou uma considerável capacidade de generalização quando aplicado a um caso de teste externo com uma falha AB, que foi classificada corretamente apesar de não estar presente no conjunto de treino. Os resultados corroboram a eficácia da metodologia proposta para o diagnóstico de avarias escalável e baseado em dados em redes de distribuição. A integração da geração de dados baseada em simulação com técnicas de aprendizagem por conjunto constitui uma estratégia robusta para facilitar a monitorização de redes em tempo real e mecanismos de proteção adaptativa. A investigação futura irá concentrar-se na expansão do espaço de recursos, no aperfeiçoamento da classificação simétrica de falhas e na incorporação da estrutura em arquiteturas de computação de ponta para implantação em tempo real.

Palavras-chave: Classificação de falhas elétricas; Random Forest; proteção inteligente; diagnóstico de avarias.

Introducction

The continual evolution of power distribution networks—propelled by the burgeoning presence of distributed generation resources and the extensive incorporation of renewable energy modalities—has markedly augmented the intricacy of fault identification and diagnostic frameworks (Hu et al., 2023). Traditional protection schemes, which rely primarily on deterministic thresholds and static configuration rules, often struggle to maintain high accuracy and adaptability under variable operational conditions. As renewable penetration and bidirectional power flows become more prevalent, fault scenarios have become more diverse, less predictable, and harder to isolate using conventional methods alone. (Li et al., 2020)

In light of these prevailing challenges, machine learning (ML) methodologies have surfaced as formidable instruments to augment fault detection and classification capabilities within smart grid systems. ML-driven frameworks possess the ability to derive insights from historical and simulated datasets to discern complex, non-linear patterns in electrical signals that either precede or coincide with fault occurrences. (Kaplan et al., 2021) This data-centric methodology facilitates enhanced flexibility, expedited adaptation to novel scenarios, and superior overall precision in the identification of anomalies. Recent developments in both shallow and deep learning paradigms have further propelled the integration of artificial intelligence into fault diagnostic processes within electrical systems. (Ajagekar & You, 2021)

Supervised learning methodologies have exhibited notable success within this particular domain. For instance, (Hu et al., 2023) introduced a tripartite framework that integrates anomaly detection with machine learning-based identification of both the existence of faults and their respective classifications, consequently achieving a high degree of classification accuracy within distribution networks. (Ren et al., 2020) conducted a comprehensive review of a diverse array of supervised algorithms, encompassing Support Vector Machines and Decision Trees, and emphasized their relevance in the classification of fault types, particularly in scenarios characterized by limited data availability. Ensemble learning techniques, such as Random Forest, have illustrated enhanced efficacy in numerous investigations, attributable to their resilience against overfitting, interpretative clarity, and proficiency in handling high-dimensional datasets (Khan et al., 2020).

Deep learning techniques have similar recognition in contemporary research. Machine learning approaches, including Convolutional Neural Networks, Recurrent Neural Networks, and Long Short-Term Memory, have been deployed to model the dynamic properties of voltage and current waveforms. For instance, (Firdausi & Ahmad, 2022) propose that CNNs trained on envelope-based signals can proficiently detect fault occurrences within the system. In a similar vein, (Wang et al., 2020) advocate for the integration of wavelet transforms into LSTM cells to enhance feature extraction across both temporal and frequency domains, thereby providing exceptional efficacy for fault identification.

A critical prerequisite for the execution of these machine learning methodologies is the availability of high-quality, annotated datasets.. Regrettably, empirical fault data in practical scenarios is frequently limited, particularly in relation to infrequent or dynamically changing fault categories. To address this limitation, investigators have more frequently utilized simulation frameworks such as MATLAB/Simulink, which support the methodical development of diverse fault scenarios. To exemplify, (Moradi et al., 2020) pointed out the essentiality of leveraging high-resolution simulation data for the instruction of machine learning models within diverse operational frameworks. In an applicable context, (Fan et al., 2017) autoencoders utilized in conjunction with principal component analysis to gather features from synthetic high impedance fault data, consequently affirming the effectiveness of simulation methodologies in mitigating issues related to data scarcity.

In this regard, we delineate an exhaustive framework for the identification and categorization of faults within power distribution systems, employing a dataset generated through simulation alongside a Random Forest classifier. Our approach encompasses the development of a six-bus power system model utilizing MAT AB/Simulink, wherein faults of diverse types are systematically introduced at various locations and temporal instances. Voltage, current, and power signals are meticulously gathered at each bus under both standard and fault-induced conditions, thereby constituting a comprehensive and annotated dataset for the training of the classifier.

The classifier is developed to discern the specific category of fault predicated on the signal dynamics observed during a designated fault window, and its efficacy is assessed utilizing novel,

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previously unencountered fault scenarios. Furthermore, the contemporary signal patterns derived from the new test cases are subjected to visual comparison with the average patterns assimilated during the training phase, thereby providing a comprehensible standard for classification determinations.

This manuscript significantly advances the existing body of research in three principal dimensions: (1) it establishes a methodologically sound framework for the generation of reproducible labeled simulation datasets pertinent to various fault scenarios; (2) it elucidates the effectiveness of a Random Forest classifier in accurately identifying fault types while demonstrating robust generalization capabilities; and (3) it introduces a signal-based pattern comparison technique aimed at validating the congruence between learned and observed current behaviors. The delineated framework provides a scalable and transparent methodology for fault classification and has the potential to serve as a foundational element for the real-time deployment in forthcoming intelligent substation or edge computing systems.

Metodology

Overview of the Proposed Algorithm

This study employs the Random Forest (RF) algorithm as the primary classification methodology for the detection and identification of electrical faults within simulated distribution systems. Random Forest is an extensively utilized ensemble learning technique that develops multiple decision trees throughout the training phase and subsequently generates the mode of their predictions for classification purposes. (Mohana et al., 2021) Originally introduced by Breiman, RF provides elevated predictive accuracy, resilience against overfitting, and the capacity to manage datasets characterized by heterogeneous data types and intricate feature interactions that render it particularly advantageous for fault diagnosis in electrical power systems. (Mrabet et al., 2022)

Every decision tree in the Random Forest methodology is formulated by employing a bootstrap sample from the original dataset, along with a randomly chosen subset of input features at each node. This inherent duality of randomness contributes to the enhancement of tree diversity and alleviates the correlation among individual trees, culminating in an ensemble model characterized by diminished variance and superior generalization capabilities. Upon completion of the training phase, the prediction associated with a specific input is derived by aggregating the outputs of all constituent trees through the mechanism of majority voting. (Nakahara et al., 2017)

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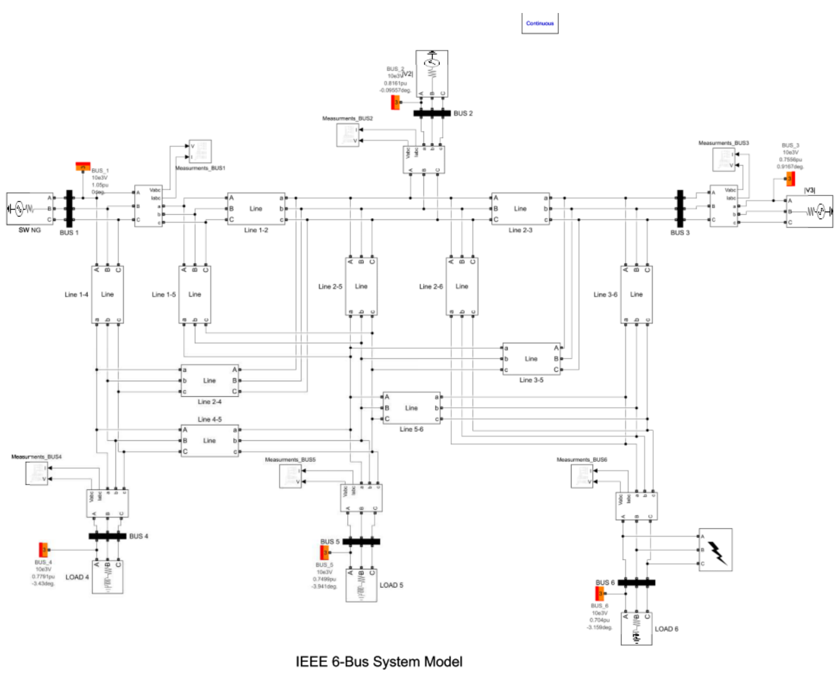
In the domain of fault classification, the RF model is provided with a collection of time-series features that are extracted from electric signals recorded throughout the distribution network under both normal operational conditions and fault scenarios. Each data sample is systematically categorized according to the specific type of fault, which may include single line-to-ground, line-to-line, double line-to-ground, or three-phase faults. The model acquires the capability to associate these input features with the appropriate fault type by discerning distinctive patterns in the behavior of the signals, such as sudden fluctuations in current magnitude, phase discrepancies, or disturbances in power flow.

One of the primary benefits associated with the implementation of Random Forest within this context is its clarity of interpretation and minimal susceptibility to hyperparameter optimization. The feature importance rankings generated by the model facilitate the identification of which signals or measurements play a pivotal role in influencing fault classification outcomes, thereby supporting both human diagnostic efforts and the enhancement of future modeling endeavors (Han et al., 2021). Furthermore, the Random Forest model does not necessitate any presuppositions regarding the underlying data distribution, rendering it an advantageous option for datasets derived from simulations, where real-world signal noise or uncertainty is replicated.

Simulation-Based Dataset Generation

Figure 1. *Simulink Model Diagram*



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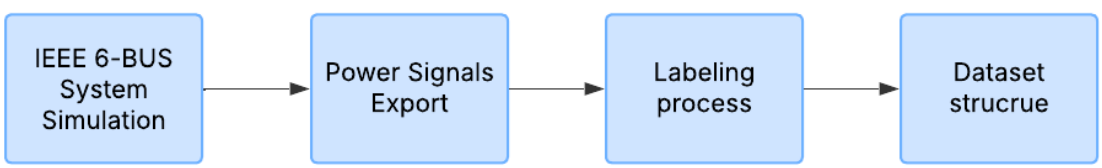
In pursuit of generating labeled data within systematically controlled and reproducible parameters, an intricate six-bus electrical distribution system was meticulously simulated utilizing MATLAB Simulink alongside the Simscape Electrical toolbox. The simulation framework encompasses voltage and current sensors strategically positioned at each bus and line, possessing the capability to incorporate various fault types through a configurable Three-Phase Fault block. The simulated fault scenarios encompass single line-to-ground (SLG), line-to-line (LL), double line-to-ground (DLG), and three-phase (ABC) faults. Faults were systematically introduced at each of the six buses, with fault activation occurring between different time intervals within a 1-second simulation window, thereby ensuring the comprehensive capture of both steady-state and transient dynamics. Figure 1 illustrates the schematic representation of the modeled distribution network, emphasizing the placement of sensors and fault injection locations.

Throughout the simulation interval, electrical parameters such as per-phase current, RMS voltage, as well as both active and reactive power were meticulously recorded. For each distinct fault condition, a specific CSV file was generated, embedded with metadata pertaining to the fault's type and geographic location. These datasets constituted the foundation for a methodologically structured and automated pipeline for feature extraction and labeling, as depicted in Figure 2, which delineates the complete workflow from the Simulink simulation to the preparation of a structured dataset.

Figure 2. *Dataset Generation Workflow*



Feature Extraction and Preprocessing

Each simulation output underwent processing to delineate a centered 200 ms temporal window surrounding the initiation of the fault. This specific window was selected to encapsulate the commencement of the transient phenomena and the initial dynamics of fault propagation. Within this temporal interval, both time-domain and statistical characteristics were derived from the voltage and current signals, encompassing RMS values, signal energy, mean, standard deviation,

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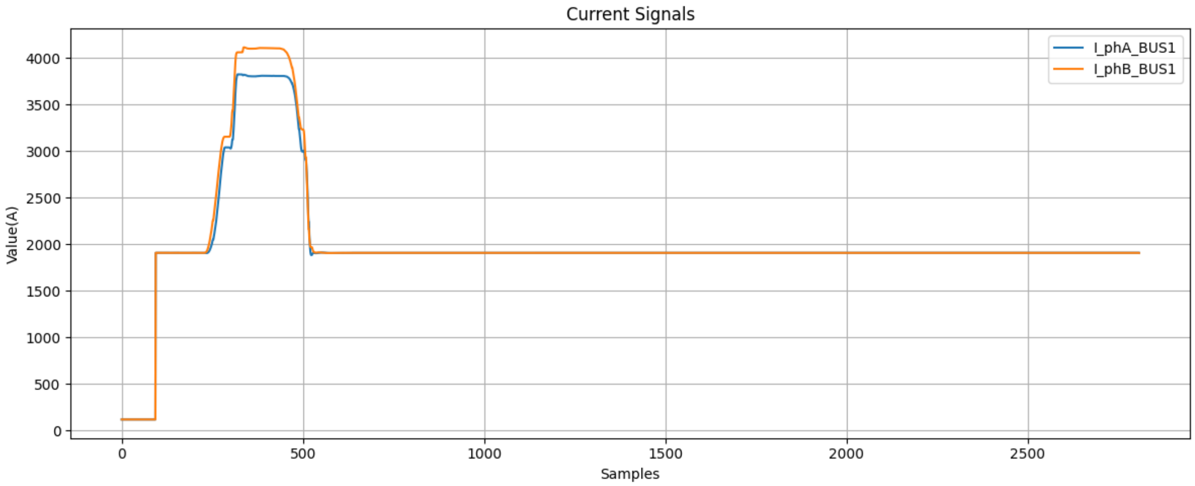
and peak-to-peak amplitude. The selection of these features was predicated on their capacity to elucidate anomalous system behavior correlated with the initiation and progression of faults. The methodology for feature extraction is depicted in Figure 3, which presents a representative current signal prior to and during a fault event, annotated with the corresponding extracted statistical attributes.

Figure 3. *Current Fault Signals*



All features underwent normalization via Min-Max scaling to ensure uniform input ranges across the variables and to enhance the numerical stability of the learning algorithm. Furthermore, categorical labels were transformed into numeric representations to facilitate supervised classification.

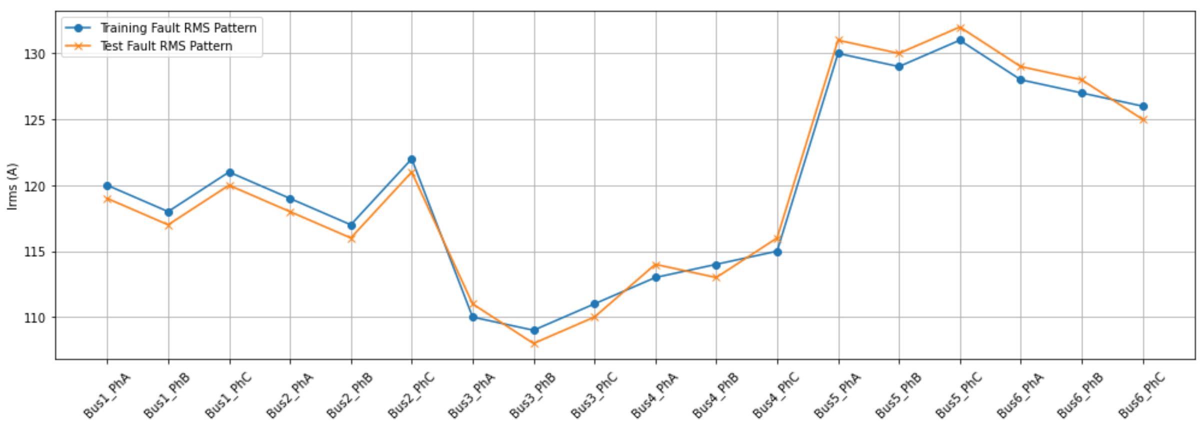
Random Forest Model Training

The Random Forest classifier was executed within the Python programming environment utilizing the Scikit-learn library. The model underwent training utilizing a set of 100 decision trees, each permitted to expand without restrictions on depth in order to comprehensively capture the intrinsic signal-fault correlations. The Gini index was employed to ascertain the optimal splits at each node. Throughout the training process, the model acquired the capability to differentiate among the various fault categories predicated upon the input features derived from voltage and current signals. An assessment of performance was performed utilizing five-fold cross-validation to guarantee robustness. Evaluation metrics, including accuracy, precision, recall, and F1-score, were computed for each fault classification.

Testing with Unseen Fault Scenarios

In order to evaluate the generalization capacity of the trained model, an independent collection of test scenarios was developed. These scenarios encompassed faults introduced at buses that were not part of the training set, faults occurring at varied times, and instances with altered system load conditions. The model underwent an assessment on this novel dataset to ascertain its proficiency in accurately identifying fault types under slightly modified circumstances. Figure 4 illustrates a comparative analysis between the learned current waveform patterns of a known fault and the waveform of an unobserved test case exhibiting the same fault type. The visual congruence in shape and magnitude substantiated that the model successfully captured critical fault characteristics and demonstrated the ability to extrapolate to new, yet related, situations.

Figure 4. *Comparison of RMS Current Patterns: Known Fault vs. Unseen Test Case*



Fault Type Decision Pipeline

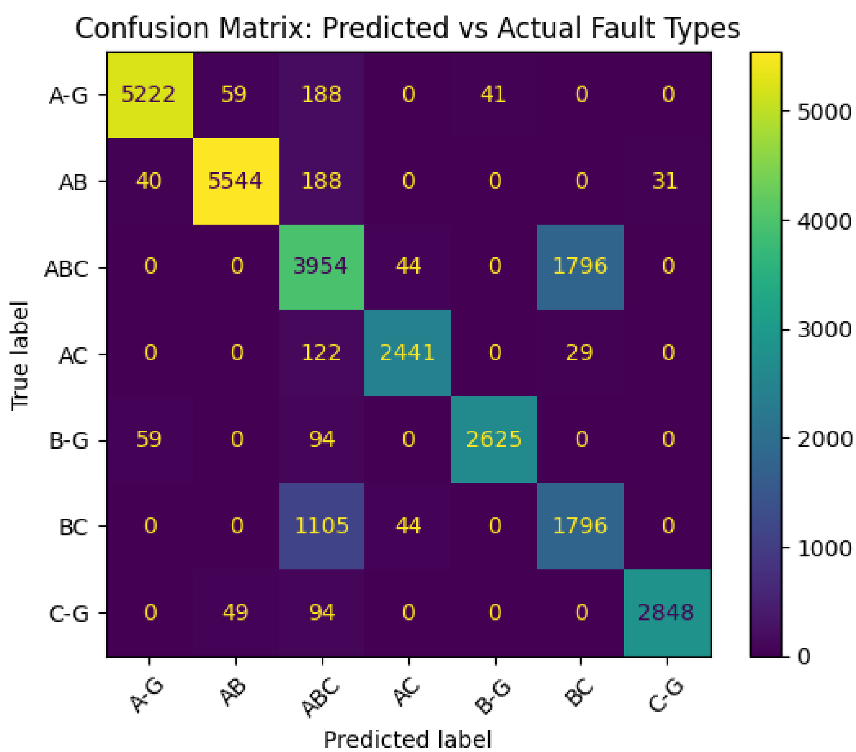
In accordance with the proposed methodology, a comprehensive detection and classification pipeline has been established. This pipeline comprises multiple stages: real-time acquisition of electrical measurements from the system, preprocessing of time-series data, extraction of features within the specified fault interval, and classification utilizing the trained Random Forest model. The output generated by the classifier signifies the existence and category of the fault, which can subsequently be employed to activate protective measures or to inform grid operators. This architecture is intended for implementation in edge computing environments or within substation-level controllers, where low-latency decision-making is critical for ensuring operational reliability.

Analysis and results

Model Evaluation and Classification Results

The performance of the Random Forest classifier was evaluated using a comprehensive dataset consisting of 28,413 labeled fault instances representing seven distinct types of electrical faults. As shown in Figure 5, the confusion matrix reveals a generally high degree of accuracy, particularly for fault types such as A-G, AB, AC, and B-G, which exhibit strong diagonal dominance and minimal misclassifications. However, certain fault categories, specifically ABC and BC, display considerable overlap with other classes, as evidenced by notable off-diagonal values. This confusion is particularly pronounced between the ABC and BC classes, indicating challenges in distinguishing between symmetrical and multi-phase faults that may exhibit similar signal characteristics.

Figure 5. *Confusion Matrix of the Random Forest Classifier for Fault Type Classification*



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The comprehensive classification metrics are encapsulated in Table 1, which delineates the precision, recall, and F1-score corresponding to each distinct fault category. The model attained an aggregate accuracy of 86%, accompanied by macro- and weighted-average F1-scores of 0.86. The A-G and AB fault categories were recognized with considerable reliability, with both exhibiting precision values of 0.98 and F1-scores of 0.96 and 0.97, respectively. The AC and B-G classes also demonstrated commendable performance, with F1-scores of 0.95 and 0.96, respectively. C-G faults were classified with exceptional precision (0.99) and an F1-score of 0.97, thereby illustrating the model's proficiency in identifying faults associated with ground reference and exhibiting unbalanced current profiles.

Table 1. *Classification Performance Metrics of the Random Forest Model on the Test Dataset*

Fault Type	Precision	Recall	F1-score
A-G	0.98	0.95	0.96
AB	0.98	0.96	0.97
ABC	0.69	0.68	0.69
AC	0.97	0.94	0.95
B-G	0.98	0.94	0.96
BC	0.50	0.61	0.55
C-G	0.99	0.95	0.97

In contrast, the classifier struggled with the three-phase (ABC) and line-to-line (BC) fault types. The ABC fault category achieved only 0.69 in both precision and recall, while the BC class performed the worst among all, with a precision of 0.50 and recall of 0.61. These reduced scores are consistent with the visual patterns observed in the confusion matrix and suggest that the RMS-based features used in this study, although effective for unbalanced and ground-based faults, may be insufficient for resolving complex, multi-phase fault signatures that produce overlapping measurement responses.

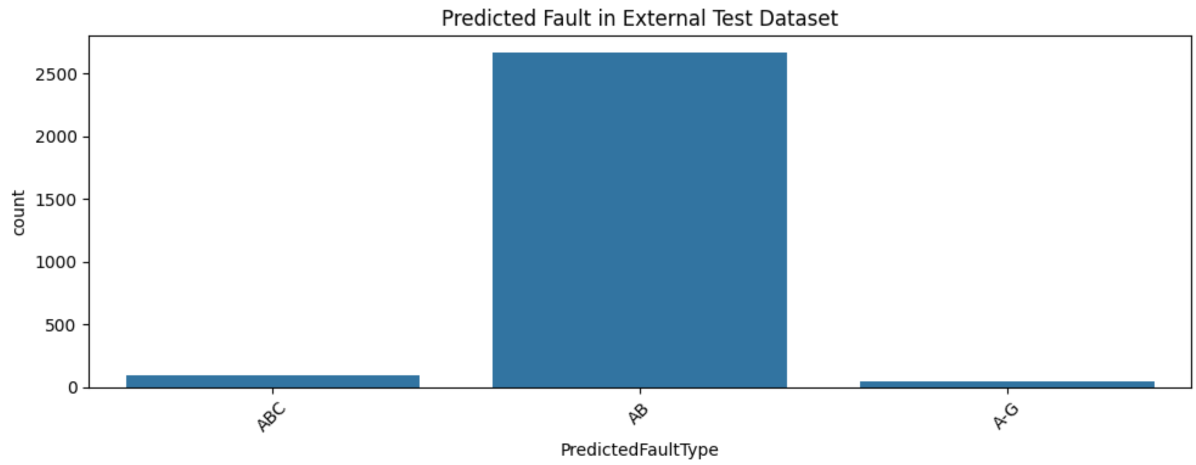
The imbalance in classification performance among fault types highlights a need for further refinement in the feature space, particularly for distinguishing between classes that generate similar waveform disturbances. Techniques such as time-frequency decomposition or the inclusion of directional protection features could potentially enhance the model’s discriminative capacity for symmetrical faults. Nonetheless, the model demonstrated high stability and robustness across the majority of classes, confirming the viability of ensemble-based methods like Random Forest for intelligent fault classification in power distribution systems.

Generalization to Unseen Fault Scenarios

To evaluate the generalization proficiency of the trained Random Forest classifier, an external dataset comprising previously unencountered fault instances was employed. This dataset encompassed novel fault conditions that were simulated under various system parameters that were not incorporated during the training phase, including modified load profiles, slightly altered fault initiation timings, and fluctuations in power injection levels. The objective was to scrutinize the classifier's capacity to accurately identify fault types under conditions that more closely mimic real-world applications, wherein the data distribution may deviate from that observed throughout the model development stage.

Figure 6 illustrates the distribution of predicted fault types for the external test dataset. The results indicate that the majority of the samples were classified as AB faults, with only minor occurrences predicted as ABC and A-G. This dominant classification is consistent with the actual condition simulated in the test scenario, which involved a line-to-line AB fault. The model’s ability to identify the correct fault type in a previously unseen case supports its robustness and reliability, particularly in the face of temporal shifts and operating condition variations. Although the classifier exhibited minor dispersion in its predictions, assigning a small number of instances to ABC and A-G, this misclassification rate was negligible relative to the overall fault detection accuracy.

Figure 6. *Prediction Distribution for an Unseen Fault Scenario*



The results confirm that the model effectively generalized the fault signatures learned during training to new instances that shared core features but differed in temporal alignment and system loading. This generalization capability is critical for real-time diagnostic applications, where faults may not always manifest identically to training conditions. Furthermore, the use of high-dimensional statistical features such as RMS values and current imbalance measures proved effective for capturing class-invariant fault characteristics that remain distinguishable even under system variability.

The results of this investigation indicate that the advocated methodology possesses the capability not merely to proficiently classify faults within regulated testing environments, but also to sustain performance in more adaptable and realistic contexts. This situates the model favorably for prospective implementation in real-time safeguarding systems or as a diagnostic component within intelligent substations, wherein resilience amidst uncertainty constitutes a fundamental necessity.

Conclusions

This manuscript introduces a machine learning-oriented framework aimed at the automated categorization of electrical faults within distribution power systems, utilizing data generated through simulations and employing a Random Forest classifier. The suggested methodology encompassed the rigorous simulation of a six-bus IEEE test system subjected to a variety of fault scenarios. Time-domain characteristics, predominantly extracted from the root mean square (RMS) values of current and voltage signals, were utilized to train a supervised learning model proficient in accurately identifying different fault types.

The classifier shows a robust classification efficacy across various fault categories, achieving an overall accuracy rate of 86% on an extensive dataset of over 28,000 samples. Elevated precision and recall metrics were recorded for the majority of fault types, particularly A-G, AB, AC, B-G, and C-G. The model exhibited certain constraints in differentiating between three-phase (ABC) and line-to-line (BC) faults, thereby highlighting prospective avenues for enhancement through the integration of superior signal representations or sophisticated learning architectures.

Beyond classification accuracy, the framework was validated against an external test scenario involving an AB fault under previously unseen simulation conditions. The classifier correctly identified the fault type, thereby demonstrating its ability to generalize across different temporal

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settings and load profiles. The comparison of predicted and true fault labels confirmed the model's robustness and practical applicability in adaptive protection systems.

Overall, the results support the conclusion that Random Forest classifiers, when trained on carefully structured and labeled datasets from realistic simulation environments, can provide a scalable and interpretable solution for fault diagnosis in smart distribution networks. Future research will focus on expanding the feature space to include time-frequency and impedance-based descriptors, exploring deep learning models for more complex fault morphologies, and deploying the framework in edge computing environments for real-time grid monitoring and response.

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