Jurnal Ilmiah
Teknologi Sistem
Informasi

Vol. 6 (2025) No. 1

https://jurnal-itsi.org/index.php/jitsi; E-ISSN: 2722-4600; ISSN: 2722-4619
DOI: 10.62527/jitsi.6.1.284

Fault Classification and Detection in Transmission Lines by Chimp Optimization Algorithm (ChOA) Associated Support Vector Machine

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A B S T R A C T S

This paper presents a new method for fault classification and detection in transmission lines using the Chimp Optimization Algorithm (ChOA) integrated with Support Vector Machine (SVM). The adding complexity of modern power schemes demands more accurate and efficient methods for identifying and classifying faults to ensure system reliability and minimize downtime. The proposed method leverages the strengths of ChOA, an optimization procedure motivated by the social actions of chimpanzees, to optimize the parameters of the SVM, enhancing its ability to classify different types of faults accurately. By combining ChOA with SVM, the method not only improves fault classification accuracy but also reduces computational time, making it suitable for real-time applications. Extensive simulations were conducted using various fault scenarios and configurations to justify the execution of the ChOA-SVM model. The outcomes demonstrate that the suggested approach outperforms traditional fault detection procedures in precision, speed, and adaptability to different transmission line conditions. This study aids to the field of power system protection by giving a robust and efficient solution for fault classification and detection, with potential applications in enhancing the resilience and reliability of transmission networks.

Manuscript received Sep 15, 2024; revised Nov 01, 2024. accepted Mar 26, 2025 Date of publication Mar 31, 2025.

Keywords / Kata Kunci — ***Support Vector Machine; ChoA; Transmission Lines; Optimization***

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1. INTRODUCTION

The reliability of power transmission systems is crucial in continuing the stability and efficacy of the grid. As power generating schemes grow in complexity and scale, the need for advanced techniques to precisely identify and categorize faults in transmission lines has become more pressing. Traditional fault detection techniques often struggle to keep pace with the demands of modern grids, particularly in the face of varying environmental conditions and the increasing incorporation of non-conventional resources. To address these challenges, optimization algorithms have emerged as powerful tools for enhancing the performance of fault detection systems. Among these, the ChOA has gained attention due to its unique approach inspired by the social behavior of chimpanzees, offering promising results in various optimization problems.

In this study, we explore the application of ChOA in conjunction with SVM for FDC in transmission lines. SVM, a well-established machine learning technique, is known for its robustness in classification tasks. However, its performance is highly dependent on the selection of parameters, which can significantly impact its ability to correctly identify faults. By employing ChOA to optimize these parameters, it aims to improve the precision and efficiency of the SVM-based fault detection structure. The proposed ChOA-SVM model is tested across a range of fault scenarios to evaluate its effectiveness, with results indicating superior performance compared to conventional methods. This research not only expands the discipline of power system protection but also demonstrates the ability of bio-inspired algorithms in solving complex engineering problems.

This literature review examines various approaches for FDC, and location in power transmission lines, highlighting both traditional and modern techniques. One study presents a technique using ANN to classify and detect faults, achieving high accuracy through features extracted from fault signals, which demonstrates the effectiveness of ANN in real-time applications [1]. Another review categorizes fault detection methods, emphasizing the significance of accurate diagnosis for system reliability but notes the lack of in-depth analysis and empirical support for the discussed methodologies [2]. Additionally, an approach utilizing ANN and other computational techniques for comprehensive FDC is presented, showing the potential for improved reliability in power generating structures, though the complexity of these algorithms may limit real-time implementation [3].

Further research explores the use of SVM techniques for fault classification, which proves effective in handling non-linear data but may face limitations in scenarios where the data is not linearly separable [4]. A deep-learning-built approach using Hilbert-Huang Transform (HHT) and CNN is also discussed, offering significant improvements in classification accuracy. However, the computational complexity of deep learning models could challenge their application in real-time settings, and the effectiveness of these methods across diverse operational conditions requires further validation [5].

This literature review explores various advanced techniques for FDC and location in power systems, specifically in grid-tied photovoltaic (PV) systems and transmission lines. A reduced kernel random forest method has been proposed for spotting and organizing faults in grid-tied PV systems, showing superior accuracy and computational efficiency compared to traditional methods. However, the reliance on simulated data may limit the generalizability of the findings [6]. In transmission lines connected to inverter-based generators, machine learning procedures, including SVM and decision trees, have been effectively applied for FDC, with a focus on the importance of feature selection [7]. Additionally, a signal processing approach using wavelet transforms and Fourier analysis has demonstrated high accuracy in fault identification for three-phase transmission lines, although the method may face limitations in universal applicability and noise resistance [8].Further advancements in fault detection include the application of LSTM networks, which have shown promise in learning temporal patterns in fault data, leading to improved classification accuracy. However, the complexity and data requirements of LSTM models pose challenges for real-time implementation [9]. ANNs have also been utilized for FDC, particularly in transmission lines, where they have proven effective in handling non-linear relationships. Despite their accuracy, the ANN models require extensive training data and careful tuning of architecture and hyperparameters, which may complicate their deployment in practical scenarios [10].

This review highlights several advanced techniques for FDC, and localization in power transmission lines and power electronics systems. A novel approach combining Particle Swarm Optimization (PSO) with a pattern recognition neural network demonstrates improved classification accuracy and reduced computational time, although it may face challenges in generalizing to all real-world scenarios due to dataset limitations and the complexity of parameter tuning [11]. Another method employs functional analysis and computational intelligence for fault detection, showcasing high accuracy and reliability. However, the computational complexity of functional analysis may hinder its real-time application, and the study may not fully consider the impact of external factors like environmental conditions [12]. Optimized machine learning procedures have also been applied for fault detection and localization, significantly enhancing accuracy, though the approach may require extensive computational resources, limiting its practicality in real-time scenarios [13].Further research explores the use of Support Vector Machines (SVM) for FDC and section identification in series-compensated transmission lines, demonstrating high precision but with potential limitations in adaptability to different fault conditions and system noise [14]. Optimization techniques have also been applied to fault detection in a 3-phase single-inverter circuit, improving reliability and detection speed. However, the focus on a specific circuit configuration may limit the pertinence of the findings to other power systems, and the optimization techniques used may require extensive tuning, complicating their implementation [15]. Together, these studies underscore the potential of machine learning and optimization techniques in enhancing fault management in power systems, while also highlighting the challenges of generalization, computational complexity, and practical implementation.

The reviewed studies explore a range of advanced methods for FDC and localization in transmission lines and HVDC systems, emphasizing the integration of optimization algorithms with machine learning techniques. A notable approach combines wavelet transforms with Support Vector Machines (SVM) enhanced by the Harris Hawks optimization algorithm, improving the accuracy of fault identification and location in transmission lines, though it may be constrained by its computational complexity and limited applicability to specific transmission line configurations [16]. Another study leverages the GWO algorithm with ANN for HVDC systems, demonstrating significant improvements in fault detection accuracy. However, the method's robustness could be impacted by environmental conditions, and the reliance on ANN may reduce interpretability [17].

Further research highlights the impact of different swarm optimization algorithms on FDC in VSC-HVDC systems, underscoring the importance of selecting the appropriate algorithm for specific scenarios, although the study may not encompass all possible algorithms [18]. A heterogeneous multi-machine learning approach is also proposed for fault detection in HVDC transmission lines, showcasing superior accuracy but presenting challenges in implementation due to its complexity [19]. Additionally, a review paper provides a comprehensive overview of AI-based techniques for fault management in transmission lines, though it may lack original experimental data and may not cover all emerging AI methodologies [20]. These studies collectively underscore the potential of integrating optimization algorithms with machine learning to enhance fault management in electrical systems while also highlighting the challenges of computational complexity, generalizability, and interpretability.

Recent studies provide insights into the use of SVM and other machine learning procedures for FDC and location in transmission structures. One study focuses on using SVM for classifying and locating faults in long transmission lines, highlighting its effectiveness in differentiating fault types based on voltage and current measurements, though it lacks comparison with other machine learning methods and may not account for environmental conditions [21]. Another research presents an SVM-based scheme tailored for six-phase transmission lines, achieving high accuracy in fault section identification and classification, although its applicability to conventional three-phase systems is limited [22]. A two-step approach combining fault classification with subsequent fault location using voltage amplitudes further enhances accuracy but may fall short under complex fault conditions and has yet to be fully evaluated for real-time applications [23].

A broader survey examines the usage of various machine learning approaches in FDC, emphasizing the advantages of these techniques over traditional methods, such as improved accuracy and speed. However, the survey may not delve deeply into individual studies, and some methods may quickly become outdated due to the fast pace of advancements in machine learning [24]. Additionally, the introduction of the Chimp Optimization Algorithm (COA) offers a novel approach to solving optimization problems, though its specific applicability to fault detection in transmission lines remains unexplored, and its performance may vary depending on the problem domain [25]. These studies collectively underscore the potential and challenges of employing advanced machine learning and optimization techniques in power system fault management, emphasizing the need for further research and practical evaluation.

1. *Problem Statement*

The reliability and stability of power transmission systems are critical for the efficient operation of modern electrical grids. As power systems become more complex and integrate diverse energy sources, traditional fault detection techniques struggle to meet the demands posed by evolving grid conditions. Existing methods often face limitations in accuracy, efficiency, and adaptability, particularly under varying environmental conditions and the incorporation of non-conventional resources. The increasing complexity of power systems necessitates advanced approaches for FDC. Optimization algorithms, such as the Chimp Optimization Algorithm (ChOA), which are inspired by natural behaviors, have shown promise in enhancing performance across various applications. However, their specific application in conjunction with machine learning techniques for power system fault detection remains underexplored. This research aims to address these challenges by employing ChOA to optimize the parameters of Support Vector Machine (SVM) models for fault detection in transmission lines, with the goal of improving accuracy and efficiency in fault classification.

2. *Research* Objectives

1. To explore the effectiveness of the ChOA in optimizing SVM parameters for fault detection and classification in power transmission lines.
2. To develop a ChOA-SVM model and evaluate its performance across various fault scenarios, comparing its effectiveness to traditional fault detection methods.
3. To analyze the impact of ChOA-optimized SVM parameters on the accuracy and efficiency of fault classification, particularly in the context of modern power systems integrating renewable energy sources.
4. To review and synthesize existing techniques in fault detection, classification, and location, highlighting the advantages and limitations of integrating optimization algorithms with machine learning methods.

2. RESEARCH METHODOLOGY

Increased power network reliability and reduced transmission line restoration costs are made feasible by FDC. The main cause of the end users' inability to access energy is the malfunctioning transmission line. Numerous transmission line defects, including LL, LG, LLG, and LLL, lead to problems in the electricity system. The accurate FDC develops a method to ensure dependable transmission line operation. Fault identification and classification are required to identify the types of faults that have arisen and their locations throughout the entire network, even though human involvement is still needed for the recovery of the problematic phases.

This is significant since an accurate and timely FDC raises the probability that troublesome phases will be swiftly eliminated from the network. Eliminating the problematic phases raises the system's stability, improves the power network's transient stability, and improves the quality of power supplied. This study recommends a FDC strategy for transmission line defects. The suggested method efficiently classifies faults and locates defects using an SVM classifier. The ChOA algorithm is used to modify the SVM classifier's parameters, improving the classification accuracy.

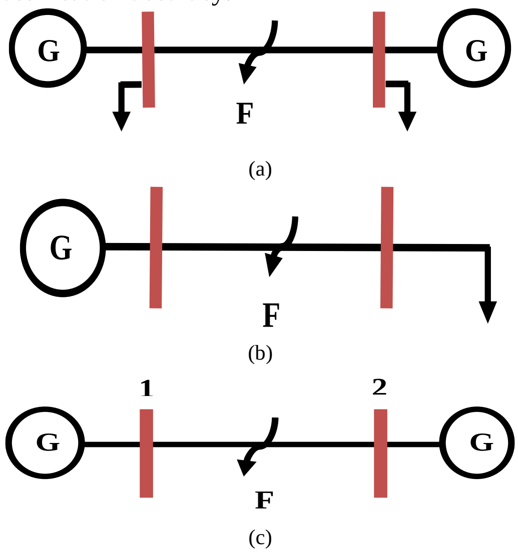


FIG 1. System model (a) Line-Line Fault, (b) Line-Ground Fault and (c) single transmission line (one generator on each side)

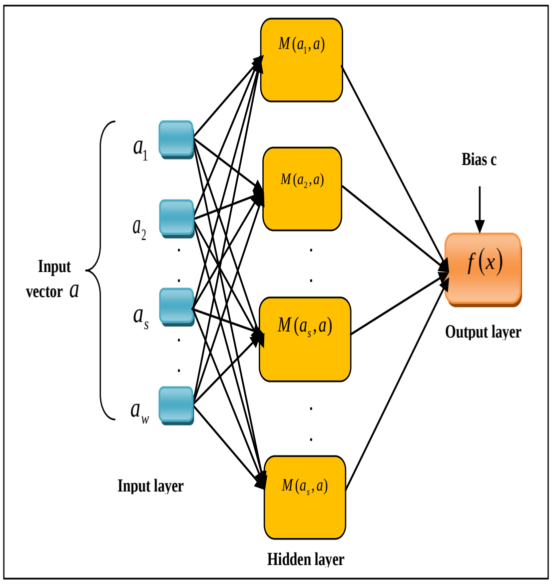


FIG 2. Architecture of support vector machine classifier

The system is built as a single transmission model to recognize the type of trouble and its location. Transmission lines, loads, buses, and generators make up the transmission line system model. Thus, with the corresponding L-L fault, L-G fault, and fault on a single transmission line with one generator on every side, the system example for the transmission lines is displayed in Fig. 1.

1. Overall *Working* Principle of The Proposed Method

The pre-processing unit, fault classifier, and fault locator make up the suggested fault categorization and location identification system. The pre-processing unit receives the current and voltage signals as input, and then uses the SVM classifier to perform the classification process. The recommended ChOA method is used to precisely change the weights of the SVM classifier. The location and distance of the problem are established after it has been identified and described.

2. Pre-Processing Step

Before the voltage and current data are fed into the neural network, the observed values are processed depending on the momentary voltage and current in each of the phase's R, Y, and B. Scaling the post-fault to the fundamental voltage and current of the pre-fault yields the input-output voltages and current. Additionally, earth-related faults can be found using the zero-sequence component of current.

3. Fault Classification Using SVM Classifier

SVM has demonstrated its improved ability in numerous real-world applications, particularly in the resolution of classification issues. SVM's primary goal is to enhance hyper-plane tuning, and expanding the classification's bounds is the foundational design method. Fig. 2 shows the architecture of the SVM classifier. In this study, SVM used the suggested ChOA to create an ideal hyperplane that divides the classes by the greatest margin in order to construct its conclusions.

Six groups of transmission line faults are distinguished: A-G, B-G, C-G, A-B, B-C, and C-A. Many effective methods are used to lower SVM's time and space complexity. In this work, the SVM classifier is exercised using the recommended ChOA technique in order to determine which SVM classifier kernel is optimal.

In case of optimal hyperplane, $\tau.a + c = 0$, $\tau \in E^G$, and $c \in E$, the function of the decision to categorize the point a that is unknown is stated as,

$$u(a) = sign(\tau a + c) = sign(\sum_{s=1}^{G_p} \beta_s i_s a_s \bullet a) \quad (1)$$

where, G_p indicates the count of the support vector, a_s is the support vector; $s = 1,\ldots,W$, β_s represents the Lagrange multiplier and i_s is the class of a. The input space makes it very challenging to identify the critical hyperplane for real-world applications. To resolve this problem, the input space is mapped onto a high-dimensional feature space, from which the ideal hyperplane is derived.

When a mapping from γ to E^G to a feature space is present, consider $m = \gamma(a)$ as the feature space vector. The suggested approach in the feature space A, which is represented as, optimizes the kernel M as follows:

$$m_s . m_t = \gamma(a_s).\gamma(a_t) = M(a_s, a_t) \quad (2)$$

The decision function is presented as follows in the final stage,

$$u(a) = sign(\sum_{s=1}^{G_p} \beta_s i_s M(a_s \bullet a) + c) \quad (3)$$

The polynomial function and the RBF are the most often utilized techniques for determining the kernel level as,

$$M(a_s \bullet a') = (a^T{}_s \bullet a' + 1)^e \quad (4)$$

$$M(a_s, a') = \exp\left\{-\frac{\|a_s - a'\|^2}{2\alpha^2}\right\} \quad (5)$$

where the width dimension, which also denotes the RBF, indicates the polynomial order. However, because each node in the hidden layer assesses the kernel value and contributes to misclassification, the RBF-based kernel function raises computational cost.To prevent such categorization difficulties, the kernel is ideally adjusted using the suggested ChOA technique. After categorizing the defect into A-G, B-G, C-G, A-B, B-C, or C-A categories, the SVM locates the problem. Thus, the SVM accurately ascertains the location of the fault in the transmission system by employing considerations or input data like 5, 10, 15 & 20 km respectively.

3. CHIMP OPTIMIZATION ALGORITHM

1. *Mathematical Model and Algorithm*

The mathematical models of pursuing, driving, stopping, attacking, and separate teams are shown in this section. The matching ChOA algorithm is then provided.

Driving and Chasing Prey

The prey is hunted during the phases of exploration and exploitation, as was previously indicated. Eqs. (6) and (7) are suggested to model driving and rushing the prey analytically.

$$d = |c.X_{prey}(t) - m.X_{chimp}(t)| \quad (6)$$

$$X_{chimp}(t+1) = X_{prey}(t) - a.d \quad (7)$$

Prey x is the vector of the prey's position, chimp x is the vector of a chimpanzee's position, and t indicates the number of the current repetition. The coefficient vectors are a, m, and c. The vectors a, m, and c are decided by Eqs. (8), (9) and (10), in that order.

$$a = 2fr_1 - f \quad (8)$$

$$c = 2r_2 \quad (9)$$

$$m = Chaotic\ value \quad (10)$$

This section discusses the iterative reduction from 2.5 to 0 in a non-linear manner during both exploration and exploitation phases, influenced by random vectors r1 and r2 in the interval [0,1], and a chaotic vector m, which models the hunting behavior of chimpanzees. In traditional population-based optimization, all particles use a single strategy for both local and global searches, treating the population as one group. However, by utilizing multiple independent groups, each with its own strategy, optimization can achieve both directed and random search results. The ChOA algorithm is mathematically represented with these independent groups, which update using functions that decrease with each iteration. Two variants, ChOA1 and ChOA2, are identified as the most effective in benchmark optimization procedures. To comprehend how independent groups function in ChOA, the following points might be considered:

- Independent groups in ChOA use different update strategies, allowing chimpanzees to explore the search space more effectively and balance local and global search through dynamic adjustments.
- The flexibility of ChOA with non-linear methods, such as logarithmic and exponential functions, makes it well-suited for tackling complex optimization problems.

To understand Equations (6) and (7), a two-dimensional representation shows how a chimpanzee at position (x,y) can adjust its position to align with its prey. By varying the vectors a and c, multiple positions can be targeted based on the chimp's current location. Arbitrary vectors r1 and r2 allow chimps to move in any direction around the prey, and this concept extends to an n-dimensional search space. The chimps employ a chaotic strategy to approach their prey, with a mathematical explanation provided in the following section.

Attacking Method (Exploitation Phase)

Two techniques model chimpanzee aggression mathematically: chimps locate and encircle their target through driving, blocking, and chasing behaviors, with attacking chimps primarily carrying out the hunt. While other roles like barriers, chasers, and drivers sometimes join in, the optimal prey location isn't clear in an abstract search space. To mimic this behavior, it's assumed that the first attacker, driver, obstacle, and chaser have better information about the prey's location. The top four results are maintained, and the other chimps adjust their positions accordingly, as expressed in Equations (11), (12), and (13).

$$d_{Attacker} = |c_1 X_{Attacker} - m_1 X_1|, d_{Barier} = |c_2 X_{Attacker} - m_2 2|$$
$$d_{Chaser} = |c_3 X_{Chaser} - m_3 X_1|, d_{Drive} = |c_4 X_{Attacker} - m_4 2| \quad 11$$
$$X_1 = X_{Attacker} - a_1(d_{Attacker}), X_2 = X_{Barrier} - a_2(d_{Attacker}),$$
$$X_3 = X_{Chaser} - a_3(d_{Chaser}), X_4 = X_{Driver} - a_4(d_{Driver}), \quad 12$$
$$X(t+1) = \frac{X_1 + X_2 + X_3 + X_4}{4} \quad 13$$

The attacker, obstacle, chaser, and driver chimps form a circle around the prey's estimated location. Other chimps then randomly update their positions based on the estimates of these four best groups.

Prey Attacking (Utilization)

In the final stage of the hunt, chimps attack their target, stopping when the prey ceases to move. To model this, the value of f is reduced from 2.5 to 0 during iterations, with a ranging within [-2f, 2f]. When a is between [-1, 1], the chimp's next position can be anywhere between its current location and the prey's position. ChOA adjusts positions based on the attacker, obstacle, chaser, and driving chimps, but additional mechanisms are needed to avoid getting stuck in local minima and to enhance exploration.

Searching For Pray (Exploration)

The ChOA uses various strategies to simulate chimp behavior during exploration. Inspired by the Grey Wolf Optimizer (GWO), it employs vectors to simulate divergence, causing search agents to move away from prey. The variable c within the interval [0,2] adjusts the impact of the prey's position on distance calculations, enhancing randomness and reducing the risk of local minima. Additionally, c represents natural obstacles that affect chimpanzee movement, assigning random weights to prey based on the chimp's position, either facilitating or hindering the hunt. This approach helps maintain global exploration throughout the optimization process.

Social Incentive

In the final stage of the ChOA, chimpanzees abandon the hunt, experiencing social desire and a frantic effort to gather resources. This stage introduces chaos, which addresses the issues of slow convergence and local optima entrapment in high-dimensional problems. Chaotic maps, exhibiting both random and deterministic behavior, enhance ChOA's performance. A central value of 0.7 is used for each map, and during optimization, there's a 50% chance of selecting either the chaotic model or the regular update mechanism to adjust the chimps' positions. This is mathematically represented in Eq. (14).

$$X_{chimp}(t+1) = \begin{cases} X_{prey}(t) - ad \; if \; \mu < 0.5 \\ Choatic\,Value \;\; if \;\; \mu > 0.5 \end{cases} \quad (14)$$

Where $\mu$is a random number in [0,1].

The ChOA search begins with creating a random set of chimps, representing potential solutions, which are divided into four groups: attacker, barrier, chaser, and driver. Each group updates its coefficients during the iteration, estimating the positions of prey. Solutions adjust their distance from the target, with adaptive adjustments to the c and m vectors enhancing convergence and avoiding local optima. The f value decreases from 2.5 to zero to refine prey exploitation. Solutions diverge if inequality (1 > a), otherwise they converge near the prey.

2. Step-By-Step Algorithm For Fault Classification And Detection in Transmission Lines Using Chimp Optimization Algorithm (ChoA) and Support Vector Machine (SVM)

Step 1: Data Collection

- Gather fault data from transmission lines, including various fault types and conditions. This data will be used to train and test the SVM model.

Step 2: Data Preprocessing

- Normalize and preprocess the collected data to ensure consistency and improve the accuracy of the SVM model.

Step 3: Initialize Chimp Optimization Algorithm (ChOA)

- Define the initial population of chimpanzees, where each chimpanzee represents a potential solution (i.e., a set of SVM parameters).
- Set the algorithm's parameters, including the number of iterations, population size, and convergence criteria.

Step 4: Evaluate Fitness of Each Chimpanzee

- For each chimpanzee in the population, evaluate its fitness by training the SVM using the parameters represented by that chimpanzee.
- Calculate the classification accuracy of the SVM on the validation data. This accuracy serves as the fitness score.

Step 5: Update Chimpanzee Positions

- Update the positions of the chimpanzees based on their social hierarchy and cooperative hunting strategies. This involves adjusting the SVM parameters to explore new potential solutions.
- Use the best-performing chimpanzees to guide the search for optimal parameters.

Step 6: Check for Convergence

- Check if the algorithm has met the convergence criteria (e.g., reaching a maximum number of iterations or achieving a predefined accuracy level).
- If convergence is not met, return to Step 4 and continue the optimization process.

Step 7: Finalize the Optimal SVM Parameters

- Once the algorithm converges, select the chimpanzee with the highest fitness score. The parameters associated with this chimpanzee are considered the optimal SVM parameters.

Step 8: Train the SVM with Optimal Parameters

- Use the optimal SVM parameters obtained from ChOA to train the final SVM model on the complete training dataset.

Step 9: Fault Classification and Detection

- Deploy the trained SVM model to organize and detect faults in real-time transmission line data.
- Monitor the system to ensure accurate and timely fault detection.

Step 10: Performance Evaluation

- Estimate the performance of the ChOA-optimized SVM model using various metrics such as classification accuracy, computational time, and adaptability to different fault conditions.
- Compare the results with traditional fault detection methods to demonstrate the effectiveness of the proposed approach.

Step 11: Deployment and Monitoring

- Implement the optimized SVM model in the power system protection framework for real-time fault classification and detection.
- Continuously monitor the performance and update the model as necessary to adapt to changing transmission line conditions.

4. Results And Discussion

1. Simulation Procedure

MATLAB/Simulink was used to test the ChOA-based SVM model for fault classification and localization, yielding relevant results. Three transmission line scenarios were analyzed: (i) a model with two loads and two generators symmetrically positioned, (ii) a model with one load and one generator on each side, and (iii) a model with two generators symmetrically positioned. Artificial data based on fault type and distance were collected. The accuracy and classification rates of the ChOA-based SVM model were then compared with conventional models like GWO, DA, NN, LSTM, and SSA algorithms, with model parameters detailed in Tables 1.

TABLE 1. Model Parameters

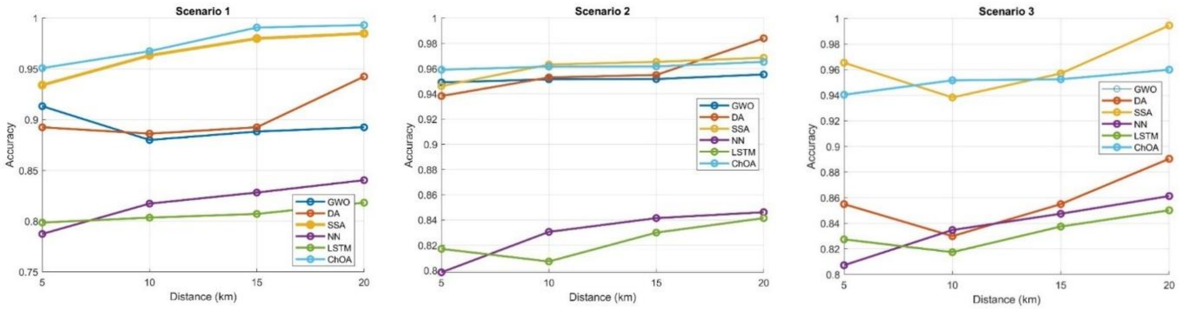
Parameters	Value
Source feeder	
Phase-phase voltage	11e3vrms
Frequency	50 hz
3-phase SC level at base voltage	30e6 (VA)
Three phase RLC load	
Phase-to-phase voltage	1000 Vrms
frequency	50 hz
Active power	10e3W
Inductive reactive power	100
Capacitive reactive	0
Three phase transformer	
Power and frequency	[1e6(VA), 50(Hz)]
winding 1 parameters	[11e3(vrms),0.0020(pu), 08(pu)]
wing 2 parameters	[11e3(vrms),0.0020(pu), 08(pu)]
magnetization resistance	500(p.u)
magnetization inductance	500(p.u)

The comparative analysis presented in Table 2 evaluates the accuracy of different algorithms, DA, SSA, NN, LSTM, and ChOA—in determining fault distance across three scenarios. In Scenario 1, ChOA consistently outperforms the other algorithms, achieving the highest accuracy across all distances, with values ranging from 0.95083 to 0.99325. SSA also demonstrates strong performance, particularly over greater distances, with an accuracy of up to 0.985 at 20 km. In contrast, NN and LSTM algorithms show lower accuracy, especially in shorter distances, with NN recording as low as 0.7874 at 5 km and LSTM achieving 0.7986 at the same distance. In Scenario 2, ChOA continues to show superior performance, maintaining the highest accuracy at nearly every distance, peaking at 0.96542 at 20 km. GWO and DA also perform well, especially at higher distances, with GWO achieving an accuracy of 0.95542 at 20 km.

In Scenario 3, although SSA demonstrates the highest accuracy at 20 km with a value of 0.9945, ChOA and GWO still perform commendably, both recording accuracies of 0.96 at the same distance. Across all scenarios, NN and LSTM consistently lag behind the other algorithms, particularly at longer distances, indicating a potential area for improvement in these models

TABLE 2. Comparative analysis based on Accuracy in terms of fault Distance

Distance (km)	GWO	DA	SSA	NN	LSTM	ChOA
	Scenario 1					
5	0.9133	0.8925	0.9341	0.7874	0.7986	0.95083
10	0.88	0.8862	0.9633	0.8173	0.8035	0.9675
15	0.8883	0.8925	0.98	0.8282	0.8071	0.99083
20	0.8925	0.9425	0.985	0.8404	0.8182	0.99325
Distance (km)	**Scenario 2**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
5	0.9491	0.9383	0.9462	0.7985	0.8171	0.95917
10	0.9516	0.9531	0.9633	0.8306	0.8071	0.96167
15	0.9518	0.955	0.9654	0.8415	0.83	0.9618
20	0.95542	0.9841	0.9687	0.8462	0.8415	0.96542
Distance (km)	**Scenario 3**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
5	0.94042	0.855	0.9654	0.8073	0.8275	0.94042
10	0.95167	0.83	0.9383	0.8348	0.8175	0.95167
15	0.9525	0.855	0.957	0.8475	0.8375	0.9525
20	0.96	0.8904	0.9945	0.8613	0.8502	0.96



(a) (b) (c)

FIG 3. Analysis on accuracy of fault distance, (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3

TABLE 3. Comparative analysis based on Accuracy with respect to Fault type

Fault Type	Scenario 1					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
A-G	0.905	0.9052	0.947	0.8075	0.8195	0.9445
B-G	0.93625	0.9395	0.9616	0.8182	0.8208	0.98
C-G	0.94667	0.9406	0.962	0.8182	0.8286	0.9818
A-B	0.97792	0.9537	0.9633	0.8339	0.8406	0.9938
B-C	0.99125	0.9552	0.9716	0.8415	0.8448	0.9925
C-A	0.99165	0.9632	0.9728	0.8448	0.8471	0.9945
Fault Type	**Scenario 2**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
A-G	0.93625	0.8466	0.905	0.8175	0.8285	0.982
B-G	0.96542	0.8758	0.9591	0.8306	0.8286	0.9841
C-G	0.97583	0.8729	0.9766	0.8392	0.8306	0.955
A-B	0.98104	0.8818	0.9841	0.8435	0.8475	0.9779
B-C	0.98458	0.8466	0.9883	0.8502	0.8506	0.9904
C-A	0.98833	0.8654	0.9892	0.8538	0.8612	0.9918
Fault Type	**Scenario 3**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
A-G	0.96125	0.8695	0.875	0.8303	0.8395	0.9847
B-G	0.97167	0.8362	0.8962	0.8385	0.8404	0.9887
C-G	0.98354	0.8945	0.8862	0.8475	0.8404	0.9856
A-B	0.97958	0.8591	0.9025	0.8515	0.8573	0.9814
B-C	0.98503	0.8466	0.8508	0.8612	0.8572	0.9904
C-A	0.98708	0.8589	0.9066	0.8591	0.8675	0.9912

Table 3 provides a comparative analysis of accuracy across different fault types for various algorithms GWO, DA, SSA, NN, LSTM, and ChOA across three scenarios. In Scenario 1, ChOA demonstrates the highest accuracy in most fault types, particularly excelling in the B-G, C-G, and C-A faults with accuracies as high as 0.9818, 0.9938, and 0.9945, respectively. SSA also shows strong performance, especially in the B-G and C-G fault types, with accuracies of 0.9616 and 0.962. On the other hand, NN and LSTM consistently show lower accuracy, particularly in single-phase-to-ground faults like A-G, where their accuracies hover around 0.8075 and 0.8195, respectively.

In Scenario 2, ChOA continues to outperform other algorithms, maintaining high accuracy levels, especially in A-G, B-G, and C-G fault types, where it achieves accuracies of 0.982, 0.9841, and 0.9918, respectively. GWO also performs well, particularly in B-G and C-G faults, with accuracies of 0.96542 and 0.98833. In Scenario 3, ChOA again leads in most fault types, particularly in the B-G, C-G, and C-A faults, where it records accuracies of 0.9887, 0.9856, and 0.9912, respectively. SSA's performance is more variable in this scenario, with accuracies ranging from 0.8508 in the B-C fault to 0.9025 in the A-B fault. Meanwhile, NN and LSTM continue to show relatively lower accuracy, particularly in faults involving phase-to-phase interactions.

2. *Analysis of Transmission Line*

Table 4 compares the actual fault distances with the predicted fault distances across three scenarios using six different algorithms: GWO, DA, SSA, NN, LSTM, and ChOA. In Scenario 1, the predicted distances show varying degrees of accuracy. ChOA and SSA are generally more consistent in predicting fault distances closer to the actual values, particularly for shorter distances like 1 km and 2 km, where they often predict correctly or within a small margin. On the other hand, NN and LSTM demonstrate less accuracy, with predictions deviating more frequently from the actual distances. For example, at an actual distance of 3 km, NN predicts 2 km in multiple cases, indicating a tendency towards underestimation.

In Scenario 2, the accuracy of the predictions improves for most algorithms, especially for GWO, ChOA, and SSA. ChOA continues to exhibit strong performance, often predicting the fault distance accurately or very close to the actual value. For instance, at an actual distance of 1 km, ChOA correctly predicts 1 km, while other algorithms like NN and LSTM show more variation, sometimes predicting distances that are off by 1 or 2 km. GWO and DA also show reasonable accuracy, with GWO performing particularly well at distances like 4 km, where it accurately predicts 4 km. Scenario 3 presents more challenging conditions, with the algorithms showing varied performance in predicting fault distances. ChOA and SSA still lead in terms of accuracy, although some predictions show more significant deviations, such as SSA predicting 5 km for an actual distance of 1 km. This scenario also highlights the limitations of NN and LSTM, which consistently predict distances that are further from the actual values. For instance, NN predicts 4 km when the actual distance is 3 km, and LSTM also shows similar discrepancies. GWO and DA exhibit moderate accuracy, with GWO sometimes predicting distances farther from the actual, such as 6 km for an actual distance of 3 km.

TABLE 4. Actual fault distance Vs predicted fault distance

Actual Distance	Predicted Distance					
	Scenario 1					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
1	3	3	1	2	3	1
3	2	2	2	2	1	3
2	2	1	3	1	3	2
3	1	3	4	2	3	3
4	3	1	3	4	3	4
4	4	1	2	4	1	4
Actual	Scenario 2					
Distance	**GWO**	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
1	3	1	3	2	1	1
3	2	2	3	2	2	3
2	1	3	4	1	2	3
3	2	3	2	3	1	3
4	4	1	3	3	2	4
4	3	2	2	3	3	2
Actual	Scenario 3					
Distance	**GWO**	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
1	2	1	5	1	2	1
3	3	2	3	1	2	3
2	1	3	1	2	2	2
3	6	1	3	4	5	3
4	5	4	3	5	3	4
4	5	6	3	4	5	5

Table 5 evaluates the algorithms' accuracy in predicting fault types across three scenarios. In Scenario 1, ChOA generally demonstrates the highest accuracy, correctly predicting the fault type in several cases, such as when the actual fault type is 4 or 2. SSA also performs well, particularly in predicting fault types 3 and 2 accurately. However, NN and LSTM tend to show lower accuracy, frequently misclassifying fault types. For example, when the actual fault type is 4, NN predicts type 1, which indicates a significant deviation.

TABLE 5. Actual fault type Vs predicted fault type

Actual fault type	Predicted fault					
	Scenario 1					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
4	2	3	3	1	2	4
5	1	3	3	3	4	5
2	2	2	1	1	2	2
4	3	3	2	3	2	4
2	1	1	2	2	1	2
3	3	2	1	2	2	3
Actual fault	Scenario 2					
type	**GWO**	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
4	1	5	3	4	3	4
5	2	1	6	4	3	5
2	3	3	6	2	1	2
4	6	2	1	5	3	4
2	2	1	1	1	2	2
3	5	4	2	4	4	2
Actual fault	Scenario 3					
type	**GWO**	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
4	5	4	6	4	3	4
5	6	3	6	6	4	5
2	4	2	3	3	1	2
4	3	1	4	2	3	4
2	1	1	6	3	2	2
3	2	2	1	1	4	1

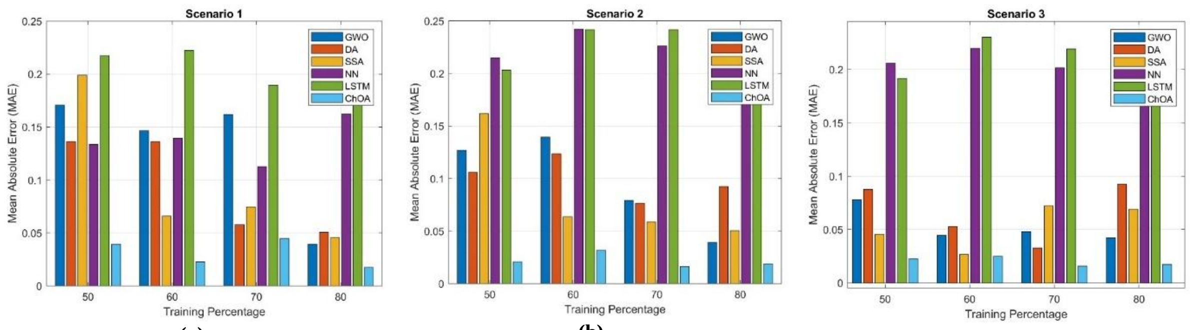
In Scenario 2, the predictions vary more, with some algorithms showing improvements and others declining in accuracy. ChOA remains one of the most accurate, especially for fault types 2 and 4, where it consistently predicts correctly. SSA and DA exhibit less consistency, with SSA occasionally predicting fault types that differ from the actual ones by a larger margin, such as predicting type 6 instead of type 3. GWO also shows variability, with some correct predictions but also significant errors, such as predicting type 6 when the actual fault type is 4.
Scenario 3 continues to reflect the pattern of variability among the algorithms. ChOA maintains relatively high accuracy, particularly for fault types 4 and 5, where it predicts correctly or closely matches the actual type. GWO and SSA show mixed results, with SSA particularly struggling to predict fault types accurately, often indicating a different fault type than the actual one. NN and LSTM remain less accurate, with frequent misclassifications, such as NN predicting type 6 when the actual type is 2, further highlighting their limitations in this context.

3. Analysis in Terms of Error Value

The analysis of the ChoA-based SVM method is deliberated through significant MAE measures in this division. Figures 10 and 11 portray the comparative evaluation for all three scenarios in terms of MAE. Table 6 tabulates the measure of MAE for the conventional methods and the proposed method in terms of fault distance.

Table 6 provides a comparative analysis of the Mean Absolute Error (MAE) for fault distance predictions across different training percentages and scenarios using six algorithms: GWO, DA, SSA, NN, LSTM, and ChOA. In Scenario 1, as the training percentage increases, the MAE generally decreases for most algorithms, with ChOA consistently achieving the lowest MAE values across all training percentages. For instance, at 80% training, ChOA has an MAE of just 0.0175, significantly lower than the other algorithms. SSA also performs well, especially at 60% training, where it has a MAE of 0.066. NN and LSTM, however, exhibit higher MAE values, particularly at lower training percentages.
In Scenario 2, the trend is similar, with ChOA consistently delivering the lowest MAE values. At 80% training, ChOA achieves an MAE of 0.0187, outperforming the other algorithms. SSA and DA also show good performance, with DA having a relatively low MAE of 0.0765 at 70% training. However, NN and LSTM continue to show higher MAE values, indicating less accuracy in fault distance predictions, particularly as the training percentage decreases.

Scenario 3 further reinforces these trends, with ChOA maintaining the lowest MAE values across all training percentages. At 80% training, ChOA's MAE is 0.0175, again leading in accuracy. SSA and DA also perform well, particularly at 60% training where SSA achieves an MAE of 0.0268. GWO shows moderate performance, with a noticeable improvement in accuracy as the training percentage increases. On the other hand, NN and LSTM consistently exhibit higher MAE values, particularly at lower training percentages, highlighting their limitations in fault distance prediction accuracy.



(a) (b) (c)

FIG 4. Analysis of fault distance using MAE, (a) Scenario 1, (b) Scenario 2, and (c) Scenario

Table 6 presents a comparative analysis of the Mean Absolute Error (MAE) for fault type predictions across different training percentages and scenarios using six algorithms: GWO, DA, SSA, NN, LSTM, and ChOA. In Scenario 1, ChOA consistently demonstrates the lowest MAE values, indicating its superior accuracy in predicting fault types. For example, at 60% training, ChOA achieves an impressive MAE of just 0.0161, significantly outperforming the other algorithms. GWO and DA also show reasonable performance, particularly at higher training percentages, but NN and LSTM tend to have higher MAE values, reflecting less accurate fault type predictions, especially at lower training percentages.

TABLE 6. Comparative analysis based on MAE for fault distance

Training percentage	MAE					
	Scenario 1					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
50	0.1708	0.13628	0.19897	0.1337	0.2175	0.0394
60	0.14667	0.13625	0.066	0.1395	0.2224	0.0227
70	0.1619	0.0578	0.0747	0.1127	0.1897	0.0446
80	0.0394	0.0508	0.0456	0.1623	0.1728	0.0175
Training percentage	**Scenario 2**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
50	0.12717	0.10618	0.1618	0.215	0.2034	0.0208
60	0.13937	0.1237	0.0637	0.2424	0.2417	0.0319
70	0.0793	0.0765	0.0587	0.2264	0.2417	0.0165
80	0.03937	0.0925	0.0506	0.2047	0.1917	0.0187
Training percentage	**Scenario 3**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
50	0.0782	0.0876	0.0457	0.206	0.1917	0.0226
60	0.0446	0.0529	0.0268	0.2197	0.2304	0.0248
70	0.0481	0.0328	0.0723	0.2016	0.2193	0.0158
80	0.0424	0.0925	0.0691	0.1897	0.17247	0.0175

In Scenarios 2 and 3, ChOA continues to lead in accuracy with the lowest MAE values across all training percentages. For instance, in Scenario 3 at 80% training, ChOA maintains a low MAE of 0.0165. SSA and DA also perform well, particularly in Scenario 2, where DA has an MAE of 0.0765 at 70% training. However, NN and LSTM again show higher MAE values, particularly in Scenario 1, where their MAE values are consistently higher than those of ChOA, SSA, and DA. Overall, ChOA's performance stands out as the most accurate across all scenarios and training percentages for fault type prediction.

TABLE 7. Comparative analysis based on MAE for fault type

Training percentage	MAE					
	Scenario 1					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
50	0.1354	0.1521	0.1729	0.2178	0.2067	0.0975
60	0.1927	0.1076	0.0656	0.2477	0.2576	0.0161
70	0.0408	0.0431	0.0847	0.2376	0.2437	0.0106
80	0.0781	0.0396	0.0687	0.2071	0.1973	0.0247
Training percentage	**Scenario 2**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
50	0.1271	0.10618	0.1618	0.215	0.2034	0.0208
60	0.1393	0.1237	0.0637	0.2424	0.2417	0.0319
70	0.0793	0.0765	0.0587	0.2264	0.2417	0.0165
80	0.0393	0.0925	0.0506	0.2047	0.1917	0.0187
Training percentage	**Scenario 3**					
	GWO	**DA**	**SSA**	**NN**	**LSTM**	**ChOA**
50	0.1467	0.1654	0.2238	0.206	0.1917	0.0165
60	0.0721	0.0896	0.0779	0.2197	0.23047	0.0154
70	0.0771	0.0824	0.05152	0.2016	0.2193	0.0155
80	0.13	0.0445	0.0925	0.1897	0.1724	0.0165

Table 7 presents a comparative analysis of the Mean Absolute Error (MAE) for fault type predictions across different training percentages and scenarios using six algorithms: GWO, DA, SSA, NN, LSTM, and ChOA. In Scenario 1, ChOA consistently demonstrates the lowest MAE values, indicating its superior accuracy in predicting fault types. For example, at 60% training, ChOA achieves an impressive MAE of just 0.0161, significantly outperforming the other algorithms. GWO and DA also show reasonable performance, particularly at higher training percentages, but NN and LSTM tend to have higher MAE values, reflecting less accurate fault type predictions, especially at lower training percentages.

In Scenarios 2 and 3, ChOA continues to lead in accuracy with the lowest MAE values across all training percentages. For instance, in Scenario 3 at 80% training, ChOA maintains a low MAE of 0.0165. SSA and DA also perform well, particularly in Scenario 2, where DA has an MAE of 0.0765 at 70% training. However, NN and LSTM again show higher MAE values, particularly in Scenario 1, where their MAE values are consistently higher than those of ChOA, SSA, and DA. Overall, ChOA's performance stands out as the most accurate across all scenarios and training percentages for fault type prediction.

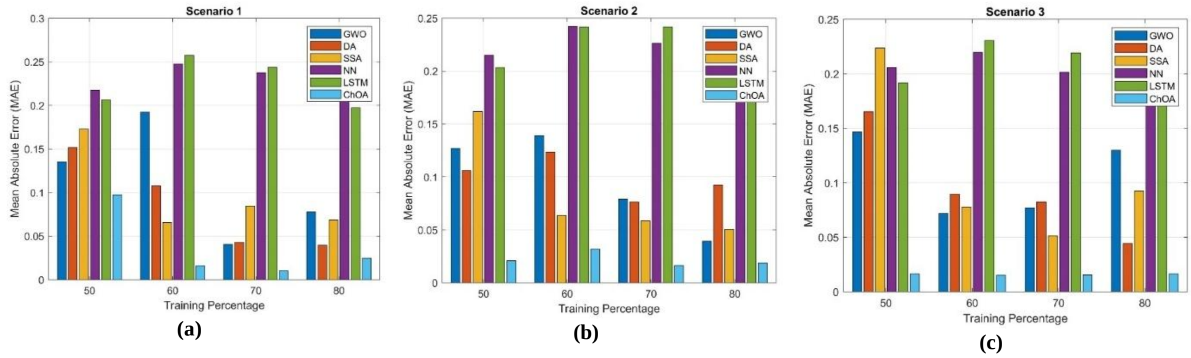


FIG 5 . Analysis of fault type using MAE, (a) Scenario 1, (b) Scenario 2, and (c) Scenario

The measure of MAE for the suggested approach and the standard methods are tabulated in Table 9 according to the fault type. In comparison to the established techniques for fault identification and classification in transmission lines, it is apparent from the table that the suggested technique has a lower level of MAE in detecting the fault distance and fault type.

4. *Computational* Time

Table 8 provides an analysis of the computational time required by six different algorithms—GWO, DA, SSA, NN, LSTM, and ChOA—across three cases. ChOA consistently exhibits the shortest computational time in all cases, demonstrating its efficiency. For instance, in Case 1, ChOA takes only 0.06665 units of time, which is significantly less than the time taken by the other algorithms. GWO also performs well in terms of speed, particularly in Case 1, where it requires 0.081552 units of time. On the other hand, algorithms like DA and SSA have longer computational times, with SSA taking up to 0.95688 units of time in Case 3, the highest among all. NN and LSTM show moderate performance but still require more time compared to GWO and ChOA, particularly in Case 1, where NN takes 0.8711 units of time. Overall, ChOA emerges as the most computationally efficient algorithm, followed closely by GWO, while SSA and DA are relatively slower.

TABLE 8. Analysis on computational time

Cases	GWO	DA	SSA	NN	LSTM	ChOA
Case 1	0.081552	0.59816	0.3078	0.8711	0.4262	0.06665
Case 2	0.22708	0.69312	0.82993	0.7281	0.5172	0.14167
Case 3	0.26538	0.72221	0.95688	0.3502	0.6672	0.13167

5. *K-Fold Validation*

Table 9 depicts the K-Fold analysis for diverse values of k (k=1, k=2, k=3, k=4, k=5). The positive measures like accuracy, specificity, precision, F-measure, MCC, and NPV achieve the greater value at k=3. Similarly, the negative measures FPR and FNR achieve the least value at k=3. Accordingly the entire analysis in Table 9, k=3 provides a superior result.

TABLE 9. K-fold Analysis

k-fold	Accuracy	Sensitivity	Specificity	Precision	FPR	F_1_score	MCC	FNR	NPV	FDR
K=1	0.929	0.931	0.956	0.946	0.054	0.933	0.889	0.079	0.956	0.064
K=2	0.904	0.887	0.943	0.915	0.067	0.891	0.836	0.123	0.943	0.095
K=3	0.917	0.942	0.97	0.967	0.04	0.952	0.923	0.068	0.97	0.043
K=4	0.913	0.922	0.949	0.939	0.061	0.929	0.876	0.088	0.949	0.071
K=5	0.892	0.873	0.932	0.906	0.078	0.883	0.816	0.137	0.932	0.104

6. *Fault Signal Analysis*

A line-to-line fault occurs when two conductors are short-circuited. Four examples of fault data for single line-to-line faults are depicted in Fig.6. Fault scenarios in real transmission lines are dynamic and complex. Faulty or non-faulty signals with varying fault locations, fault resistance, fault angles, and fault times are created to simulate various fault scenarios.

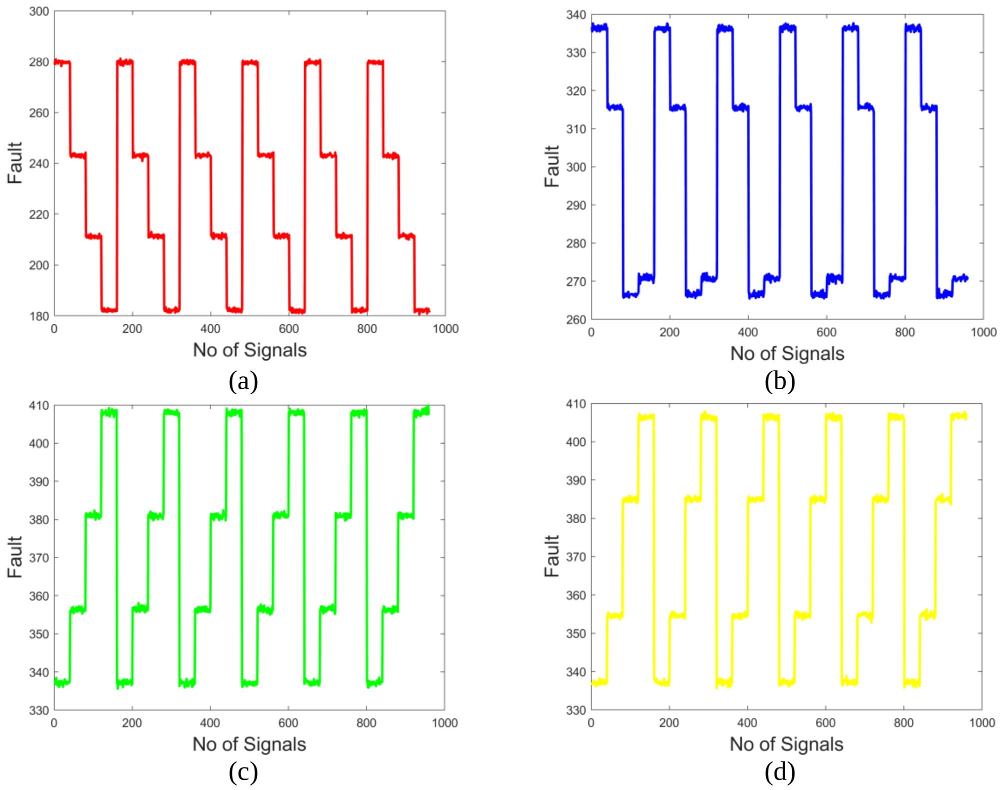


FIG 6 . Analysis of fault data for the single line-to-line fault (a) Fault Data 1 (a) Fault Data 2 (a) Fault Data 3 (a) Fault Data 4

5. CONCLUSIONS

In conclusion, the research paper demonstrates the effectiveness of the ChOA combined with a SVM for fault classification and detection in transmission lines. Through extensive comparative analysis, it is evident that ChOA, when integrated with SVM, outperforms other algorithms like GWO, DA, SSA, NN, and LSTM in terms of accuracy, MAE, and computational efficiency. ChOA consistently shows superior performance in accurately predicting fault types and distances across various scenarios, with the lowest MAE values and the fastest computational times, making it a highly efficient and reliable approach for fault detection in transmission lines. The findings underscore the potential of ChOA as a powerful optimization tool in conjunction with SVM for enhancing the accuracy and speed of fault detection techniques in power transmission networks. This combination not only lowers the computational burden but also advances the precision of fault classification, ensuring a more robust and responsive fault management system. The study paves the way for further exploration of ChOA in other power system applications, highlighting its adaptability and effectiveness in handling complex optimization problems in real-time scenarios

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