Prevention of Maloperation of the REF Relays Using Artificial Intelligence and Wavelet Transform

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***Abstract*-Restricted Earth Fault (REF) Relay, a type of differential protection, is responsible for detecting single-phase-to-ground faults at the terminal of a transformer or faults in the winding to the core. This protection scheme is inherently sensitive and rapid; however, due to current transformer saturation during external fault conditions with high currents and the transient magnetizing current flowing through the transformer core, it may be susceptible to false operation. In this paper, an intelligent restricted ground fault protection scheme based on wavelet transform (WT) is presented. In the initial step, the differential current resulting from the simulation is analyzed using WT, and various features of decomposed signals are extracted as sample patterns for training intelligent classifiers. The performance of the proposed method is evaluated using data obtained from the simulation of a 230/63.5 kV power transformer in the PSCAD/EMTDC software environment. Additionally, to accurately simulate the transformer current during saturation, the valid Gill's model is employed. The results of implementing this intelligent protection scheme confirm its high reliability against false operation.**

***Index Terms*-- Artificial Intelligence, Current Transformer Saturation, Internal and External Fault, Restricted Earth Fault Protection, Power Transformer, Wavelet Conversion.**

Nomenclature

REF	Restricted Earth Fault
WT	Wavelet Transform
PNN	Probabilistic Neural Networks
SVM	Support Vector Machines
STFT	Short Term Fourier Transforms
$p_r(S_i\|x)$	Probability Density Function
$S_1, S_2, \ldots., S_k$	Corresponding Classes
k	Number of Possible Classes
x_j^i	Example j From Class i
C	Penalty Coefficient
σ_i	Smoothing Factor
α_i and η_i	Lagrange Multiplier Auxiliary Variables.

I. INTRODUCTION

Due to the critical role of transformers in power systems, the use of protective equipment with high-speed and precise detection capabilities is a requirement that must always be considered.

A. motivation, contribution

Ground faults at the terminals or windings of transformers, including internal faults, can lead to catastrophic consequences such as fires or transformer explosions if proper and timely protection measures are not in place [1]. At present, one of the most common methods of protecting power transformers against internal faults is differential protection [2]. Although biased differential protection units provide effective protection against phase-to-phase and phase-to-ground internal faults, they exhibit limited sensitivity to internal ground faults occurring in the vicinity of the neutral-grounded windings [3]. Furthermore, in certain operating conditions such as transformer energization and current transformer saturation, spurious differential currents can be generated, leading to incorrect operation of the differential relay[4]. According to [5], differential relays are susceptible to maloperation during transformer energization without load because the inrush currents are mistakenly interpreted as internal faults.

B. literature review

Consequently, a number of strategies, such as maintenance and harmonic blocking techniques, have been put forth to improve the performance of differential relays [6, 7]. Furthermore, the fault current magnitude is %X of the maximum fault current (which occurs at the terminals) when a single-phase-to-ground fault happens at a distance of %X from the neutral point in the star-winding. The phase differential relay can only protect %37.96 of the transformer's winding against ground faults if the differential relay's pickup setting is set at %20 of the rated current, leaving %62.04 of the winding exposed [8]. Therefore, due to insufficient sensitivity in detecting internal ground faults occurring near the transformer's neutral point, REF protection is used as a supplementary protection to the differential relay [9, 10]. The REF protection is divided into two categories: high impedance and low impedance [11]. One of the ongoing challenges in REF protection is preventing false operation of such relays during current transformer saturation caused by transformer inrush currents and external faults [12, 13]. Although precise measurement of transformer current can improve the performance of REF protection, it may not eliminate the effects of current transformer saturation [14].

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One of the methods to prevent incorrect operation of this scheme due to current transformer saturation is the use of high-impedance REF protection [15]. In this type of protection scheme, a high-value impedance is connected in series in the differential branch to prevent false relay operation during severe external faults. In other words, this scheme is resistant to current transformer saturation and does not lead to incorrect relay operation. However, one of the reasons why this type of scheme is rarely used today is the presence of essential requirements that must be considered for its implementation, including:

• Equality of current transformer turns ratios in phases and the neutral point of the transformer.

• Identical magnetic characteristics for all current transformers.

• Equality of knee-point voltage [16].

Considering the factors mentioned above, coupled with advancements in microprocessor technology, low-impedance REF protection has gained significant popularity compared to high-impedance REF due to its fewer constraints. This type of protection scheme does not have the limitations associated with high-impedance REF. However, the impact of current transformer saturation still affects the accuracy of this relay [1]. Various methods, including adaptive restraint current [17] and direct supervision methods [18] have been proposed to prevent false operation of low-impedance REF protection. Nevertheless, the possibility of false operation still exists under certain specific operating conditions [19, 20]. In [19] presents a combined method based on both low-impedance and high-impedance REF protection to mitigate false operation. However, this protection scheme may not be effective against inrush currents and external faults with high neutral currents. In [21, 22], a time-domain-based digital phase comparator method has been proposed to improve the performance of the low-impedance REF protection scheme. However, this method only assesses inrush currents and single-phase-to-ground faults in this protection scheme. Authors in [23] have introduced an intelligent algorithm based on waveform recognition using pattern detection. Nevertheless, due to its high computational load, this approach results in relatively slower detection and trip command transmission. In [24] presents another intelligent algorithm with a smaller training vector, based on certain parameters derived from conventional methods. In [25], a time-frequency analysis-based method is proposed using direct supervision. In this approach, distinctive features for detecting internal ground faults are extracted by employing the S-transform. By determining suitable threshold values for these features, a relatively efficient algorithm is suggested. It is worth noting that the complexities and computational burdens of these methods may pose challenges in practical implementation. A list of main novelties and contributions of this work can be listed as follows:

- For the first time, the SVM and Wavelet Transform are used to design a new supervision method for the REF relay.
- Artificial intelligence has been used to design the REF protection, which increases the reliability of the REF protection and reduces the amount of time delay of the operation.
- In this method, all types of external and internal faults are considered to provide classifier training models, which makes the proposed method comprehensive in dealing with all types of faults.
- The time delay imposed by the new method is acceptable.

C. paper organization

Therefore, in this paper, an intelligent REF protection scheme based on WT is presented. In the first stage, suitable features are extracted based on the analysis of the differential current signal using WT. Subsequently, in the second stage, the extracted features are separated from each other by intelligent classifiers. This allows for the detection of internal faults from magnetizing inrush currents and external faults. To achieve this goal, the tools used are briefly introduced in Section 2. Section 3 provides a detailed description of the proposed method. The results of implementing the new method and comparative evaluations are presented in Section 4. Finally, the paper concludes with a summary in Section 5.

II. THE EMPLOYED TOOLS INCLUDE

As mentioned in the introduction, to prevent the false operation of the REF protection scheme, an intelligent protection algorithm based on WT is proposed. In this scheme, the differential currents obtained from simulations under various operating conditions are analyzed using WT, and the resulting features from this transformation are employed as training patterns for intelligent classifiers. In this paper, for the intelligentization of REF protection, PNN and SVM classifiers are used. Therefore, in this section, a brief introduction to PNNs and SVMs, as well as WT, is provided. Subsequently, the preparation and utilization of these tools for the implementation of the proposed algorithm are detailed.

A. Probabilistic neural network (PNN)

PNNs are a type of feedforward neural network primarily designed for estimating the probability density function using Parzen window estimation and the Bayes classification theorem. These networks are introduced for classification tasks and fall into the category of supervised learning. PNNs can efficiently handle pattern recognition tasks with relatively lower computational time compared to other neural network architectures. The network is constructed by determining weight vectors for each distinct pattern unit in the set of sample patterns from a specific class. Then, the outputs of pattern units are connected to the corresponding summation unit of that class.

To avoid the lengthy training process that poses challenges in most neural networks, PNNs have been employed as the core classifier for detecting inrush currents and severe external faults from internal faults in power transformers. The structure of PNNs is illustrated in Fig. 1, depicting a four-layer feedforward network with an optimized structure. In PNNs, Gaussian functions are commonly used due to their favorable behaviour and simpler computations. Suppose $x \in R^d$ represents d-dimensional pattern vectors. The posterior probability $p_r(S_i|x)$ of belonging to class S_i is expressed using the Bayes theorem as follows:

$$p_r(S_i|x) = \frac{p_r(x|S_i)p_r(S_i)}{p(x)} \tag{1}$$

where $p_r(S_i|x)$, $i = 1 \dots. k$, represents the probability density function of this pattern in the classes that need to be separated, $i = 1.\dots.k$, and $p_r(S_i)$ is the probability of occurrence of classes. $p(x)$ is assumed to be a constant value. The decision rule for class S_i is to maximize the value of $p_r(S_i|x)$. This will happen when for all $j \neq i$, the following condition holds:

$$p(x|S_i)p_r(S_i) > p(x|S_j)P_r(S_j) \tag{2}$$

This ensures that the pattern is classified into the class S_i where its posterior probability is maximized compared to other classes.

It is assumed that the probabilities $P_r(S_i)$ are specified for different classes, and the probability density function is Gaussian. The estimation of the probability density function will be as follows:

$$p(x|S_i) = \frac{1}{(2\pi)^{d/2}\sigma_i^d|S_i|} \sum_{j=1}^{n_i} exp\left[\frac{-(x-x_j^i)^T(x-x_j^i)}{2\sigma_i^2}\right] \tag{3}$$

Where x_j^i represents example j from class i, $|S_i| = n$, and σ_i is a smoothing factor. The input vector has d values, as the input vector $x \in R^d$ is of dimension d. The first hidden layer encodes the training patterns. Therefore, each such pattern unit for class

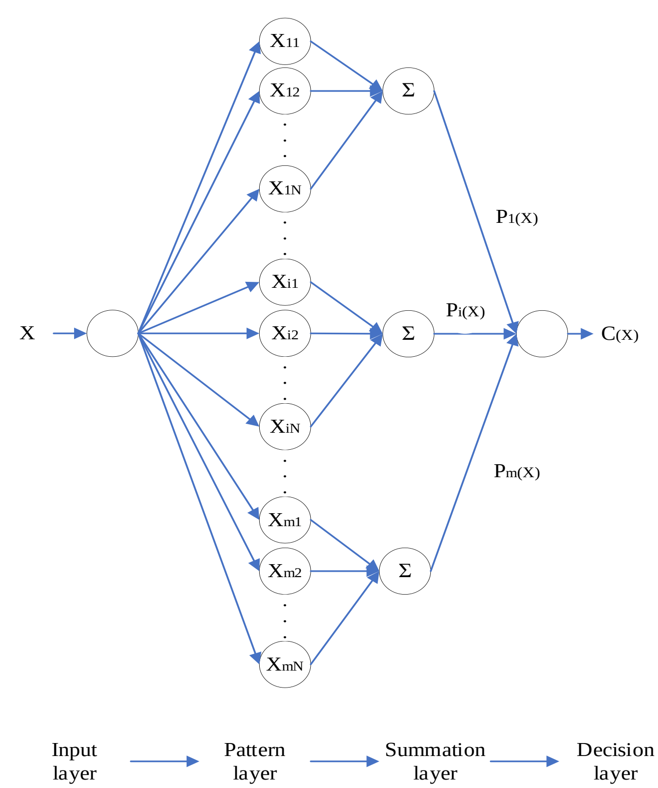

Fig. 1. Structure of PNN

i will be obtained as an expression similar to what is shown in (3).

B. *Support Vector Machines (SVMs)*

SVMs have been widely used in recent years for various classification problems [26]. This classifier finds a hyperplane to separate the input data based on their corresponding classes, maximizing the margin between classes [27]. For further explanation, if $\{x_i, y_i\}_{i=1}^N$ is considered as the training set consisting of N data points, including two classes, where x_i is the i-th value of an N-dimensional input vector, and y_i represents the class labels (-1 and +1), the equation $W^T x_i + b = 0$ is considered as a hyperplane capable of separating the data according to their classes. In this equation, the weight vector and bias are denoted as w and b, respectively. The goal of this classifier is to find values for the weight vector and bias that maximize the separation between classes. For this purpose, the concept of the separation margin, as defined in (4), is introduced [28]:

$$m = \left\|\frac{2}{w}\right\| \tag{4}$$

To increase the separation power of SVMs, the value of m should be maximized according to the above expression. Therefore, the value of $\|w\|$ should be minimized. Finally, for linearly separable data, the SVM minimizes the function $v(w)$ presented in (5), along with satisfying the constraint in (6).

$$v(w) = \frac{1}{2}w^T w \tag{5}$$

$$y_i(w^T x_i + b) \geq 1 \qquad i=1,2,\dots,m \tag{6}$$

It's worth noting that most classification problems are not linearly separable. For solving non-linear problems, a type of non-linear SVM has been introduced, where the training data is mapped to a higher-dimensional space. To achieve this, a non-linear transformation $\emptyset(x)$ is used for mapping. Therefore, the required function and constraints for realizing the non-linear SVM, like (7) and (8), are taken into account.

$$v(w,\varepsilon) = \frac{1}{2}\frac{1}{2}w^T w + C\sum_{i=1}^{N}\varepsilon_i \tag{7}$$

$$y_i(w^T\emptyset(x_i) + b) \geq 1 - \varepsilon_i \qquad i=1,2,\dots,N \tag{8}$$

In the above equations, ε_i are auxiliary variables with values greater than or equal to zero, used to account for the obtained error. The quantity C is called the penalty coefficient, and its value is always greater than zero. Furthermore, the vectors that satisfy the mentioned constraints are called support vectors. These vectors are the ones that only depend on the decision boundary or separating hyperplane. The mentioned equation can be written using the Lagrange principle as (9), and it should also satisfy the conditions presented in (10).

$$L(w,b,\varepsilon,\alpha,\eta) = \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{N}\varepsilon_i\right) - \sum_{i=1}^{N}\alpha_i(y_i(w^T\varphi(x)+b) - 1 + \varepsilon_i) - \sum_{i=1}^{N}\eta_i\varepsilon_i \quad (9)$$

$$\frac{\partial L}{\partial b} = \sum_{i=1}^{N}\alpha_i y_i = 0$$
$$\frac{\partial L}{\partial b} = w - \sum_{i=1}^{N}\alpha_i\, y_i \emptyset(x_i) = 0 \quad (10)$$
$$\frac{\partial L}{\partial \varepsilon_i} = C - \alpha_i - \eta_i = 0$$

In the above equations, $\alpha_i \geq 0$ and $\eta_i \geq 0$ are Lagrange multiplier auxiliary variables. By applying these conditions, the optimization problem is formulated as (11), and the constraints for this problem are also seen in (12).

$$Maximize\left\{\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\,\alpha_j y_i\, y_j\left(\emptyset(x_i)\varphi(x_j)\right)\right\} \quad (11)$$

$$0 < \alpha_i < C$$
$$\sum_{i=1}^{N}\alpha_i y_i = 0 \quad (12)$$

The x_i for which $\alpha_i > 0$ are chosen as support vectors. After that, the separating hyperplane is determined from (13).

$$\sum_{SV}\alpha_i y_i k(x_i, x) + b = 0 \quad (13)$$

Finally, the nonlinear classifier will be like (14) [28].

$$y = sign(\sum_{SV}\alpha_i y_i k(x_i, x) + b) \quad (14)$$

As mentioned earlier, for effective and accurate classification, it is necessary to map the input vectors to a higher-dimensional space using a nonlinear transformation. In practice, this is done indirectly by using well-known kernel functions. The most popular kernel functions include linear, polynomial, sigmoid, and radial basis functions.

C. The Wavelet Transform (WT):

Before the emergence of the WT, the Fourier transform was used as a practical and important tool for the frequency analysis of a signal. However, the Fourier transform, being fixed in time for a signalto could not detect specific frequencies of a signal at different times. To address this issue, STFT was introduced. STFT uses a sliding window to extract time-frequency data from a signal. However, a challenge arises in determining the length of this window, as the window length directly affects the frequency resolution of the extracted data. Ultimately, the WT was introduced to alleviate some of these issues [29].

One instrument for time-frequency analysis of signals is the WT, which is especially helpful for studying transitory signals. Time-series signals can be divided into several levels using this transform. There are high-frequency components in the detail levels and low-frequency components in the approximation levels. A time-series signal can be broken down into several levels, as shown in Fig. 2.

Among the applications of WT in power systems, we can mention transient state analysis [30], power quality assessment [31], data compression [32], and fault detection. In the WT, various filters, referred to as wavelet functions, are used to decompose signals. Eventually, wavelet coefficients at each point of the signal (b) and for each scale value (a) can be calculated using (15):

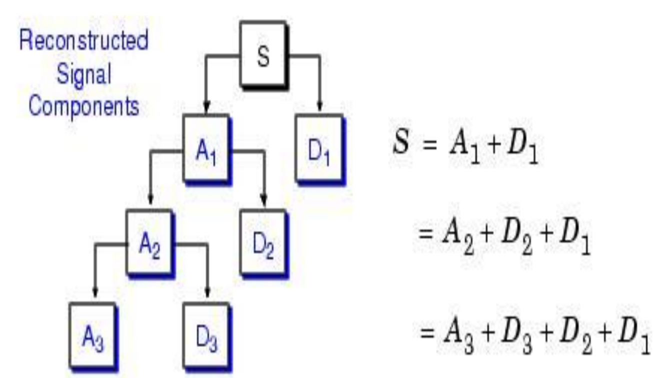

Fig. 2. Signal tree analysis using wavelet transform

$$CWT(a,b) = Wf(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(x)\left(\frac{x-b}{a}\right)dx = \int_{-\infty}^{+\infty} f(x)\psi_{a,b}(x)dx \quad (15)$$

Where $f(x)$ is the desired signal and $\psi(x)$ is the wavelet function.

III. INTELLIGENT RESTRICTED EARTH FAULT PROTECTION SCHEME

In order to enhance the performance of the REF relay intelligently, it is essential to consider that this relay functions effectively in the case of internal faults. However, it still exhibits incorrect behaviour during severe external faults and inrush currents, which can be attributed to the fixed settings of the relay under various operational conditions [33]. The characteristic of the biased REF protection used in this article is illustrated in Fig. 3. The relay settings can be chosen to make the relay more sensitive to internal faults. Still, it should be noted that this may lead to an increased rate of false relay operations in the presence of external faults and inrush currents. Therefore, there is a strong need for intelligent relay adaptation and decision-making based on the prevailing conditions. In this regard, this research proposes an intelligent structure based on wavelet transform for REF protection.

As seen in Fig. 3, the differential currents and the resistor current are considered as determining variables in the performance characteristic of the mentioned relay. These currents are calculated using (16) and (17). In these equations, I_a, I_b, I_c represent phase currents, and I_n is the neutral current. It's worth noting that the manufacturer provides a detailed description of this characteristic and its recommended settings in [34].

$$I_{diff} = |I_a + I_b + I_C - I_n| \quad (16)$$

$$I_{bias} = 0.5(max\{|I_a|, |I_b|, |I_c|\} + |I_n|) \quad (17)$$

In light of these explanations, the first step is to select suitable input parameters for training the PNN and SVM. The differential current in the REF protection scheme appears due to internal faults, but in external fault conditions and the presence of a power transformer, the transformer saturation causes the appearance of differential current. As a result, it is possible to differentiate between internal, external, and inrush currents using the distinct waveform forms of the differential currents. The differential current from the power transformer simulation under different operating conditions, such as internal fault, external fault, and inrush current, is taken into consideration as an input parameter for the wavelet transform based on the explanations given. To conduct simulation studies, the power system shown in Fig. 4 is considered, which includes a 230 kV/63.5 kV power transformer and a current transformer and ground. The specifications of the current transformers are listed in Table I.

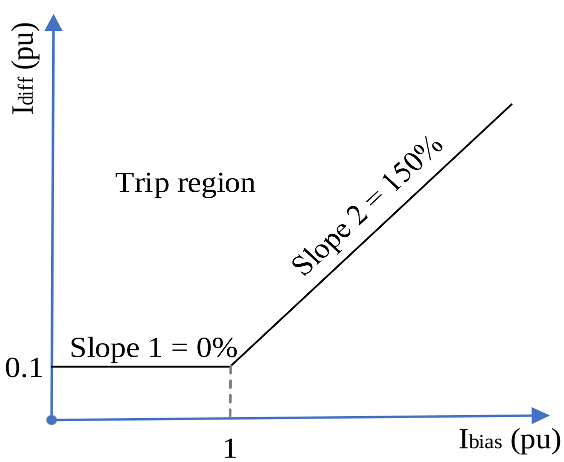

Fig. 3. Characteristic of the REF protection scheme

TABLE I
Specifications of Current Transformer

	Current transformer ratio	Current transformer model
LV side	2000/1	*30* VA, 5P20
HV side	600/1	*30* VA, 5P20

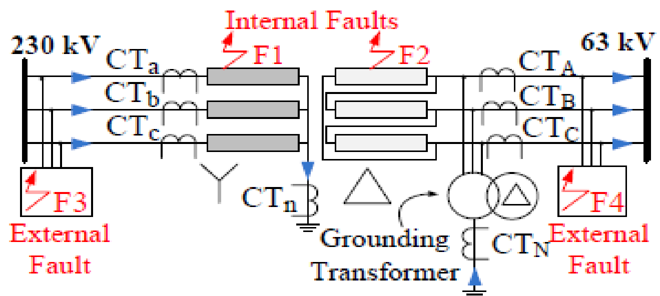

Fig. 4. The power system under study

This power system has been simulated using the reputable software PSCAD/EMTDC. For simulating the current transformer, a detailed model known as the Jiles-Atherton model is utilized. The sampling frequency in the simulations is set at 2500 Hz. Therefore, for the power system under study, which operates at a frequency of 50 Hz, one cycle consists of 50 samples, and according to the Nyquist theorem, harmonics up to the 25th harmonic can be extracted.

After analyzing the differential currents using WT and extracting the energy of each signal, the obtained data is separated according to the type of differential current resulting from internal faults, external faults, and inrush current. These data are collected in matrices. Then, the values in these matrices are normalized to be in the range between 0 and 1 to prepare them for training the PNN and SVM.

In the next step, matrices $F_{internal}$, $F_{external}$ and F_{inrush} are created, which contain feature vectors extracted under internal fault, external fault, and inrush current conditions. These matrices are used as training samples for the SVM and PNN. Finally, the input matrix for training is formulated according to (18), and the output matrix, as described in (19). It's worth noting that the number of columns in the input and output matrices are the same. The implementation steps of the proposed algorithm are illustrated in the flowchart shown in Fig. 5.

$$Input\ Matrix = \left[[F_{internal_{4*600}}][F_{External_{4*800}}][F_{Inrush_{*600}}]\right] \quad (18)$$

$$Output\ Matrix = [1 \quad \cdots \quad 1 \ 2 \quad \cdots \quad 2] \quad (19)$$

IV. SIMULATION AND RESULT EVALUATION

As previously explained in the preceding sections, a large number of simulation results were generated for various operating conditions of a power transformer, including internal faults, external faults, and inrush currents. To obtain a comprehensive spectrum of internal faults, parameters such as fault resistance, fault inception time, and magnetic flux density decay of the current transformers were considered. For inrush current studies, it was assumed that the power transformer is energized from a 230 kV source with the nominal load connected at 63 kV. Three different values of fault resistance were considered for internal faults, ranging from zero Ω to a resistance that results in approximately 10% of the nominal current. Four different fault inception times, spaced 5 ms apart (from 100 ms to 115 ms), were considered for each fault scenario. Additionally, for current transformers, magnetizing inrush current with densities of 85%+, 0, and 85%- of the nominal load current wastaken into account. In total, 600 cases of internal faults were used for training the classifiers, and 300 cases were used for testing. Similarly, for external faults, numerous severe cases iuding single-phase-to-ground, phase-to-phase, and two-phase-to-ground faults, as well as three-phase faults were simulated to obtain the necessary data for training the classifiers. Again, four different fault inception times, spaced 5 ms apart, were considered. Different magnetizing inrush current conditions, as well as varying voltage angle settings, were applied for the current transformers. In total, 800 cases of external faults were used for training, and 400 cases were used for testing the PNN and SVM classifiers.

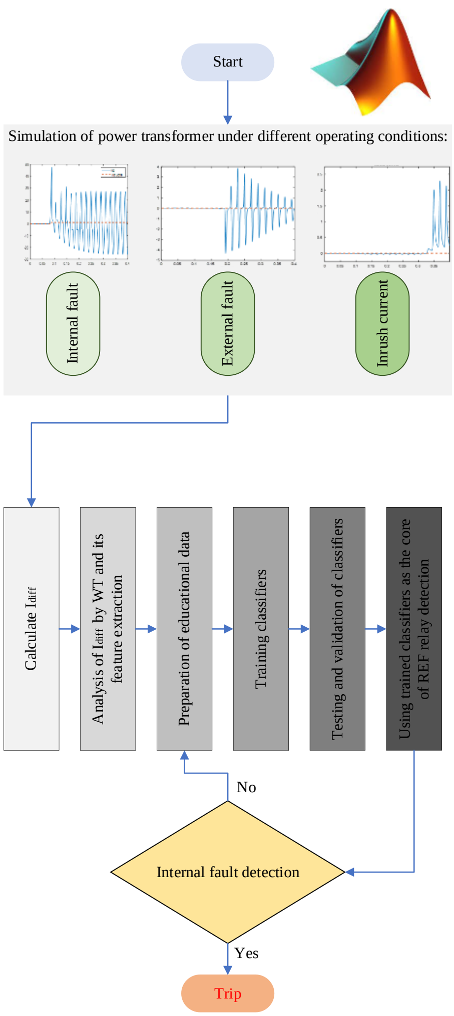

Fig. 5. Flowchart of the proposed method

All these steps, including simulation and evaluation, were carried out using MATLAB on a computer with a dual-core processor running at 2.6 GHz and 8 GB of RAM. The simulation settings, times, and results of the proposed method for both the PNN and SVM classifiers are presented in Tables II and III. Additionally, the classification accuracy of the classifiers in detecting internal faults, external faults, and inrush currents is provided in Tables IV and V. As shown in Table II, the required training time for the PNN and SVM is 3.27 ms and 9.338 ms, respectively. Also, as seen in Figs. 6 and 9, the execution time of these classifiers, considering the training time and the time interval between the start of the differential current and the issuance of the trip command by the REF protection, is 7.6 ms and 9.34 ms for the PNN and SVM, respectively.

The results obtained from the evaluation of the PNN show that this classifier correctly detected all internal faults without any false alarms, demonstrating its high sensitivity (Figs. 7 and 8). Additionally, out of 400 cases of external faults and 400 cases of inrush currents, only 1 false alarm was observed for each type when using the PNN, indicating its high accuracy and reliability compared to other protection schemes (Fig. 9 and 11). In the results of the SVM classifier, it correctly detected all 300 cases of internal faults (Fig. 10 and 12). However, in the case of external faults, out of the 400 simulated scenarios, it falsely triggered in 20 cases, issuing trip commands when it should not have (Fig. 10).

TABLE II
Settings and Simulation Time

Method	Setting	training time(s)	Execution time (ms)
PNN in the proposed method	Activation coefficient σ=0.05	0.00327	7.6
SVM in the proposed method	Radial basis kernel function C=1000	0.009338	9.34
REF protection scheme proposed by MICOM	Manufacturer's recommended settings in [34]	-	0.1
The PNN used in [22]	-	0.1	5
The protection scheme presented in [35]	Radial basis kernel function C=1000	1.4	2.6

TABLE III
The Results Of The Simulation And Comparison With Related Papers

Metod	Number of false detections out of 300 internal faults	Number of false detections out of 400 external faults	Number of false detections from 400 inrush current cases	Overall accuracy (%)
Proposed SVM classifier	0	20	0	98.18
Proposed PNN classifier	0	1	1	99.81
Conventional REF protection scheme	0	92	37	88.27
The PNN used in [22]	0	6	4	99.09
The protection scheme presented in [31]	0	12	5	98.45

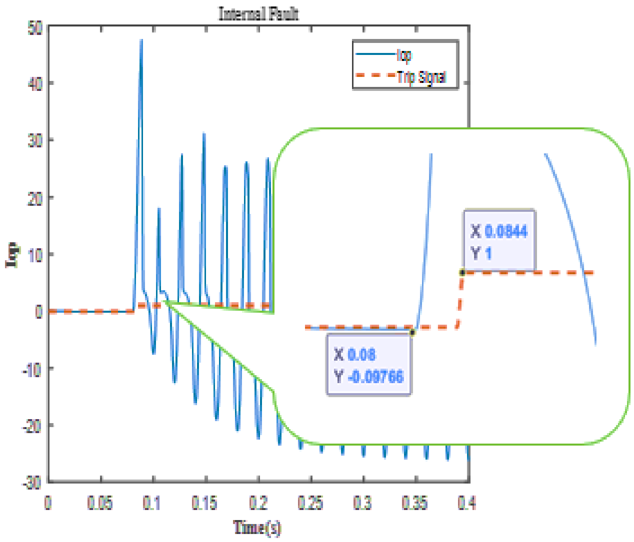

Fig. 6. Performance of REF relay during internal fault with PNN classifier

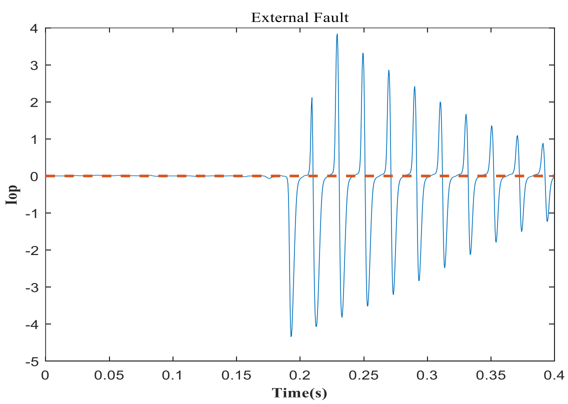

Fig. 7. Performance of REF relay during external fault with PNN classifier

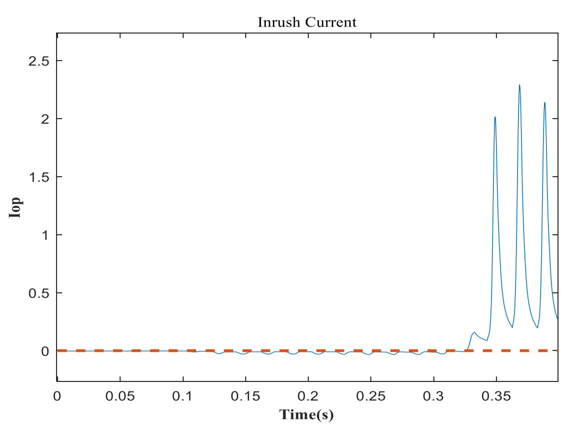

Fig. 8. Performance of REF relay during inrush current passage with PNN classifier

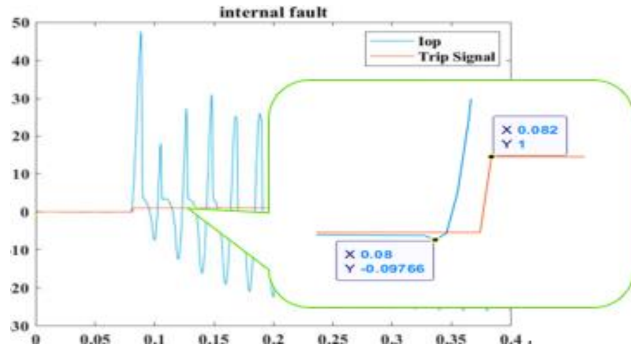

Fig. 9. Performance of REF relay during internal fault with SVM classifier

It is worth noting that the speed of these protection schemes is somewhat lower compared to conventional REF protection due to the higher computational load. Nevertheless, they still offer suitable protection while achieving their intended protection objectives. Table IV and V provide the accuracy rates of each classifier in detecting various conditions. In Table IV, the PNN classifier performed perfectly in detecting internal faults but had a single false alarm in external fault and inrush current detection. In Table V, the SVM classifier also correctly detected all internal faults and inrush currents but had 176 false alarms in external fault detection. Remarkably, out of these 176 false alarms in external fault detection, 156 were classified as inrush currents and 20 as internal faults, contributing to the misoperation of the REF protection relay.

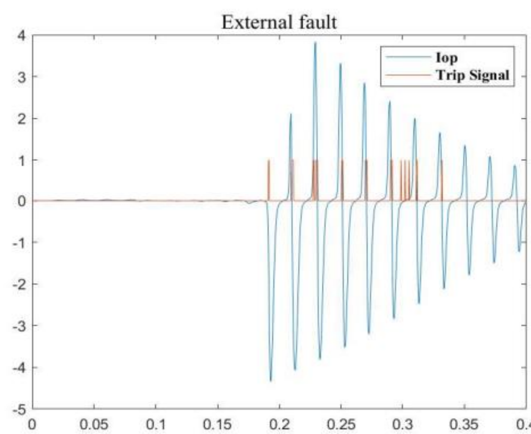

Fig. 10. Performance of REF relay during external fault with SVM classifier

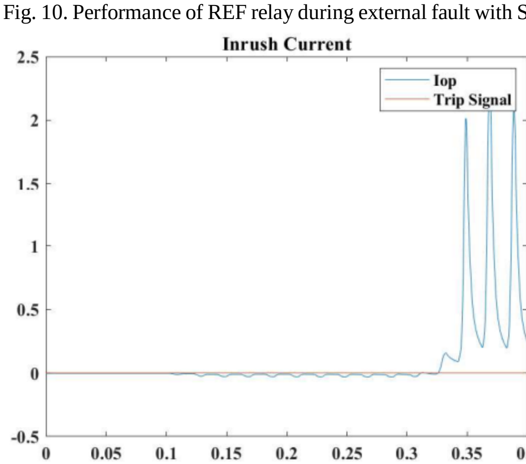

Fig. 11. Performance of REF relay during inrush current passage with SVM classifier

TABLE IV
Evaluation of the Accuracy Of The Proposed Method in Detecting Different Conditions Using the PNN Classifier

	PNN classifier	Overall accuracy (%)
The number of internal fault misdiagnosis	0	100
The number of external fault misdiagnosis	1	99.75
The number of the inrush current misdiagnosis	1	99.75
Total percentage		99.83

TABLE V
Evaluation of the Accuracy of the Proposed Method in Detecting Different Conditions Using the SVM Classifier

	SVM classifier	Overall accuracy (%)
The number of internal fault misdiagnosis	0	100
The number of external fault misdiagnosis	176	56
The number of the inrush current misdiagnosis	0	100
Total percentage		85.34

V. CONCLUSIONS

The REF protection scheme proposed in this study is a type of differential protection used to detect single-phase faults to ground at the power transformer terminals and wire-to-core faults. The current protection strategy still has difficulties identifying exterior faults with huge current magnitudes, especially during the inrush current induced by transformer saturation, even though it shows great accuracy and speed in detecting internal faults. To address the issue of maloperation of this protection relay in detecting external faults and inrush currents, a new intelligent protection scheme based on PNN classification has been introduced. The evaluation results have demonstrated that this protection scheme significantly improves the detection of external faults and inrush currents. It has been shown that the PNN classifier outperforms SVMs and other conventional protection methods, accurately detecting all internal faults. However, one limitation of this proposed protection scheme is the execution time or processing time of the algorithm, which is longer compared to conventional protection methods due to higher computational requirements. Nonetheless, the proposed protection scheme remains suitable for protection research, and the evaluation results indicate its high accuracy and safety. Another advantage of this method is its flexibility, as it does not require specific conditions or constraints for the use with different types of transformers and currents. The authors recommend exploring other classification methods and intelligent techniques for future research in REF protection.

VI. REFERENCES

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