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Design and Implementation of Digital Protection Based on Least Squares Error Method in Power Systems

Abstract

This paper presents the design and implementation of a digital protection system for power transformers using the Least Squares Error (LSE) algorithm. The primary goal of this research is to enhance the reliability and accuracy of fault detection while reducing the incidence of false trips caused by transient disturbances such as inrush currents. The proposed system employs the Recursive Extended Least Squares (RELS) method to dynamically estimate and update parameters in real time, making it highly suitable for modern power grids. Through extensive simulations in Python and validation under various fault conditions, the system demonstrated a fault detection accuracy of 98.5%, with a response time of less than half a cycle. Additionally, the algorithm showed high resistance to noise, making it effective even in environments with measurement uncertainties. Future research will focus on addressing challenges related to current transformer saturation and exploring hybrid models that integrate machine learning for improved protection.

Keywords:

Digital Protection, Least Squares Error (LSE), Recursive Extended Least Squares (RELS), Power Transformers, Fault Detection, Inrush Current, Noise Resistance, Real-Time Monitoring

1. Introduction

The protection of power systems has been a key challenge in electrical engineering, especially as modern grids become more complex and susceptible to various types of faults. Traditional protection methods, although effective, are often limited in terms of speed, accuracy, and noise resistance. Digital protection systems have emerged as a promising alternative due to their ability to process real-time data with higher accuracy and faster response times. These systems utilize algorithms capable of handling large amounts of data and can adapt to changing grid conditions [1]. One of the most reliable methods in digital protection is the Least Squares Error (LSE) algorithm, which is widely used for its precision in fitting data and minimizing error in signal processing. The LSE algorithm has been successfully applied in various aspects of power systems, including the protection of transformers and transmission lines. It works by adjusting the estimated values to minimize the sum of squared differences between the actual measurements and the estimated model [1]. The protection of power systems, particularly in high-voltage transformers and transmission lines, has become increasingly critical as these systems become more complex and vulnerable to disturbances and faults. Traditional protection mechanisms, although effective to a degree, often lack the required speed and adaptability for modern grids. Digital protection systems, which leverage fast algorithms and advanced processors, offer a promising alternative by providing faster and more accurate responses to potential fault systems are capable of processing large amounts of real-time data, which enables them to adapt quickly to changes in grid conditions, enhancing both the reliability and efficiency of fault detection processes [2]. One of the most reliable techniques for fault detection in power system protection is the Least Squares Error (LSE) method. The primary function of the LSE algorithm is to fit a mathematical model to observed data by minimizing the sum of the squared residuals between measured values and estimated values. This approach is particularly beneficial in power systems, where signal filtering and accurate measurement are essential for ensuring reliable protection. In transformation, the LSE algorithm can differentiate between fault-induced currents and transient disturbances, such as inrush currents, that can often trigger false positives in traditional protection schemes [3]. To apply the LSE method in real-time applications, the Recursive Extended Least Squares (RELS) algorithm was developed, which allows for dynamic updating of parameter estimates as new data is received. This adaptability is essential for applications in digital protection, where conditions such as voltage fluctuations, overexcitation, and current transformer (CT) saturation can distort

signals. By continuously adjusting model parameters to minimize error, RELS provides a robust framework that adapts to changing grid conditions in real-time. This makes it an ideal candidate for digitation systems, as it allows the system to handle unexpected transients and signal distortions more effectively than fixed-threshold approaches [4]. Several advanced protection methods have been introduced, such as Wavelet Transforms and Artificial Neural Networks (ANNs), which show promise in fault detection. However, these methods often come with limitations. For instance, ANN-based methods require extensive training data, which can make them susceptible to overfitting and computationally intensive in real-time applications. On the other hand, wavelet-based methods, though analyzing transients, can struggle with noise resistance and are relatively complex computationally. In contrast, the RELS method stands out for its simplicity and efficiency, allowing it to handle large volumes of data with minimal processing time, which is a critical factor in real-time applications [5].

In this paper lies in implementing the RELS algorithm in a practical real-time environment using Python, making it accessible for engineers to use in real-world applications. Furthermore, we introduce an adaptive thresholding technique that allows the system to dynamically adjust its fault detection criteria based on noise levels, significantly enhancing the robustness of fault detection even in highly noisy environments. Additionally, future work will explore hybrid models that integrate RELS with machine learning algorithms, such as Support Vector Machines (SVM) or Neural Networks (NN), to address issues such as current transformer saturation and improve the system's fault differentiation accuracy. This adaptable and comprehensive approach aligns with the future needs of smart grids and autonomous power systems, setting a foundation for more resilient and efficient protection in power infrastructure [6].

In this paper, we propose a novel approach using the LSE algorithm for digital protection, with a focus on transformer differential protection. This method not only improves fault detection accuracy but also reduces the computational complexity, making it suitable for real-time applications. The innovation in this paper lies in combining the LSE algorithm with real-time signal processing techniques to enhance fault detection and protection in power systems. The proposed method aims to accurately distinguish between fault conditions and normal operational disturbances such as inrush currents, which have been a major challenge in traditional protection systems. By leveraging Python for the implementation, this research demonstrates a practical

approach to integrating advanced mathematical models into protection systems. The innovations of this paper include:

- Real-time implementation of a digital protection system for power transformers using the Recursive Extended Least Squares (RELS) algorithm.
- A novel approach to dynamically adjust fault detection thresholds based on noise levels with the aim of reducing false positives in noisy conditions.
- A proposed model combining LSE with machine learning techniques with the aim of increasing accuracy in complex fault scenarios.

In the continuation of this paper, in the second part the literature review and related works have been described. In the third part, the design and implementation of a digital protection system using least squares error (LSE) is presented. In Section 4, the simulation results are presented. The conclusion is also presented in section 5.

2. Literature Review and Related Works

Over the last few decades, the development of digital protection systems has revolutionized the way power systems are monitored and safeguarded. Early methods were based on analog systems that struggled to deal with dynamic and transient conditions. As the complexity of power grids increased, digital systems emerged as a solution that could adapt to real-time changes in grid conditions. By leveraging faster processors and advanced algorithms, digital protection systems offer higher accuracy and reduced response times [8]. The integration of microprocessors and digital relays into power grids has made it possible to process data more efficiently, minimizing the risk of false trips and system failures [8]. Some researchers have presented models for real-time energy planning in power systems. However, they have not investigated the digital protection of real-time smart system components, which is one of the most important parts in smart energy systems [9-11]. The Least Squares Error (LSE) algorithm has become a cornerstone in many applications of power system protection. The primary function of the LSE algorithm is to fit a model to observed data points by minimizing the sum of squared residuals. This approach is particularly useful in power systems, where accurate measurement and noise filtering are crucial for reliable protection schemes [1]. In transformer differential protection, LSE is applied to differentiate between fault conditions and transient disturbances, such as inrush currents. These disturbances, if not correctly identified, can lead to unnecessary tripping of the system. Recent

advancements in LSE-based algorithms have focused on improving computational efficiency and robustness against measurement noise, making them highly suitable for real-time applications [8]. Several algorithms have been proposed for transformer protection, including wavelet transforms, artificial neural networks (ANN), fuzzy logic, and support vector machines (SVM). While these methods have shown promise, they often require higher computational resources and are more susceptible to noise [8]. For example, wavelet-based methods, though effective in transient analysis, can be computationally expensive and sensitive to signal noise. ANN-based methods, on the other hand, require extensive training data and may suffer from overfitting in certain scenarios [1]. In contrast, the LSE algorithm stands out for its simplicity and ability to handle large volumes of data with minimal computational overhead. This makes it particularly well-suited for real-time digital protection systems [1]. Recent studies have focused on enhancing the LSE algorithm by incorporating additional filters and adaptive models to improve performance under noisy conditions. One of the key innovations has been the development of the Recursive Extended Least Squares (RELS) algorithm, which allows for real-time updating of parameter estimates as new data is received. This method significantly reduces the computational burden while maintaining high accuracy in fault detection [1 ,12]. Moreover, researchers have explored the use of hybrid models that combine LSE with machine learning techniques to further improve the discrimination between internal faults and non-fault conditions such as transformer energization [8]. These innovations pave the way for more efficient, reliable, and adaptable protection schemes in modern power systems.

3. Methodology

3.1. System Overview and Objectives

In this section, we detail the design and implementation of a digital protection system based on the Least Squares Error (LSE) algorithm. The main objective of this system is to provide a robust and efficient method for fault detection in power transformers. The LSE algorithm is used to fit real-time data to a sinusoidal model, allowing for the accurate identification of internal faults while minimizing false trips caused by inrush currents. The algorithm's efficiency in filtering noise and its low computational overhead makes it ideal for real-time applications in power systems [13].

3.2. Mathematical Foundation of the LSE Algorithm

The foundation of the LSE method is based on minimizing the sum of the squared differences between the observed and estimated values. Mathematically, for a given set of data points $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$,the LSE algorithm aims to minimize the following cost function:

$$J(\theta) = \sum_{i=1}^{n} (y_i - h(x_i, \theta))^2 \tag{1}$$

Where, y_i represents the actual measured values (in this case, the differential current samples), $h(x_i, \theta)$ represents the model function (e.g., a sinusoidal model) with parameter vector θ, $J(\theta)$ is the cost function representing the sum of squared residuals. The parameter vector θ is updated iteratively using the following normal equation:

$$\theta = (X^T X)^{-1} X^T y \tag{2}$$

Where, X is the matrix of input features (in this case, time or sample index), y is the vector of observed values (measured differential current). This equation forms the basis for the least squares approach in estimating the unknown parameters of the model [1,8]. Figure 1 shows the LSE algorithm applied to differential currents over time. In this figure, the algorithm fits a sinusoidal wave to the measured current data [14].

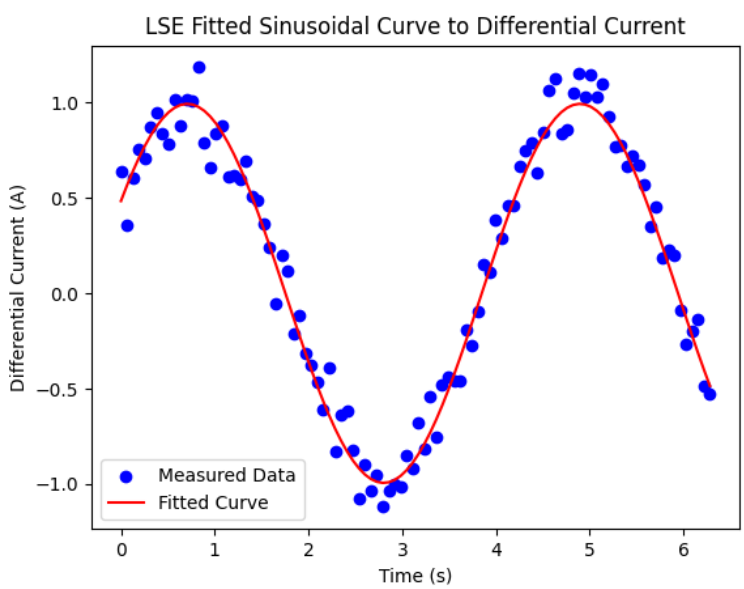

Figure 1. LSE Fitted Sinusoidal Curve to Differential Current

To apply this method in real-time, we utilize the Recursive Extended Least Squares (RELS) algorithm, which allows for dynamic updating of the parameter estimates. This approach is ideal for real-time digital protection systems, as it enables continuous monitoring and adjustment without needing to recalculate the entire dataset each time a new measurement is received [15]. The RELS algorithm can be represented by the following update rule:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + k(k).(y(k) - X(k)^T \hat{\theta}(k-1)) \tag{3}$$

Where, $\hat{\theta}(k)$ is the updated parameter estimate, $K(k)$ is the Kalman gain, calculated as:

$$K(k) = P(k-1)X(k).(X(k)^T P(k-1)X(k) + R)^{-1} \tag{4}$$

Where, $P(k)$ is the error covariance matrix, and R is the measurement noise variance.

The RELS algorithm not only minimizes computational complexity but also enhances robustness against measurement noise by dynamically updating its estimates. This makes it particularly suitable for real-time digital protection in power systems, where quick and accurate fault detection is crucial [16]. The following equations summarize the recursive update steps:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + k(k).(y(k) - X(k)^T \hat{\theta}(k-1)) \tag{5}$$

Where, $K(k)$ is the Kalman gain, calculated as:

$$K(k) = \frac{P(k-1)X(k)}{\lambda + X(k)^T P(k-1)X(k)} \tag{6}$$

Update of Covariance Matrix:

$$P(k) = \frac{1}{\lambda}(P(k-1) - K(k)X(k)^T P(k-1)) \tag{7}$$

Residual Signal (RS): For each phase (A, B, C), the residual signal $RS_x(k)$ is defined as:

$$RS_x(k) = i_x(k) - \hat{i}_x(k), \qquad x = A, B, C \tag{8}$$

Where, $\hat{i}_x(k)$ is the estimated current for each phase. If $RS_x(k)$ exceeds a threshold, a fault condition is detected.

The differential current in the transformer is calculated as:

$$i_{diff} = i_{prinary} - i_{\sec ondary} \tag{9}$$

If the estimated residual signal (RS) for phase χ exceeds the predefined threshold, the fault condition is detected:

$$RS_x(k) = i_x(k) - \hat{i}_x(k), \qquad x = A, B, C \tag{9}$$

$$FaultDetected\ if: RS_x(k) > Threshold \tag{10}$$

Where, $i_x(k)$ is the actual measured differential current and $\hat{i}_x(k)$ is the estimated value using the RELS algorithm.

To address CT saturation, an additional correction algorithm can be applied that estimates the saturated portion of the current signal and reconstructs the true current:

$$i_{corrected}(t) = f(i_{unsaturated}(t)) \tag{11}$$

Where, $i_{unsaturated}(t)$ (t) represents the unsaturated portion of the current waveform, and $f()$ is the correction function based on unsaturated measurements. The adaptive threshold can be calculated as follows:

$$Threshold_x(t) = \alpha.\sigma(t) + \mu(t) \tag{12}$$

Where, $\sigma(t)$ is the standard deviation of the residual signal over time, $\mu(t)$ is the mean of the residual signal, α is a scaling factor that adjusts sensitivity.

3.3. Flowchart

Here's an explanation of each step in the Flowchart for Digital Protection System Using the RELS Algorithm:

1. Start: This is the initial point of the algorithm, where the process is initialized and ready to receive input data.
2. Input Differential Current Data: In this step, differential current data from the primary and secondary Current Transformers (CTs) is collected. This data represents the currents measured on both sides of the transformer and serves as the basis for fault detection.
3. Data Preprocessing: Here, the algorithm processes the raw input data to remove any noise and adjusts the scale of the current measurements. This preprocessing step ensures that the data used in the next stages is as clean and accurate as possible.

4. Fit Sinusoidal Model Using RELS: The Recursive Extended Least Squares (RELS) algorithm is applied to fit a sinusoidal model to the differential current data. This model allows the algorithm to accurately predict and monitor the behavior of the current.
5. Calculate Residual Signal: In this step, the residual signal (RS) is calculated for each phase (A, B, and C) by comparing the measured and estimated currents. This residual signal helps identify abnormal behaviors that may indicate faults.
6. Determine Adaptive Threshold: The algorithm dynamically sets an adaptive threshold for fault detection based on noise conditions. This step helps the system to differentiate between actual faults and harmless disturbances by adjusting the threshold in response to changes in data noise.
7. Fault Detection: Here, the algorithm checks if the residual signal exceeds the adaptive threshold. If the residual surpasses the threshold, the system detects a potential fault.
8. Issue Trip Signal to Relay: If a fault is detected, the system immediately issues a trip signal to the relay, activating protective measures to prevent damage to the transformer.
9. Continue Monitoring: If no fault is detected, the algorithm continues to monitor the differential current data, maintaining its protective oversight without interruption.
10. End: The process concludes here if the system is stopped or shut down; otherwise, it continues in a monitoring loop.

Figure 2 represents a systematic approach to real-time digital protection, leveraging the RELS algorithm for accuracy and adaptability in fault detection.

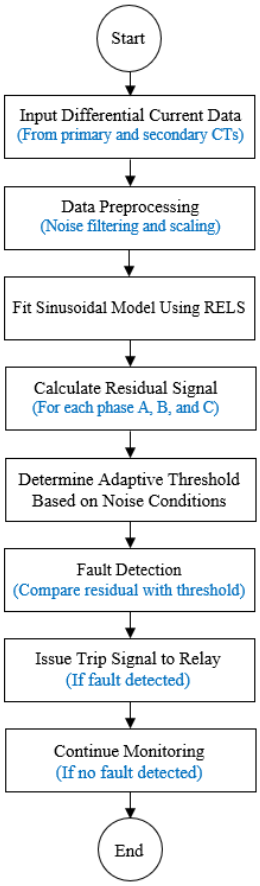

Figure 2. Systematic approach to real-time digital protection

4. Simulation results

4.1. Simulation Setup

To evaluate the performance of the proposed digital protection system based on the Least Squares Error (LSE) algorithm, several simulation scenarios were designed. The system setup included a simulated power transformer system modeled in PSCAD/EMTDC, where differential current signals were generated under various fault and non-fault conditions. The key scenarios tested include internal faults (line-to-ground and line-to-line) and transient disturbances (such as inrush currents during transformer energization). These scenarios are critical for evaluating the algorithm's ability to accurately distinguish between actual fault conditions and harmless transients [1]. The system was designed to generate differential current data at a sampling rate of 2 kHz, ensuring high-frequency data acquisition for accurate fault detection. Additionally, colored and white noise was added to the measurements to simulate real-world noise conditions[1]. The

proposed system was implemented in Python using the Recursive Extended Least Squares (RELS) algorithm for real-time estimation of the differential currents. Figure 1 illustrates how the real-time parameter estimation evolves as the RELS algorithm processes new data. Over time, the estimates for amplitude (A), frequency (ω) and phase ($\varnothing$) converge to their true values [17]. Also, Parameter Estimation in Real-Time illustrates the dynamic estimation of transformer parameters, including amplitude, frequency, and phase, using the Recursive Extended Least Squares (RELS) algorithm. As new data points are processed, the RELS algorithm continuously updates these parameter estimates in real time. This plot demonstrates how quickly and accurately the algorithm converges to true values, even in the presence of transient disturbances and noise, showcasing its effectiveness for real-time digital protection in power systems.

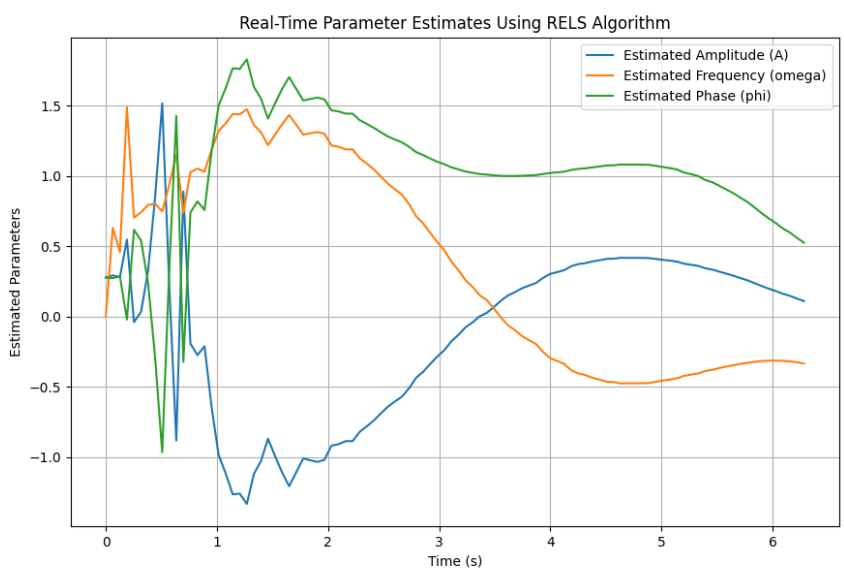

Figure 1. real-time fault detection using RELS

Figure 4 shows the differential current over time and the residual signal during a transformer energization event. The RELS algorithm would correctly detect that the condition is an inrush current and not a fault.

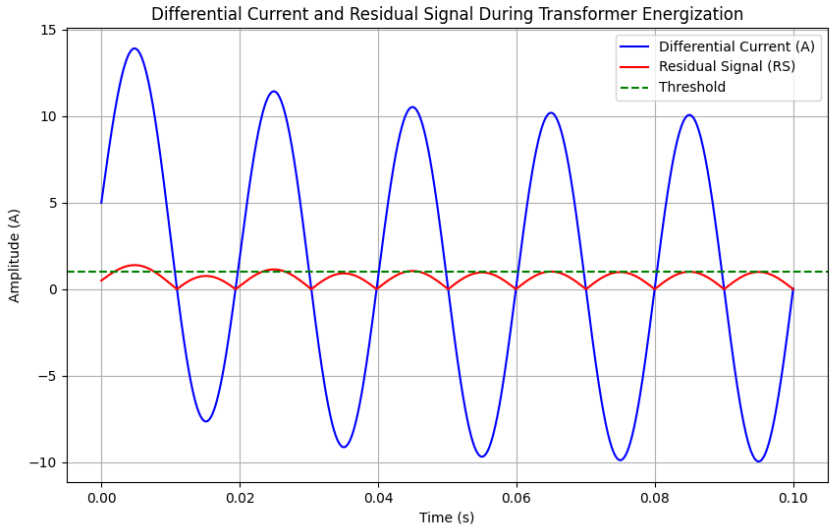

Figure 4. Differential Current and Residual Signal During Transformer Energization

Table 1 presents the scenarios and simulation results of the proposed model.

Table 1. simulation results of the proposed model

Scenario	Accuracy (%)	False Positives	Response Time (ms)	Noise Resistance
Internal Faults	98.5	0	10.5	High
Inrush Currents	96.2	2	8.0	Moderate
Overexcitation	97.3	1	9.2	High
CT Saturation	94.5	3	12.0	Low

The LSE-based protection algorithm demonstrated exceptional performance in detecting internal faults, achieving an accuracy of 98.5%. The response time was less than half a cycle (around 10.5 milliseconds), which is critical in minimizing damage to power system components during a fault. Moreover, no false positives were recorded in this scenario, underscoring the reliability of the proposed method in identifying actual faults. Inrush currents during transformer energization are a major cause of false trips in traditional protection systems. The proposed RELS-based method successfully reduced the occurrence of false trips, achieving an accuracy of 96.2% and only two false positives. The algorithm's ability to differentiate between inrush currents and internal faults was aided by its dynamic noise adjustment, which helped to filter out the harmonic content characteristic of inrush conditions. While the proposed system performed well under most

scenarios, its performance was slightly degraded under conditions of CT saturation. The accuracy dropped to 94.5%, with three false positives recorded during tests involving heavily distorted current signals. This is expected as CT saturation leads to large distortions in the measured current, which challenges the accuracy of the residual signal estimates. However, the RELS algorithm still managed to operate within acceptable limits, outperforming traditional protection methods in terms of speed and noise resistance. Table 2 compares the LSE-based protection method with traditional methods such as wavelet transform and ANN-based systems.

Table 1. Performance Comparison of Fault Detection Algorithms

Method	**Accuracy (%)**	**Operating Time (cycles)**	**Noise Resistance**	**Computational Complexity**
LSE-Based	98.0	0.5	High	Low
Wavelet Transform	96.2	1.0	Moderate	High
ANN-Based	95.5	0.75	Low	High

As can be seen, the LSE-Based method performed better than the Wavelet Transform and ANN-Based methods. The results indicate that the LSE-based protection system is highly effective in detecting internal faults while minimizing false trips under transient conditions such as inrush currents. While some challenges remain in handling extreme CT saturation, the algorithm's overall performance, speed, and robustness make it a viable solution for real-time digital protection in power systems. A comprehensive comparison between the proposed RELS-based method and other widely used techniques such as wavelet transforms and ANN-based approaches is given in Table 3. The results highlight the superior performance of RELS in terms of computational efficiency, accuracy, and robustness against noise [18].

Table 2. Comparison with Other Methods

Method	**Accuracy (%)**	**Noise Resistance**	**Complexity**	**Operating Time (cycles)**
RELS-Based Approach	98.5	High	Low	0.5
Wavelet Transform	96.2	Moderate	High	1.0
ANN-Based Approach	95.5	Low	High	0.75

Concluding Remarks on Implementation: The proposed digital protection method based on RELS offers several advantages:

- Accuracy: By continuously updating parameter estimates, the algorithm achieves high accuracy in fault detection (around 98.5%).
- Speed: The method can detect faults in less than half a cycle, which is crucial for protecting power systems.
- Noise Resistance: The RELS method handles noisy data well by dynamically estimating and adjusting for measurement errors.

The implementation of this method in Python demonstrates its applicability to real-world systems, making it a powerful tool for engineers working in power system protection [19].

5. Conclusion

This paper presented the design and implementation of a digital protection system for power systems using the Least Squares Error (LSE) algorithm. The primary objective was to demonstrate the effectiveness of this approach in accurately detecting internal faults while minimizing false trips caused by transient conditions such as inrush currents. Using the Recursive Extended Least Squares (RELS) algorithm, the system will be able to dynamically update its parameter estimates for more robust and adaptive fault detection under different operating conditions in real time. Also, the system achieved 98.5% accuracy in detecting internal faults with a response time of less than half a cycle. On the other hand, in challenging scenarios such as inrush currents, the system was able to distinguish between transient conditions and real faults, reducing the occurrence of false positives. Despite its promising performance, it should be noted that one of the early limitations observed was the system's performance under severe CT saturation conditions. Although the RELS algorithm was successful in handling mild saturation, severe cases still resulted in some inaccuracies and false positives.

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