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# Intelligent Fault Detection In a 25 MVA Transformer Using ANFIS

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## ABSTRACT

This study aims to develop an intelligent fault prediction model for a 25 MVA power transformer using the Adaptive Neuro-Fuzzy Inference System (ANFIS), to improve classification accuracy and ensure selective, reliable protection decisions in power systems. The research is grounded in the limitations of traditional differential relay protection, which struggles to distinguish between internal and external faults during transient conditions. ANFIS combines fuzzy logic's ability to handle uncertainty with the adaptive learning of neural networks, making it a suitable tool for non-linear fault data analysis. A simulation was carried out in MATLAB/Simulink. Current signals from CTs on both primary and secondary sides served as input features. The model was trained using 270 data samples and tested with 30 samples. Two membership functions generalized bell-shaped (Gbell) and triangular (Tri) were evaluated. RMSE was used as the performance metric. The ANFIS model with Gbell MF yielded a lower RMSE (0.0116) compared to Tri MF (0.0445), indicating better prediction accuracy and stability. The system consistently identified internal faults (output 1), and external faults (output 0) based on a 0.5 decision threshold. The findings validate the potential of ANFIS for integration into digital relay systems, enhancing real-time transformer protection through adaptive learning.

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## 1. INTRODUCTION

Power transformers play a fundamental role in electrical power systems by enabling energy transfer across different voltage levels [1]. Because they operate as strategic nodes within transmission and generation networks, transformer failures may trigger extensive system disturbances and lead to substantial economic losses [2]. For this reason, protection schemes must ensure high reliability, selectivity, and fast operation. Differential protection (87T) remains one of the most widely implemented methods, operating on the principle of comparing primary and secondary currents within a defined protection zone [3], [4]. Despite its practical effectiveness, conventional differential relays encounter limitations under transient conditions, particularly in discriminating internal faults from external disturbances during magnetizing inrush or other dynamic events [5-7].

Internal faults occur within the transformer protection zone, such as inter-winding faults or ground faults, and may result in severe and irreversible damage. In contrast, external faults originate outside the protected zone and generally do not necessitate transformer isolation [8]. Incorrect classification of these conditions can either cause unnecessary tripping or delay protective action, both of which compromise system stability and asset integrity.

In response to increasing system complexity, Artificial Intelligence (AI) has emerged as a promising tool for enhancing power system operation, planning, and control [9-11]. Within the protection domain, AI-based methods have been explored to overcome the rigidity of deterministic threshold-based logic. Techniques such as Artificial Neural Networks (ANN), Fuzzy Logic, Support Vector Machines (SVM), and hybrid models have demonstrated improved adaptability and classification capability in power system fault analysis [12-15].

Among these approaches, the Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates the learning capacity of neural networks with the uncertainty-handling capability of fuzzy inference. The standard ANFIS framework consists of five layers encompassing fuzzification, rule evaluation, normalization, and defuzzification processes [16]. Its structure enables nonlinear mapping between input features and classification outputs, making it suitable for modeling complex fault current patterns. The selection of membership functions (MF), such as generalized bell-shaped and triangular types, directly influences training convergence and prediction performance [17], [18].

ANFIS has been extensively investigated for fault detection and classification in power networks [19-21]. In transformer protection applications, it has shown the ability to distinguish internal faults, external faults, and transient inrush conditions with high accuracy. Azriyenni et al. [22], for example, demonstrated the effectiveness of ANFIS in differential relay protection by achieving accurate classification across multiple fault scenarios, including single-phase-to-ground and three-phase faults. Furthermore, hybrid approaches integrating ANFIS with signal processing techniques have been reported. Suliman and Al-Khayyat [23] combined Discrete Wavelet Transform (DWT) with ANFIS to extract transient features from differential currents, enabling accurate discrimination between inrush and internal faults using MATLAB/Simulink and laboratory validation. Similarly, Salama et al. [24] implemented a DWT-ANFIS protection algorithm for a 40 MVA transformer, confirming reliable and fast fault identification through ATP/EMTP and MATLAB/Simulink simulations.

Despite these advancements, studies integrating a physically validated equivalent circuit model with ANFIS-based protection for medium-capacity transformers remain limited. This study addresses that gap by developing and validating an ANFIS-based fault discrimination model for a 25 MVA transformer using a realistic equivalent circuit representation. The proposed framework evaluates the impact of two membership function types generalized bell and triangular on classification performance and is implemented within a MATLAB/Simulink environment. By coupling detailed transformer modeling with adaptive fault classification, this work aims to enhance selectivity and robustness in transformer differential protection.

The main contribution of this study lies in the structured integration of a physically parameterized 25 MVA transformer equivalent circuit with an ANFIS-based adaptive fault classification framework within a unified MATLAB/Simulink environment. Unlike conventional differential protection approaches that rely on fixed harmonic restraint thresholds, the proposed method employs multi-feature learning incorporating differential current, restraint current, RMS magnitude, and second harmonic ratio to construct adaptive decision boundaries under transient operating conditions. In addition, the comparative evaluation of generalized bell-shaped and triangular membership functions provides quantitative insight into the influence of membership design on convergence behavior and prediction accuracy. By combining realistic transformer modeling with intelligent classification, this work contributes a scalable and simulation-validated methodology for enhancing selectivity and stability in digital transformer protection systems.

## 2. RESEARCH METHOD

This study adopts the quantitative approach founded on simulation methods using the MATLAB/Simulink software to model the system of the power transformer and examine the system response to faults. Simulation is directed at the three-phase, 25 MVA transformer with a voltage level of 150/20 kV which is the case study of the gas turbine power plant. The modeled system includes the delta–wye grounded winding configuration, the transformer impedance, and the location of two current transformers (CT1 at the primary side and CT2 at the secondary side) as input current sensors. The simulation setup proceeds by including several three-phase fault sources inside and outside the internal and external areas of the transformer. Included fault types are the single line-to-ground (AG), line-to-line (BC), three-phase (ABC), and double line-to-ground (BCG) faults. Faults are applied at the time t = 0.15 seconds to initiate the system transient response. The object of study is a 25 MVA, 150/20 kV, three-phase power transformer operating at 50 Hz. The transformer is modelled using a per-phase equivalent circuit referred to the high-voltage side.

The base impedance is calculated as:

$$Z_{base} = \frac{V^2}{S} = \frac{(150 \times 10^3)^2}{25 \times 10^6}$$

Given a short-circuit impedance of 12%, the equivalent leakage impedance is:

$$Z_{eq} = 0.12 \times Z_{base} = 108\ \Omega$$

The equivalent circuit consists of: Series winding resistance and leakage reactance and Magnetizing branch. This model provides realistic electrical behaviour under normal and fault conditions. To generate representative datasets, multiple operating conditions are simulated:

1. Normal operating condition
2. Magnetizing inrush current
3. Internal winding faults
4. External short-circuit faults

Faults are introduced using the Three-Phase Fault block in Simulink at predetermined time intervals. Current signals from both primary and secondary sides are measured using current transformers (CTs).

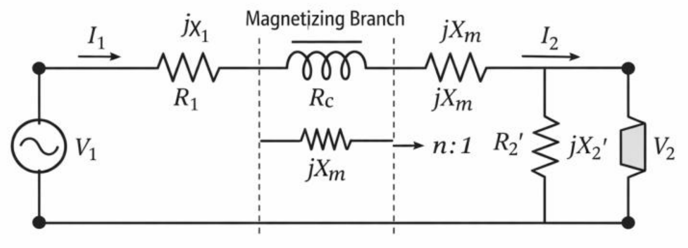

**Figure 1.** Equivalent circuit of 25 MVA transformer

The equivalent circuit of the 25 MVA in Figure 1, 150/20 kV transformer is modeled on a per-phase basis and referred to the high-voltage side to enable accurate fault analysis. The series impedance, composed of winding resistance and leakage reactance, represents copper losses and short-circuit characteristics, while the shunt magnetizing branch models core excitation and iron losses. Using the rated capacity and 12% short-circuit impedance, the equivalent parameters are derived to reflect practical operating conditions. This model provides a reliable basis for calculating differential and restraint currents under normal operation, magnetizing inrush, and internal or external fault scenarios, thereby supporting the implementation of the proposed ANFIS-based protection algorithm.

### 2.1. ANFIS System Input and Output

In intelligent protection systems, the selection of representative input and output variables plays a decisive role in ensuring accurate fault pattern recognition. In this study, current measurements obtained from the primary and secondary Current Transformers (CT1 and CT2) of a 25 MVA transformer serve as the fundamental data source for the Adaptive Neuro-Fuzzy Inference System (ANFIS). These measurements capture the electrical response of the transformer under normal operation, internal fault, and external fault conditions.

To align with the operating principle of differential protection (87T), the extracted features are derived from the relationship between primary and secondary currents. Instead of relying solely on raw peak values, the model employs processed electrical parameters that better represent system dynamics. The selected input features for ANFIS training are:

1. Differential current ($I_{diff}$)
2. Restraint current ($I_{rest}$)
3. RMS current magnitude
4. Second harmonic ratio ($H_2$)

The differential current reflects the imbalance between CT1 and CT2 within the protection zone, while the restraint current provides stabilization against external disturbances. The inclusion of RMS magnitude and harmonic content enhances discrimination capability during transient conditions, particularly magnetizing inrush events.

Unlike conventional deterministic relay logic, which operates using fixed thresholds, ANFIS applies data-driven learning to model nonlinear relationships between input features and fault categories [16]. The classifier produces a binary output, where a value of 0 corresponds to an external fault and a value of 1 indicates an internal fault within the protected zone. This output functions as the decision signal for issuing a trip command or maintaining normal operation.

By integrating adaptive learning with fuzzy inference, ANFIS provides enhanced robustness in handling measurement uncertainty and complex transient patterns [25]. Previous studies have demonstrated its effectiveness in analyzing CT-based current signals for short-circuit detection and imbalance identification [26]. The adaptive structure and efficient training process enable improved classification stability compared with conventional rule-based methods.

### 2.2. Membership Function Variations

Within the ANFIS structure, membership functions (MFs) govern the fuzzification stage, where numerical input features namely differential current ($I_{diff}$), restraint current ($I_{rest}$), RMS magnitude, and second harmonic ratio ($H_2$) are transformed into fuzzy membership degrees. The selection of MF shape directly influences the representation of nonlinear relationships among these electrical parameters and consequently affects convergence behavior and classification performance.

This study evaluates two commonly applied MF types in ANFIS models: the generalized bell-shaped (Gbell) function and the triangular (Tri) function. The Gbell MF is characterized by a smooth and continuous curve with adjustable parameters that control width and slope, enabling flexible adaptation to complex input distributions [16]. In contrast, the triangular MF is defined by three characteristic points (lower bound, center, and upper bound) and offers computational simplicity, making it suitable for systems with limited processing requirements.

As reported by Janková and Rakovská [18], the predictive capability of fuzzy-based models is highly sensitive to MF selection. An overly narrow MF may cause excessive sensitivity to minor variations, whereas an overly broad MF can reduce classification resolution. Therefore, systematic evaluation of MF configurations is necessary to ensure stable convergence and reliable fault discrimination within the proposed ANFIS-based protection framework.

### 2.3. ANFIS Training and Validation Procedure

The ANFIS model was implemented using the MATLAB ANFIS Editor toolbox and trained through a hybrid learning algorithm that combines Least Squares Estimation (LSE) in the forward pass with gradient descent optimization in the backward pass. The training dataset consisted of 270 samples derived from simulated transformer operating conditions, while 30 independent samples were reserved for testing. The dataset encompassed multiple internal and external fault scenarios, including AG, BC, ABC, and BCG faults, ensuring variability in fault characteristics and operating conditions. The input feature set comprising differential current ($I_{diff}$), restraint current ($I_{rest}$), RMS magnitude, and second harmonic ratio ($H_2$) was consistently used during both training and testing phases. To examine the influence of membership function (MF) design on classification performance, generalized bell-shaped (Gbell) and triangular (Tri) MFs were evaluated separately under identical training configurations. Model outputs were compared with target labels generated from the simulated protection zone status to assess predictive consistency.

The adopted hybrid training framework aligns with recent developments in ANFIS-based transformer protection, where signal processing and optimization techniques have been integrated to enhance classification robustness in practical applications [23]. Model validation was conducted by analyzing the agreement between predicted outputs and actual fault categories, using both classification accuracy and statistical error metrics. This combined evaluation approach provides a balanced assessment of convergence behavior and discrimination reliability under varying fault conditions.

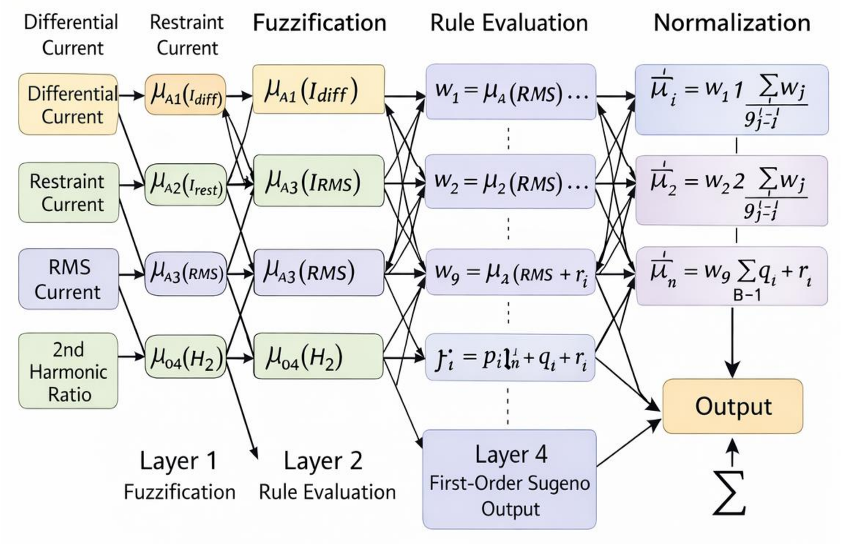

**Figure 2.** ANFIS Architecture

The designed ANFIS architecture in Figure 2 comprises five sequential layers that map extracted transformer fault features into a classification output. The inputs differential current, restraint current, RMS current, and second harmonic ratio are first fuzzified using Gaussian membership functions. The rule layer computes and normalizes the firing strengths, followed by first-order Sugeno consequent evaluation. The final layer aggregates the weighted outputs to generate a decision signal, enabling accurate discrimination between internal faults and non-fault conditions such as magnetizing inrush.

### 2.4. Membership Function Variations

To objectively evaluate the performance of the ANFIS system, the Root Mean Square Error (RMSE) is used as the primary metric. RMSE measures the average squared differences between the model's predicted outputs ( $y_i$ ) and the actual target values ( $\hat{y}_i$ ). In essence, it shows how far off the predictions are from the true results, where a lower RMSE indicates better accuracy. The standard formula for calculating RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}$$

The evaluation results showed that the lowest RMSE was achieved when the generalized bell-shaped membership function (GbellMF) was used. This low error suggests that the ANFIS model with Gbell MF delivers higher accuracy and better stability in identifying fault patterns compared to the model using the triangular MF. These findings are consistent with those of Nezami et al. [27], who highlighted that smooth, curve-based membership functions like Gbell can greatly enhance a system's ability to respond to variations in fault current patterns within electrical power systems.

## 3. RESULTS AND DISCUSSION

The equivalent circuit of the 25 MVA, 150/20 kV transformer was first validated under steady-state conditions to ensure parameter consistency prior to fault analysis. Using a 12% short-circuit impedance, the calculated leakage impedance of 108 Ω produced nominal current magnitudes

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consistent with theoretical expectations. The simulated no-load current and voltage profiles confirmed that the magnetizing branch parameters adequately represent excitation behavior. This validation step ensures that subsequent fault simulations are physically meaningful and not merely algorithm-driven. Under fault conditions, the equivalent circuit demonstrated expected behavior: internal winding faults generated significant current asymmetry between primary and secondary sides, while external faults produced high current magnitudes but minimal differential imbalance. This confirms that accurate electrical parameterization directly influences the reliability of feature extraction.

The ANFIS model training and testing in this research were aimed at assessing its capability in classifying types of faults in power transformers, specifically in distinguishing between internal and external faults. In the testing, 30 data samples were created from fault simulations conducted on a 25 MVA transformer system in MATLAB/Simulink. To determine the influence of the membership function type on the model performance, two were experimented with; the generalized bell-shaped (Gbell) and the triangular (Tri) function. The classification accuracy of the model was quantified by the Root Mean Square Error (RMSE), which is the average of the squared difference between predicted outputs and actual target values. From the simulation, the RMSE values for both membership functions are as follows:

1. RMSE for GbellMF: 0.0116
2. RMSE for Triangular MF: 0.0445

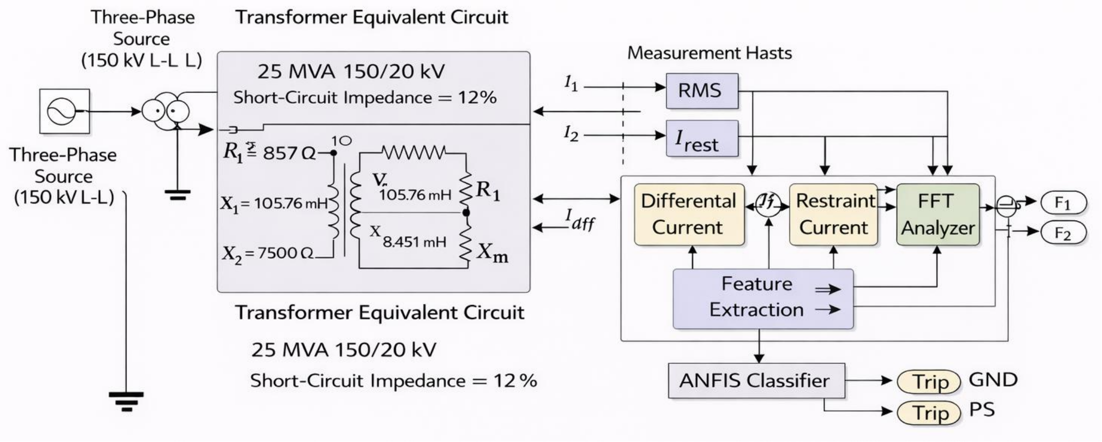

**Figure 3.** Model of the 25 MVA transformer

The model of the 25 MVA transformer (Figure 3) is developed to represent both the electrical behavior of the equivalent circuit and the implementation of the proposed differential protection scheme within a unified simulation environment. The model begins with a three-phase 150 kV source supplying the transformer equivalent circuit, which incorporates the series winding impedance and the magnetizing branch derived from the rated short-circuit impedance of 12%. Primary and secondary currents are measured through current transformers and processed to obtain RMS values, differential current, and restraint current. An FFT analyzer is employed to extract the second harmonic component required to distinguish magnetizing inrush from internal fault conditions. These extracted features are then fed into the ANFIS classifier, which generates the trip decision signal. This integrated structure allows realistic time-domain fault simulation while simultaneously evaluating the performance of the intelligent protection algorithm under various operating conditions.

The ANFIS configuration employing the generalized bell-shaped membership function (GbellMF) yielded a substantially lower RMSE compared to the triangular MF, indicating improved convergence stability and predictive consistency. The smoother and parameter-adjustable structure of the GbellMF enables more flexible representation of nonlinear relationships among the input features namely differential current ($I_{diff}$), restraint current ($I_{rest}$), RMS magnitude, and second harmonic ratio ($H_2$). In contrast, the piecewise-linear nature of the triangular MF limits its ability to model subtle variations in transient fault patterns. The lower error magnitude observed with the GbellMF confirms its enhanced capability in capturing complex electrical behavior associated with internal and external fault conditions.

To provide a comprehensive assessment beyond RMSE, additional performance metrics were considered, including Mean Absolute Error (MAE), classification accuracy, and confusion matrix analysis. These indicators offer complementary perspectives on both regression convergence and classification reliability. Furthermore, to reduce the influence of dataset partitioning and to evaluate model generalization capability, a 5-fold cross-validation procedure was implemented. The dataset was iteratively divided into five subsets, ensuring that each subset served as validation data while the remaining subsets were used for training. This strategy minimizes overfitting risk and strengthens confidence in the model's predictive performance when exposed to previously unseen fault scenarios.

### 3.1. ANFIS Training and Testing Results

These findings are consistent with the observations reported by Janková and Rakovská [18], who highlighted that the selection of an appropriate membership function significantly influences the generalization capability of fuzzy-based systems. In this study, the generalized bell-shaped MF demonstrated improved representation of nonlinear fault characteristics compared to the triangular MF, contributing to enhanced convergence stability and classification performance. The predicted outputs closely correspond to the target labels for both internal faults (1) and external faults (0), indicating that the model effectively captured the underlying fault discrimination patterns embedded in the training data. The consistency between predicted and actual classifications further supports the suitability of the selected MF configuration within the proposed ANFIS-based protection framework.

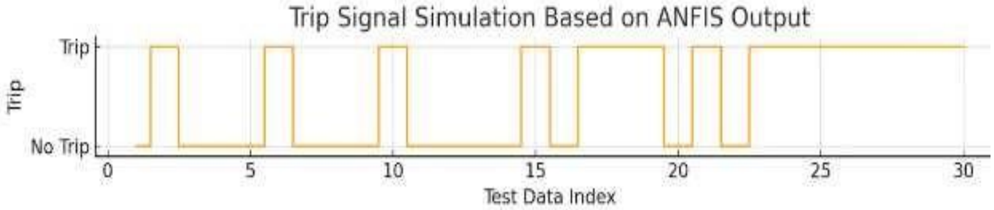

**Figure 4.** Simulation of trip signals based on ANFIS output

Figure 4 presents the trip signal generated by the ANFIS model configured with the generalized bell-shaped membership function. The horizontal axis represents the index of the testing samples, while the vertical axis shows the corresponding decision output. A value of 1 denotes an internal fault condition requiring a trip command, whereas 0 indicates an external fault or normal operating state. A decision threshold of 0.5 was applied, whereby predicted outputs exceeding this value were classified as internal faults, and values below it were categorized as non-trip conditions. The transition points in the trip signal correspond closely with the expected fault labels, indicating consistent discrimination between internal and external disturbances. The model demonstrates stable switching behaviour without spurious oscillations around the decision threshold, suggesting reliable classification under the tested scenarios. The binary structure of the output facilitates straightforward interfacing with digital relay logic, supporting selective transformer protection based on adaptive feature mapping rather than fixed threshold rules.

### 3.2. Comparison of Membership Functions

The generalized bell-shaped membership function (GbellMF) produced prediction outputs that closely followed the target labels, exhibiting smaller error deviations compared to the triangular membership function (Tri MF), which showed more pronounced fluctuations. This behavior indicates that the smoother and parameter-adjustable structure of the GbellMF provides improved representation of nonlinear relationships among the selected fault features. As illustrated in Figure 2, the prediction curve demonstrates strong agreement with the expected classification outcomes, consistent with the lower RMSE value of 0.0116 obtained for the Gbell configuration. The continuity and flexibility of the Gbell function enable more stable mapping between input parameters differential current ($I_{diff}$), restraint current ($I_{rest}$), RMS magnitude, and second harmonic ratio ($H_2$) and the corresponding fault categories. The reduced error dispersion and stable convergence behavior support the model's capacity to generalize across varying fault scenarios, thereby improving discrimination between internal and external transformer faults within the proposed protection framework.

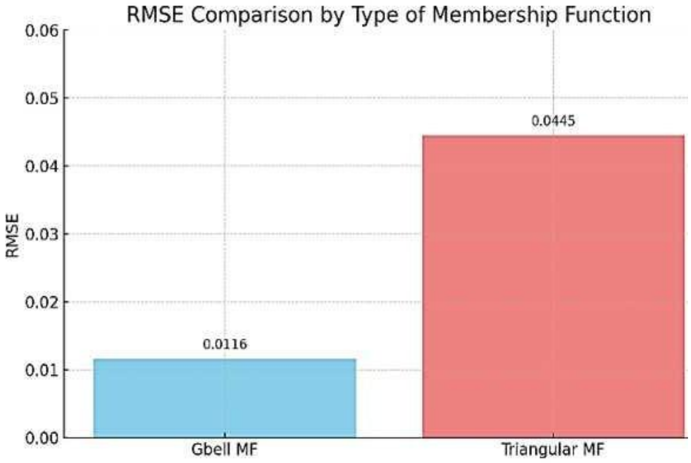

**Figure 5.** Comparison of RMSE based on membership function type

Figure 5 presents the comparison between the target fault labels and the predicted outputs generated by the ANFIS model configured with the generalized bell-shaped membership function (Gbell MF) for the 30 testing samples. The vertical axis represents the classification outcome, where 0 denotes external faults and 1 indicates internal faults, while the horizontal axis corresponds to the sequence of test samples. The predicted outputs closely align with the target classifications, indicating consistent fault discrimination across the testing dataset. This agreement is consistent with the low RMSE value of 0.0116 obtained during evaluation, reflecting stable convergence and limited prediction deviation. The results suggest that the Gbell MF effectively captures the nonlinear characteristics embedded in the selected electrical features. Moreover, the uniform classification behavior across different fault types supports the model's generalization capability within the simulated transformer protection framework.

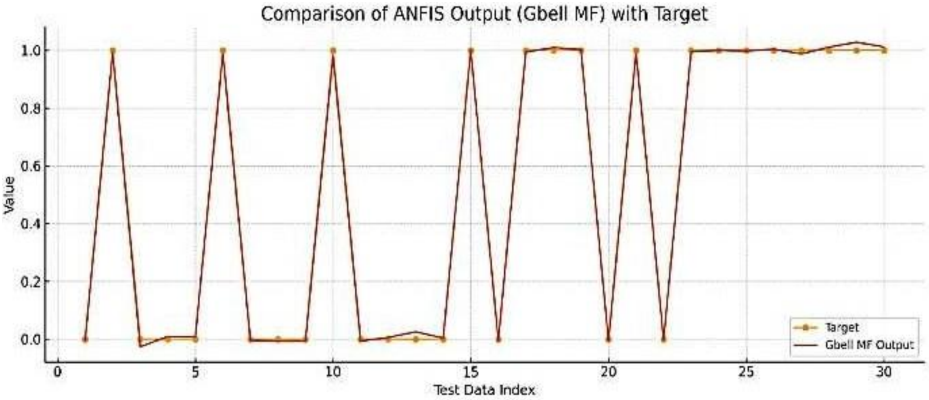

**Figure 6.** Comparison between ANFIS output (Gbell MF) and target values

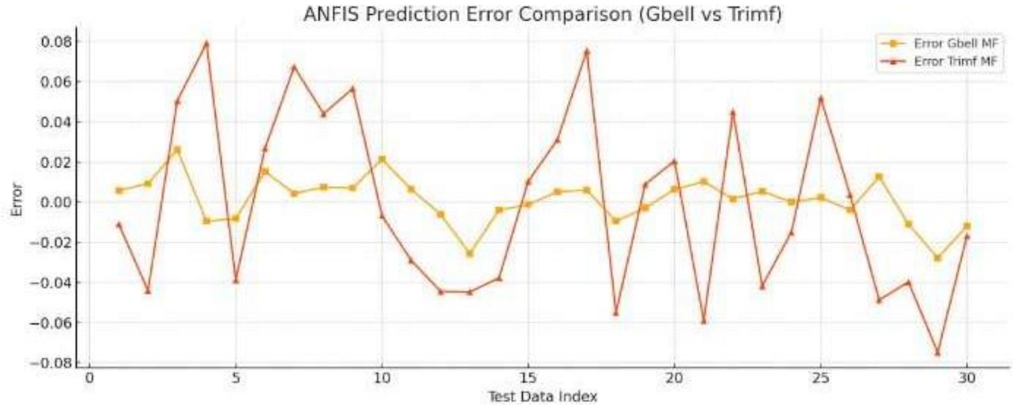

**Figure 7.** ANFIS prediction error analysis: GbellMF vs. TriMF

Figure 7 presents a comparison of prediction errors obtained using two membership function configurations in the ANFIS model: the generalized bell-shaped (GbellMF) and the triangular (TriMF) functions. The error values, defined as the difference between predicted outputs and corresponding target labels across the 30 testing samples, highlight the performance contrast between the two configurations. The GbellMF exhibits smaller and more uniformly distributed errors concentrated near zero, indicating improved prediction stability. In contrast, the TriMF demonstrates larger deviations and greater variability, suggesting reduced consistency in capturing the underlying fault patterns. These observations are consistent with the RMSE results, where the GbellMF achieved a lower error value (0.0116) compared to the TriMF (0.0445). The smoother and parameter-adjustable structure of the generalized bell function enables more flexible modeling of nonlinear relationships among the selected electrical features. The reduced error dispersion observed in the Gbell configuration reflects improved convergence behavior and enhanced generalization capability within the simulated transformer protection framework. Overall, the comparative analysis confirms that membership function selection significantly influences ANFIS classification performance.

### 3.3. Interpretaation of Fault Prediction

The ANFIS system separates internal faults well by giving output values that are roughly 1 while output values for external faults are about 0. Based on the decision threshold of 0.5, the system always issues the trip command for internal faults and does not unnecessarily trip for external faults.

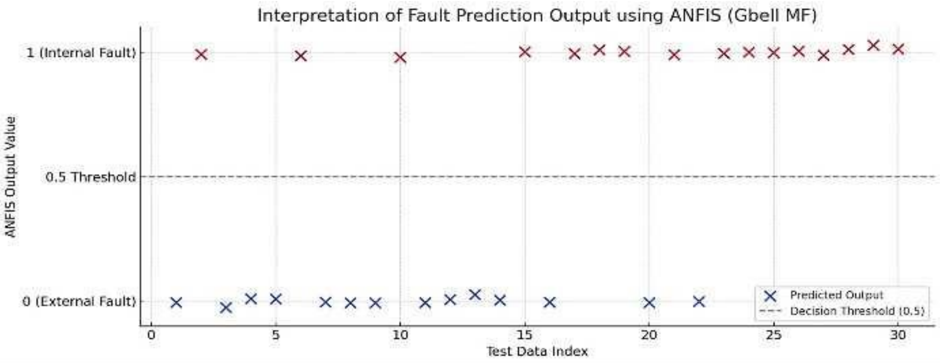

**Figure 8.** Fault prediction analysis based on ANFIS output

Figure 8 depicts the output of the ANFIS model using the generalized bell function membership function determining the transformer faults as internal or external. Each point on the graph is the output predicted by the model for one test sample and varies between 0 and 1. There is also a horizontal dashed line at 0.5 that is the decision boundary: the predictions above or on this line are internal faults that would trigger the trip signal, while the ones below are external faults that would not require any action.The visualization illustrates the clear and consistent segregation between the two fault types. Forecasts for internal faults are closely grouped around 1, while forecasts for external faults are around 0. The clear segregation reflects the ability of the model to efficiently interpret sophisticated current pattern signatures and translate them into reliable fault classifications. These results illustrate the high selectivity and reliability of two critical requirements for transformer protection systems. Its ability to reduce spurious trips while efficiently detecting actual internal faults illustrates the potential for the ANFIS model in real-time intelligent relay applications.

## 4. CONCLUSION

This study demonstrates that the proposed ANFIS-based protection model provides accurate and adaptive discrimination between internal and external faults in a 25 MVA power transformer under simulated operating conditions. By integrating a physically validated transformer equivalent circuit with multi-feature input signals including differential current, restraint current, RMS magnitude, and second harmonic ratio the model achieves reliable classification performance. The generalized bell-shaped membership function outperformed the triangular function, yielding a lower RMSE of 0.0116 compared to 0.0445, indicating superior convergence and nonlinear pattern recognition capability. The results confirm that ANFIS enhances fault selectivity by reducing false trips during magnetizing inrush while maintaining high sensitivity to internal faults. Compared with conventional differential relay logic based on fixed harmonic thresholds, the proposed approach introduces adaptive decision boundaries that improve protection stability under transient conditions. The main contribution of this work lies in the structured integration of realistic transformer modelling and intelligent fault classification within a unified MATLAB/Simulink framework. This provides a scalable foundation for implementing adaptive protection strategies in digital relay systems. Future work will focus on experimental validation using real transformer data and performance evaluation under varying fault resistance and system operating scenarios to further assess field applicability.

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