An Application of Fuzzy Logic and ANFIS in Intelligent Fault Detection and Localization in Medium-Voltage Networks

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ABSTRACT

Accurate and timely fault diagnosis in medium-voltage networks is essential for enhancing the reliability and operational resilience of power systems. Traditional protection schemes, while fast, often struggle with accuracy in the presence of high fault resistance, dynamic load variations, and unsynchronized measurements. This paper presents a hybrid intelligent framework that integrates a fuzzy logic-based module for fault detection and classification with an Adaptive Neuro-Fuzzy Inference System (ANFIS) for fault location estimation. The proposed method utilizes simple voltage and current indicators as input features and does not rely on GPS synchronization or extensive training datasets. A rule-based fuzzy inference system ensures interpretability and robustness, whereas ANFIS provides accurate fault distance estimation. The system is implemented in MATLAB/Simulink and validated under various fault scenarios. Simulation results demonstrate that the proposed approach can accurately detect, classify, and localize different types of faults, making it suitable for real-time protection in conventional substations and resource-constrained environments.

Keywords-intelligent protection systems; fault detection; fault location estimation; ANFIS; fuzzy logic

I. INTRODUCTION

Ensuring the reliability and stability of electric power systems requires fast and accurate detection, classification, and location of faults in transmission lines [1-3]. Transmission lines are particularly vulnerable to faults such as single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. These events account for the majority of disturbances in distribution and transmission networks and can result in serious consequences, including equipment damage, widespread outages, and cascading failures if not addressed promptly [4]. As power grids become more interconnected and incorporate diverse energy sources, there is a growing demand for intelligent and responsive protection strategies [5]. Conventional protection methods, such as overcurrent relays and impedance-based distance relays, have been widely implemented in transmission systems [6]. Although these techniques are valued for their simplicity and speed [7], they often fail to provide accurate results in scenarios involving high fault resistance [6, 8], dynamic load variations, or non-homogeneous line parameters [9]. To overcome these shortcomings, several signal processing techniques, including the discrete wavelet transform [10], traveling wave analysis [11], and modal component extraction [12], have been introduced. These approaches can enhance feature extraction and fault diagnosis [13], but they typically depend on synchronized measurement devices, detailed system modeling, or intensive computational resources that may not be practical in all environments [14].

In recent years, a significant research trend has emerged focusing on the application of intelligent algorithms for fault analysis [15]. Methods such as Artificial Neural Networks (ANNs) [16, 17], Support Vector Machines (SVM) [18], and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [19] have been proposed for fault classification and localization. These models have shown high levels of accuracy and adaptability by learning complex patterns from simulated or historical datasets [20-22]. However, the deployment of such models in real-time scenarios remains limited due to their computational demands [23], dependence on large volumes of labeled data, and difficulties in interpretability [24]. These limitations pose challenges in resource-constrained environments or in systems where adaptive, transparent decision-making is required.

Motivated by these challenges, fuzzy logic systems have gained attention as a promising alternative for fault detection and location. Fuzzy logic provides a flexible, rule-based framework that is capable of handling uncertainties and imprecise measurements without the need for extensive training or detailed mathematical modeling. Its linguistic inference mechanism makes it suitable for applications where expert knowledge can be incorporated into the diagnostic process. This paper proposes an integrated fuzzy logic-based approach that combines fault detection, classification, and location into a unified framework for medium-voltage distribution networks. Unlike previous studies that often address these tasks separately or rely on GPS synchronization and large training datasets, the proposed system operates effectively with simple indicators and no dependency on synchronized measurements. By leveraging easily obtainable voltage and current features, the system offers high interpretability and fast decision-making suitable for real-time deployment. The methodology not only improves diagnostic accuracy under noisy and uncertain conditions but also provides a cost-effective, low-complexity solution suitable for practical implementation in resource-constrained substations.

II. ANALYSIS OF FAULT DETECTION AND LOCATION METHODS

Fault detection and location have long been critical areas of research in power system protection. Numerous methods have been developed over the decades, which can broadly be categorized into four main groups: impedance-based methods, distributed parameter models, signal processing techniques, and intelligent algorithms. Each technique offers unique advantages but also suffers from distinct limitations, which motivates the need for alternative approaches in complex, real-world scenarios.

A. *Impedance-based Methods*

Impedance-based techniques are among the earliest and most widely implemented methods for fault location in transmission lines. These approaches use the basic relationship:

$$Z_f = \frac{V_f}{I_f} \tag{1}$$

$$d = \frac{Z_f}{Z_{line}} \cdot L \tag{2}$$

where Z_f is the fault impedance, Z_{line} is the line impedance per unit length, and L is the total length of the line. The advantage of these methods lies in their simplicity and suitability for real-time relay implementation. However, their accuracy degrades significantly under conditions such as high fault resistance, varying load flow, and non-homogeneous line characteristics. Their dependency on ideal steady-state assumptions makes them less effective in modern, dynamically changing grids.

B. *Distributed Parameter-based Models*

To overcome the limitations of lumped models, distributed parameter methods consider the line as a transmission medium supporting traveling wave propagation. The voltage at any point along the line is described as:

$$V(x,t) = V_f(x - vt) + V_b(x + vt) \tag{3}$$

Using the time delay Δt between the incident and reflected waves, we obtain:

$$d = \frac{v \cdot \Delta t}{2} \tag{4}$$

These techniques provide high-resolution fault location and are particularly effective for transient-based schemes. However, they require ultra-high-speed sampling, GPS synchronization, and advanced signal acquisition systems, making them impractical for cost-sensitive or retrofitting applications.

C. *Signal Processing-based Techniques*

To address noisy environments and extract transient features, signal processing methods such as discrete wavelet transform have been extensively applied. The wavelet coefficients are defined by:

$$W_{j,k} = \int x(t) \cdot \psi_{j,k}(t) dt \tag{5}$$

where $\psi_{j,k}$ is the scaled and translated mother wavelet at level j and position k. These techniques enable multi-resolution analysis of non-stationary signals, effectively capturing fault-induced transients. However, their performance is sensitive to threshold selection and noise, and they often require significant pre-processing or adaptive filtering schemes to improve robustness.

D. *Intelligent Algorithms*

With the growth of machine learning, intelligent algorithms have become popular for fault detection and classification. SVM, ANNs, and ANFIS are frequently adopted. For example, SVM models define decision boundaries as:

$$f(x) = w^T \phi(x) + b \tag{6}$$

where $\phi(x)$ maps inputs to a high-dimensional space. These models exhibit high accuracy and adaptability to various grid conditions. However, they face critical challenges: requiring large volumes of labeled training data, being computationally intensive, and lacking interpretability. These drawbacks limit their use in real-time or resource-constrained environments.

E. Fuzzy Logic Approaches

Fuzzy logic offers a knowledge-based alternative capable of handling imprecision and nonlinear behavior without heavy reliance on training data. It translates expert reasoning into rules and fuzzy membership functions, making it suitable for real-time applications where interpretability and adaptability are crucial. Fuzzy systems are fast, robust under noisy conditions, and require minimal parameter tuning. Despite these strengths, existing fuzzy logic applications often address detection or classification in isolation, rarely tackling integrated detection-and-location tasks. Furthermore, many works lack validation in low-cost, field-deployable systems where neither synchronized measurements nor AI models are feasible.

In summary, while traditional and data-driven methods have advanced the state of fault analysis, their limitations in terms of accuracy, hardware dependency, or computational load leave room for improved solutions. To address these gaps, this study proposes a fuzzy logic-based approach that combines rule-based reasoning with simplified voltage and current features to perform both fault detection and location.

III. FUZZY–ANFIS FAULT DIAGNOSIS MODULE

To overcome the limitations of conventional and purely data-driven techniques in transmission line fault analysis, this study proposes a hybrid intelligent framework combining a fuzzy logic-based fault classification module with an ANFIS-based fault location estimator. The method ensures reliability, interpretability, and computational efficiency, making it suitable for real-time protection, especially where synchronized measurements are unavailable. As shown in Figure 1, the system comprises three main components: an input feature generator, a fuzzy logic subsystem for fault detection and classification, and an ANFIS module for fault distance estimation. This modular design enables concurrent identification of fault type and location from processed voltage and current signals.

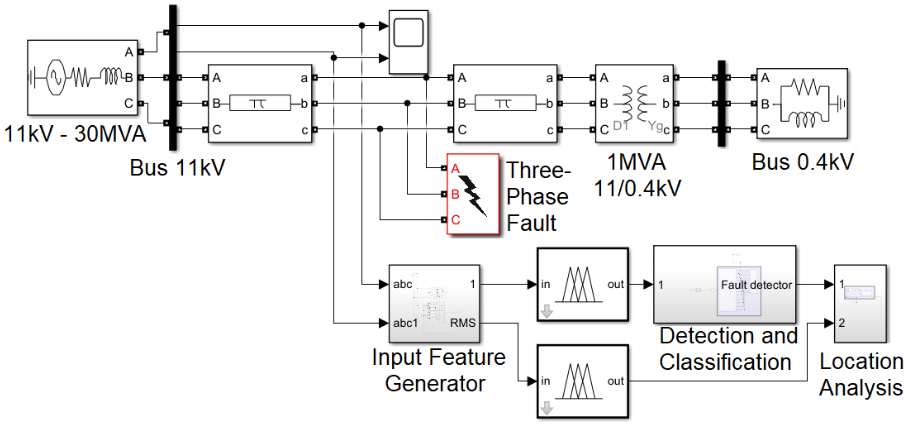

Fig. 1. Block diagram of the fuzzy–ANFIS fault diagnosis system.

The first component of the proposed framework is the fuzzy inference system, which is responsible for detecting and classifying faults based on a set of electrical indicators derived from terminal measurements. The input variables include three-phase voltages and currents (V_a, V_b, V_c, I_a, I_b, I_c), as well as the zero-sequence voltage and current components (V_0, I_0). These indicators are selected for their sensitivity to different fault types and are preprocessed through Root Mean Square (RMS) computation and normalization to mitigate noise effects and ensure consistent input scaling. Each input is mapped to corresponding linguistic labels, such as "low", "medium", or "high," using predefined triangular membership functions. These membership functions are designed based on a combination of expert knowledge and empirical analysis of signal characteristics under various fault scenarios. The fuzzification step enables the translation of numerical input data into qualitative terms that can be processed by the rule-based system.

The core of the fuzzy inference system is a rule base consisting of 12 "if–then" rules constructed using a Mamdani-type inference structure. The design of this rule base is guided by heuristic analysis and fault signature patterns observed in simulation. Each rule typically involves two to three input variables that exhibit strong correlation with a particular fault type. For example, the presence of a Single Line-to-Ground (SLG) fault on phase A can be inferred from a high zero-sequence current and a significantly reduced phase-A voltage. A representative rule for this case is: "if I_0 is high and V_a is low then fault type is AG." Similarly, line-to-line faults such as AB are identified based on the simultaneous voltage drops on phases A and B with a low zero-sequence component: "if I_0 is low and V_a is low and V_b is low then fault type is AB." The 12 rules are designed to cover all fundamental fault categories, including single line-to-ground (AG, BG, CG), line-to-line (AB, BC, AC), double line-to-ground (ABG, BCG, ACG), and three-phase (ABC) faults. This compact rule set is sufficient to ensure discriminability while maintaining computational efficiency, making it well-suited for real-time embedded applications. The inference mechanism aggregates the outcomes of all activated rules using the Mamdani framework, and the final fault classification is obtained through centroid defuzzification of the aggregated fuzzy outputs. This discrete fault type output serves as a trigger for the subsequent localization module. The use of a compact, interpretable rule base enables transparent decision-making, enhances diagnostic reliability under noisy conditions, and facilitates validation in practical deployment scenarios.

Following fault identification, the second stage of the framework estimates the fault location using an ANFIS. ANFIS integrates the structural transparency of fuzzy logic with the learning capability of neural networks, allowing it to model nonlinear relationships between fault indicators and fault distance. Notably, this module does not rely on manually crafted fuzzy rules; instead, it employs a Sugeno-type fuzzy inference structure trained using simulation data. Each training instance comprises the same input variables used in the fuzzy classifier and a corresponding target output representing the known fault distance. The training dataset consists of 210 simulated cases, covering a variety of fault types, fault resistances (1–50 Ω), and fault locations (0–10 km, in 0.5 km increments). The hybrid learning algorithm, combining least-squares estimation and gradient descent, is used to optimize both premise and consequent parameters. Convergence is typically achieved within 15–20 epochs, with final Root Mean Square Error (RMSE) values below 0.01. After training, the ANFIS model is exported and embedded into the protection framework, operating as a location estimator that is triggered only when a fault is detected. Its output is a crisp distance value representing the estimated fault location in kilometers. The input–output configuration of the ANFIS-based localization module is illustrated in Figure 2. The modular design of the system ensures that fault detection and location are decoupled, allowing for flexibility in deployment and reduced computational burden during normal operation.

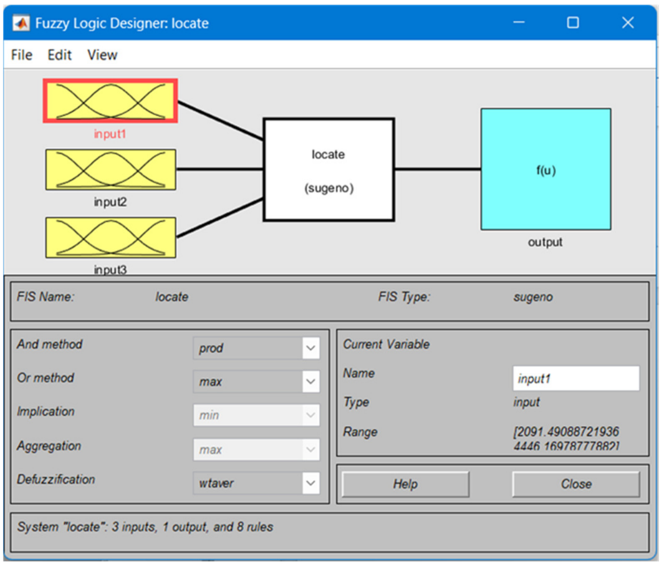

Fig. 2. Input-output configuration of the fuzzy-based fault location system.

IV. ANALYSIS RESULTS

In this study, the effectiveness of the proposed approach is verified through simulations carried out in the MATLAB/Simulink environment. The overall simulation architecture is illustrated in Figure 1, with fault scenarios being generated using the Three-Phase Fault block configuration depicted in Figure 3.

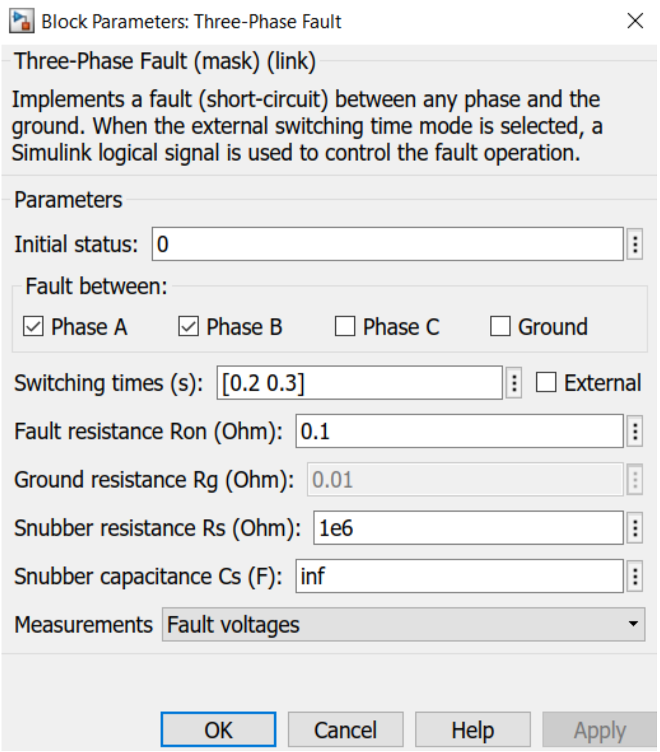

Fig. 3. Configuration of the three-phase fault block.

Specifically, fault conditions are applied to phases A–B, A–C, and B–G for performance evaluation. A line-to-line fault between phases A and B is initiated at 0.2 s. As shown in Figure 4, the fault detection module correctly identifies the occurrence of the A–B fault by producing an output signal that sharply rises to 1. In contrast, the output signals corresponding to other fault types remain at 0, indicating no false activation. This confirms that the proposed fuzzy-based detection mechanism successfully distinguishes the A–B fault from other fault types, including both phase-to-phase and phase-to-ground faults. The estimated fault location is at 5.272 km from the 11 kV bus, demonstrating the system's capability to provide accurate spatial diagnostics.

The A–C fault scenario is similarly simulated at 0.2 s and the corresponding results are illustrated in Figure 5. As observed, the A–C fault signal is accurately triggered at 0.2 s, while all other fault indicators remain inactive. The fault locator estimates the fault to be 5.321 km away from the 11 kV bus. Additionally, fault scenarios involving phase-to-ground events are also simulated.

Figure 6 presents the results of the B–G fault simulated at 0.2 s. The classification system correctly identifies the B–G fault, as indicated by a maintained output signal of 1. Although the A–B fault signal briefly responds, it is quickly suppressed and returns to zero, as the fault does not match the simulated condition. The estimated fault location is at 5.251 km from the 11 kV bus. Accurate fault identification is critical for enabling operators to determine both the fault type and location effectively, which in turn facilitates appropriate corrective actions. The timely and precise fault localization enhances the reliability and responsiveness of power system operation.

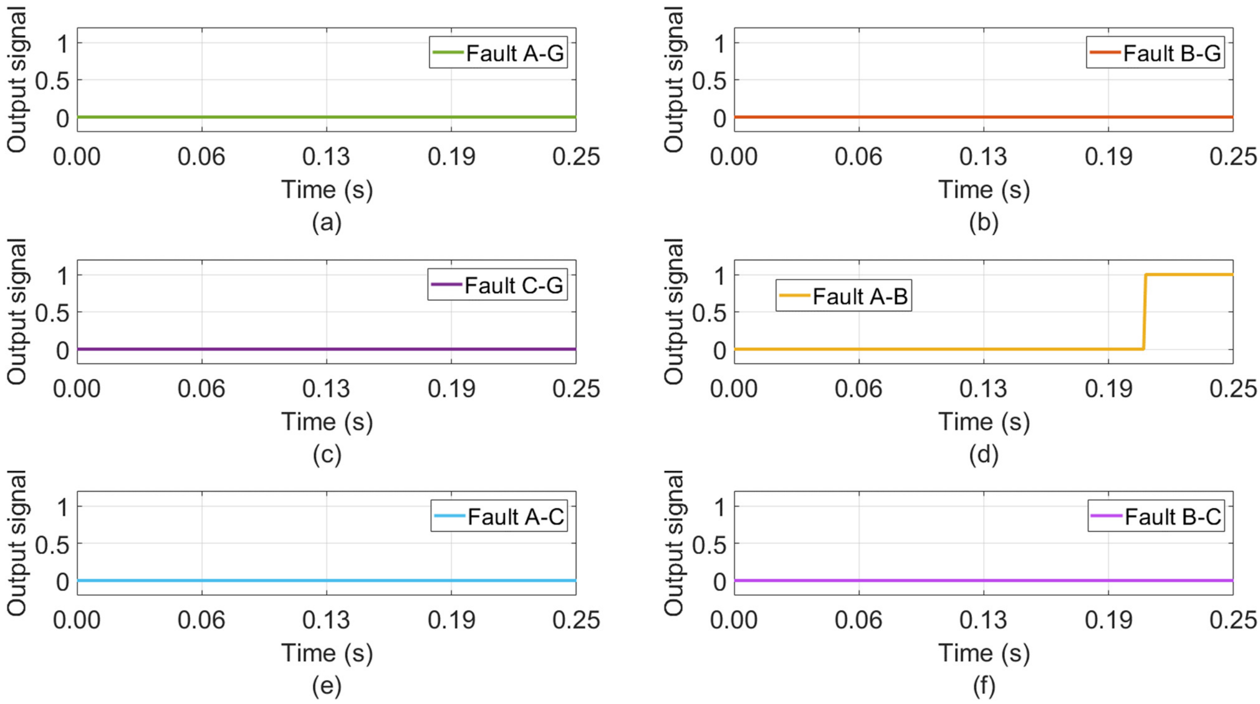

Fig. 4. Fault classification outputs for the A–B fault scenario: (a) fault A-G, (b) fault B-G, (c) fault C-G, (d) fault A-B, (e) fault A-C, and (f) fault B-C.

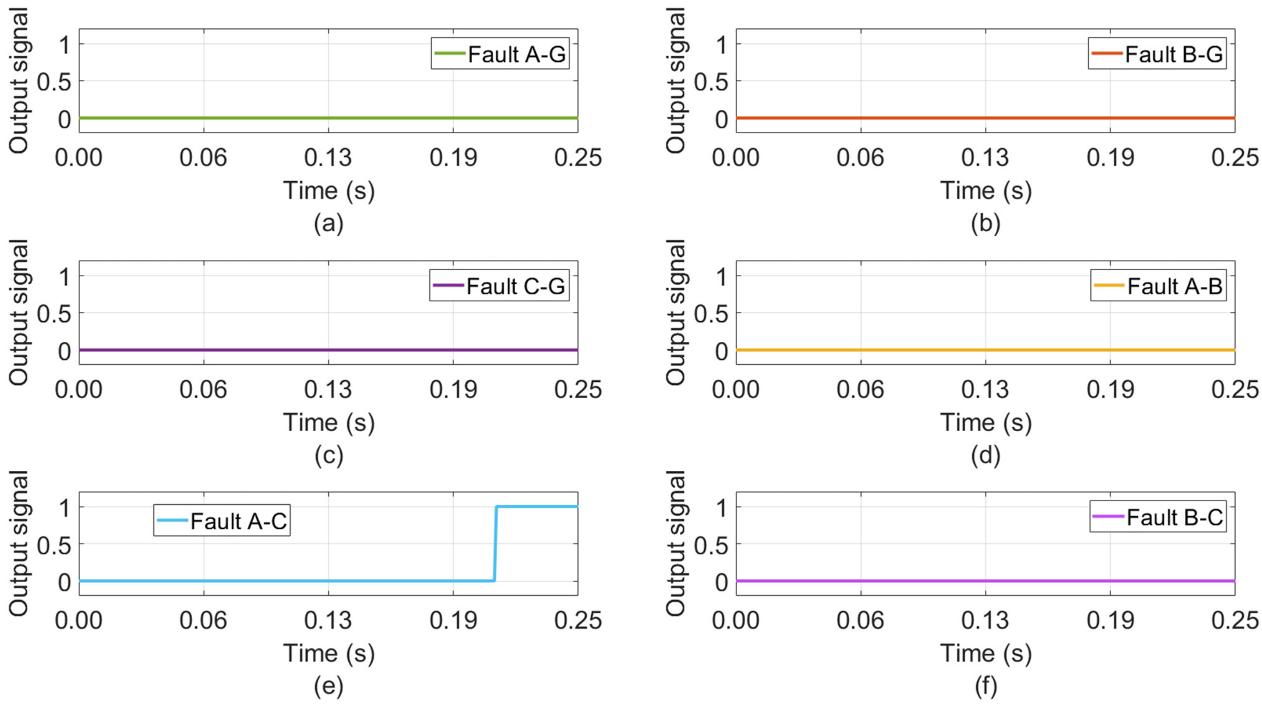

Fig. 5. Fault classification outputs for the A–C fault scenario: (a) fault A-G, (b) fault B-G, (c) fault C-G, (d) fault A-B, (e) fault A-C, and (f) fault B-C.

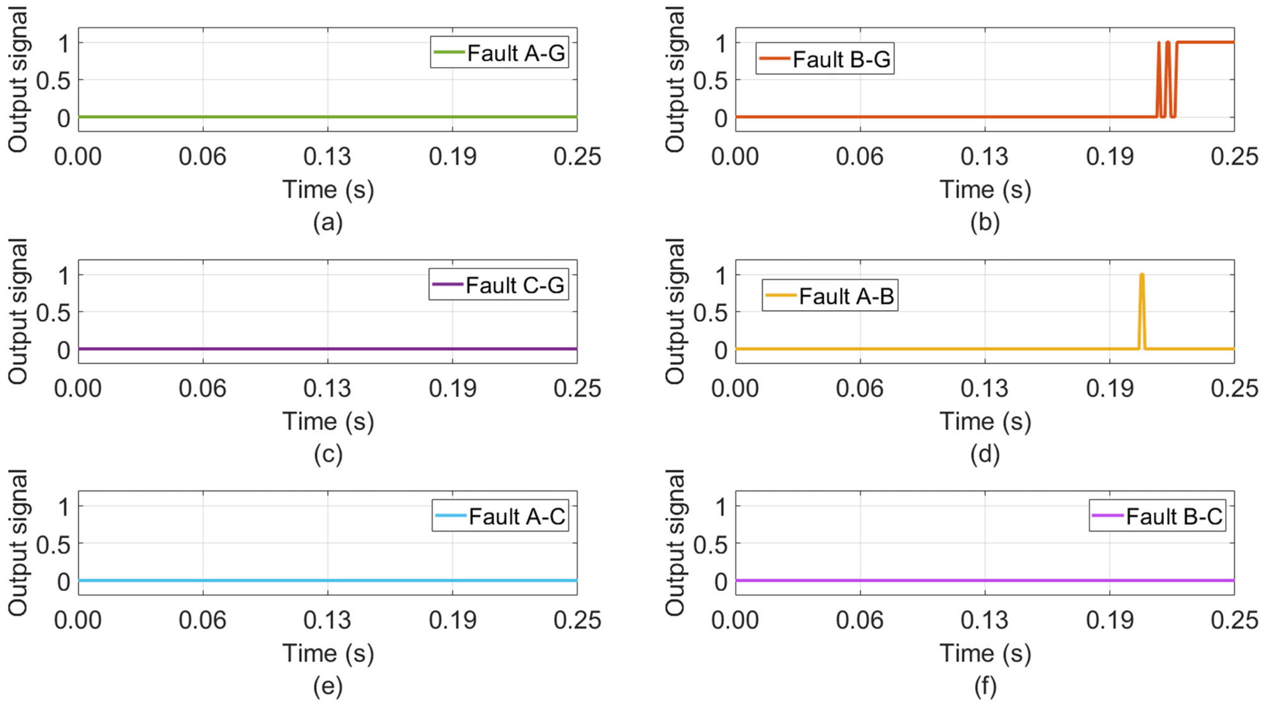

Fig. 6. Fault classification outputs for the B–G fault scenario: (a) fault A-G, (b) fault B-G, (c) fault C-G, (d) fault A-B, (e) fault A-C, and (f) fault B-C.

V. CONCLUSION

This study presents an integrated fault diagnosis solution for medium-voltage networks, combining fuzzy logic for classification and an Adaptive Neuro-Fuzzy Inference System (ANFIS) for fault location. The approach balances interpretability, accuracy, and computational efficiency without relying on synchronized measurements or large training datasets. Simulation results validate its ability to accurately identify fault types and locations under various conditions. With its modular structure, the proposed method is well-suited for real-time deployment and seamless integration into existing protection systems. Future work will focus on enhancing adaptability to evolving grid conditions and unknown system configurations.

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