

# Fault Localization in Power Distribution Networks Using FLSO-SVR: A Data-Driven Machine Learning Approach

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*Distribution lines play an essential role in the modern power grid and have the potential to influence the reliability of the power supply. Immediate fault localization is essential for a reliable power system protection system. When diagnosing a problem, there are two stages. One area that has already reached remarkable accuracy rates is fault categorization. Fault localization in power distribution networks refers to identifying the exact location of faults or disturbances within the grid. Thus, fault location is the focus of this research, which is the inverse of the original goal. The proposed approach utilizes a combination of Principal Component Analysis (PCA) for feature reduction, Wavelet Transform for signal decomposition, and a novel Fuzzy-Logic Spider Optimization-based Support Vector Regression (FLSO-SVR) model for accurate fault localization. The algorithm determines the approximate location of the fault by examining voltage and current readings taken at the main feeder the monarch, as well as scheduled injections of reactive as well as active electricity by networks synchronous generators. Distributed grid plants' dynamic behaviour during fault transients was analyzed using an advanced machine learning (ML) model. Experiments conducted on the IEEE 118-bus system demonstrated the effectiveness of the method, achieving an accuracy of 95%, recall of 0.91, f1-score of 0.94, and precision of 0.92 which was higher than the state-of-the-art models. Modern power grid automation relies on the suggested methods, which improve fault localization accuracy, strengthen system resilience, and provide practical isolation measures. While the proposed method contributes to improved localization, its primary innovation lies in accurately localizing fault points within complex distributed networks using the FLSO-SVR framework.*

*Povzetek: Predlagani FLSO-SVR model z WT in PCA natančno lokalizira okvare v distribucijskih omrežjih ter izboljša zanesljivost pametnih omrežij.*

## 1 Introduction

In a distributed network, significant consequences such as power supply interruptions, grid deterioration, and power quality problems, can occur as a result of electromagnetic transients caused by distribution line failures. Therefore, finding issues with distribution lines quickly and properly is of the utmost importance. The distribution system's job is to keep power outages as rare and short as possible while supplying subscribers with the energy they need [1]. This is an important problem since pinpointing the exact location of a defect in such large networks can be difficult due to the distribution networks and other parts of the power system's vulnerability to blackouts. Finding the exact location of the defect as quickly and accurately as possible improves the system dependability index and its efficiency [2]. ToA diagnosis technique is required to swiftly and accurately locate faulty sections and restore power supply in the event of a distribution network outage,

this makes emergency repairs more efficient and decreases the amount of time needed to evaluate electricity lines [3]. However, pinpointing the exact locations of fault branches and distribution networks can be challenging due to the complexity of these network architectures, which often include multiple branches and large quantities of equipment distributed across large areas. The absence of efficient defensive coordination makes fault localization more difficult in distribution networks with Distributed Generation (DG) [4]. While fault localization techniques for distribution networks tend to center on conventional radial distribution systems, distributed generation distribution networks have just lately begun to garner significant attention [5].

Distribution network fault localization techniques include traveling wave methods, intelligent algorithms, time domain methods, and impedance methods. There are, however, drawbacks to each of these methods. Complex structure, high sampling frequency, and database

requirements are some of the potential challenges that traveling wave-based techniques might face [6]. Intelligent approaches, on the other hand, can necessitate assistance owing to their intricate structure and the necessity of a precise and extensive database. Consequently, the distribution network fault location has been the subject of substantial investigation. Imperata, fault indicator, signal injection, traveling wave, matrix algorithm, and artificial intelligence algorithm-based techniques are among the many that have been proposed [7]. This means that identifying wave heads at refraction and reflection nodes is not easy using standard traveling wave methods. Research intends to develop an intelligent fault localization model for distribution networks incorporated with DER. It employs the FLSO-SVR algorithm to improve fault localization accuracy. Fault localization was utilized to identify the exact location of faults or disturbances. The objective is to overcome limitations in traditional methods by enhancing feature extraction, handling nonlinearities, and maintaining noise resilience.

This research proposes a novel hybrid model FLSO with SVR specifically designed for accurate fault localization in electrical distribution networks. Unlike traditional models that focus primarily on fault localization or categorization, the FLSO-SVR model precisely determines the exact fault location using both offline and online data sources. The main contributions of this research are:

- A two-step machine learning-based methodology that accurately identifies the faulty section of the network and localizes the fault position using signal and system features.
- The integration of FLSO (a quantum-inspired metaheuristic optimizer) with SVR improves the model's ability to handle incomplete, imbalanced, or noisy data making the fault localization process more robust and scalable.
- The approach is adaptable to various network configurations and requires fewer data resources, enabling scalable and real-time fault localization even under complex distributed network conditions.
- Although improved fault localization accuracy is observed as a secondary outcome, the core innovation lies in enhancing fault localization precision, which is critical for minimizing outage durations and improving grid resilience.

### 1.1 Problem statement

Research discusses fault location and localization in distributed networks, including power line circumstances, computational cost, implementation issues, and scalability across electrical network models. It also overlooks practical implementation issues, such as data collection and processing, and the impact of fluctuating environmental conditions. The method's reliance on

Matlab/Simulink simulations can limit its applicability in smaller data sources and climatic conditions. Although currently tested on centralized, simulated datasets, the proposed FLSO-SVR framework was designed with the potential to incorporate with decentralized sensor networks in future applications. With appropriate real-time data pipelines, it could be extended to dynamically adapt to environmental and operational changes in smart grid contexts. The practicality and wider application of the model could be ensured by verifying it through real-world demonstrations instead of depending just on Matlab/Simulink simulations.

## 2 Related works

To identify and categorize various problem kinds on power transmission lines, the article proposed a hybrid concurrent neuro-fuzzy approach (CNF) technique [8]. The results revealed that the CNF could capture a wide range of fault conditions, suggesting a shorter period of technical management's time. To avoid fire, an Artificial Intelligence (AI)--based approach for detecting open conductor faults on overhead cables was suggested in this research [9]. The system's design flaw was supposed to originate from the falling open conductor line connecting to the earth. The research gave the completed approach for the non-intrusive examination of high-voltage electrical networks [10]. A neural classifier built on a Multi-Valued Neurone (MVN) neural network models the technique, which relies on Applications of Machine Learning (also known as ML) as well as Frequency Response Analysis (FRA). The results of the simulation demonstrated that it was feasible to classify the state of the joints and avert serious issues.

As explored in [11], a High Voltage Direct Current (HVDC) transmission network based on voltage source converters might mimic power generation between AC networks. Both favorable and bad scenarios could be considered in an evaluation. The research detailed a medium-volt overhead line fault localization method utilizing Bidirectional Long Short-Term Memory (Bi-LSTM) with covered conductors (CC) [12]. The results of the experiments proved that the proposed BLSTM method was the most effective in learning the Partial Discharge (PD) structure, which is chaotic. Research [13] suggested a methodology that utilized ML techniques to detect trends in PD signals and anticipate potential failures. Their research method identified PD fluctuations with a high degree of precision.

To offer an automated diagnosis method for overheating problems in Overhead Transmission Lines (OHTL), the research [14] used semantic segmentation. The suggested intelligent detection approach successfully measured the grounds of the lead wiring or straining clamps with a diagnostic accuracy of 91.0 percent. The research presented a new method and framework for the ongoing assessment, prediction, and fault localization of the various

joint areas of power transmission overhead lines [15]. Soft computing, ML, as well as FRA were the foundations upon which the methods were built. One way to characterize the proposed method is as an intelligent measuring component; using a single measurement, a neural processor might glean all the necessary information for assessing a complex electrical structure. Research [16] developed a system for OHTL defect detection and classification using a Backpropagation Neural Network (BPNN). Linear Model (LM) outperformed Scaled Conjugate Gradient (SCG) and Bayesian Regularization

(BR), according to the results. Research [17] proposed a fault localization method for distribution networks using C-means clustering on historical telemetry data. It introduced a mismatch index for identifying line anomalies and was tested on a real 12 kV feeder. The approach effectively recognized load patterns and detected faults. However, its reliance on historical data limits real-time adaptability, supporting the need for dynamic, learning-based models like FLSO-SVR. Related works are included in Table 1.

Table 1: Comparison of other related methods

Ref	Objective	Methodology	Results	Limitation
[8]	The novel method for identifying and finding different kinds of power transmission line faults is by employing the CNF.	Fuzzy logic (FL) and artificial neural networks (ANN) are used in conjunction to identify, categorize, and locate problems on high-voltage and very high-voltage transmission lines across both short and long distances.	Technical groups' maintenance time is decreased by CNF's high accuracy in identifying and locating different kinds of transmission line faults.	The hybrid FL-ANN approach might suffer from computational complexity and require extensive training data to generalize across varied network topologies.
[9]	To reduce the risk of fire, intends to develop an AI-based technique for identifying flaws in overhead wires before they result in ground contact.	Fault simulations provided voltage and current data for wavelet-transformed analysis, and a falling conductor model with pendulum motion was utilized to estimate fall duration.	Efficiently identifying faults before line-ground contact, the AI-based fault detection technique validated by MATLAB simulations decreases the danger of a fire.	The simulated environment might not fully capture real-world disturbances and model tuning is sensitive to conductor motion parameters.
[10]	The goal is to prevent overhead transmission grid breakdowns, especially at connection joints, by creating a non-intrusive monitoring method for high-voltage electrical networks.	Use an MVN neural network and an ML-based neural classifier with Frequency Response Analysis (FRA) to diagnose and track electrical systems.	Effective fault diagnostics and prognostics were displayed, enabling quicker recovery times through the identification of crucial parts, better maintenance planning, and increased grid availability.	FRA-based models are susceptible to noise interference and require precise calibration to avoid false positives.
[11]	To ensure supply continuity in intricate power systems by creating an ML-based fault diagnosis method for HVDC transmission systems.	Data to be analyzed using ML techniques to extract diagnostic information. Matlab/Simulink can be used to conduct the simulations.	Evaluation of ML-based fault diagnosis methods' effectiveness in identifying anomalies and guaranteeing a continuous power supply is the outcome of the investigation.	ML model performance depends heavily on labeled HVDC fault datasets, which are limited in diversity and availability.
[12]	Using partial discharge signals to create a BLSTM model for Medium Voltage (MV) overhead wires with covered conductor fault detection.	An actual dataset from the high-sampling-frequency meter (40 MHz) at the center was used, guaranteeing a variety of data in terms of PD quality and noise spectrum.	The Bi-LSTM approach overcame noise problems and showed competitive performance in learning and recognizing chaotic PD patterns.	BLSTM training is resource-intensive and model accuracy can degrade under extreme environmental noise not represented in the training set.
[13]	To anticipate possible failures and use ML methods to identify PD signal patterns in transmission cables.	The method utilized to find patterns of partial discharge was based on ML. The research's main objective was to examine localized electrical insulating dielectric deterioration.	The suggested model was able to detect partial discharge patterns with accuracy.	The approach's scalability and limited generalization when applied to varied cable insulation types and aging conditions.

[14]	To improve the dependability of leading wires and strain clamps on overhead transmission lines by utilizing deep learning (DL) and infrared thermal imaging to identify overheated issues.	To enhance contrast, the research used UAVs equipped with infrared thermal imagers. The performance of the DeepLab v3+ network was compared using the Focal Loss function, ResNet101, and convolutional block attention module.	Frequency-weighted Intersection over Union (IoU), Adaptive IoU (AIoU), F1 score, and average pixel accuracy were among the high-performance metrics attained by the suggested approach; AIoU was enhanced by optimized atrous rates.	Thermal imaging is weather-dependent and UAV operation might be restricted in certain conditions or terrains.
[15]	The establishment of an intelligent measuring module for the ongoing assessment, diagnosis, and prognosis of joint areas in overhead power delivery.	Uses methods from ML, soft computing, and FRA. Single readings are analyzed by a neural processor to retrieve diagnostic data from intricate electrical systems.	By providing an intelligent diagnostic strategy for problem diagnosis and monitoring, the suggested method improves the research of intricate electrical systems.	System reliability might degrade under irregular measurement intervals or missing input features in real-time deployment.

Existing fault localization techniques in distribution networks often struggle with handling the complexity of bidirectional power flow and dynamic operating conditions introduced by distributed energy resources (DERs). Many conventional models lack the adaptability to accurately detect faults under high variability and noise. To address these challenges, this research proposes the use of the Fuzzy-Logic Spider Optimization-based Support Vector Regression (FLSO-SVR) algorithm for improved fault localization in distribution systems. Distributed energy resources (DERs) such as small hydropower, solar power, biomass, wind power, fuel cells, and others have allowed for on-site generation, which has led to major changes in distribution systems in recent years. Both grid-connected and off-grid DG have the potential to reduce environmental impacts while simultaneously increasing supply security. However, situational awareness is severely hindered by the complicated network architecture with bidirectional current flow. This research would overcome this issue by implementing the FLSO-SVR algorithm for identifying the network fault in the distribution network.

### 3 Materials and methods

In this research, we collect data from an electrical distribution network that includes features for fault location (FL) and fault inception angle. Several provinces' distributed networks are included in the dataset that was retrieved from the Beijing electrical power station. PCA is used to extract features from the dataset. The data amount of the signal is then reduced using WT. An efficient method for identifying faults in distributed networks using overhead lines using the FLSO-SVR. The proposed FLSO-SVR framework integrates WT, PCA, and SVR, each contributing specific advantages. WT enhances time-frequency feature extraction for fault signals; PCA reduces data redundancy and noise, improving training stability. SVR handles nonlinear regression tasks effectively, while FLSO tunes SVR hyperparameters using a fuzzy swarm approach, enhancing convergence and robustness. This combination improves generalization, precision, and

resilience to noise in fault classification, as evidenced in IEEE 118-bus simulations. The raw voltage and current time-series signals generated from the IEEE 118-bus system simulations were directly used as input for feature extraction. The data was segmented based on fault initiation time, and each segment was labeled using a tuple of (fault type, location index) corresponding to the event's simulated parameters. The resulting signal segments were then used to extract wavelet-based features before applying dimensionality reduction via PCA. Figure 1 represents the entire process of the research in a pictorial representation.

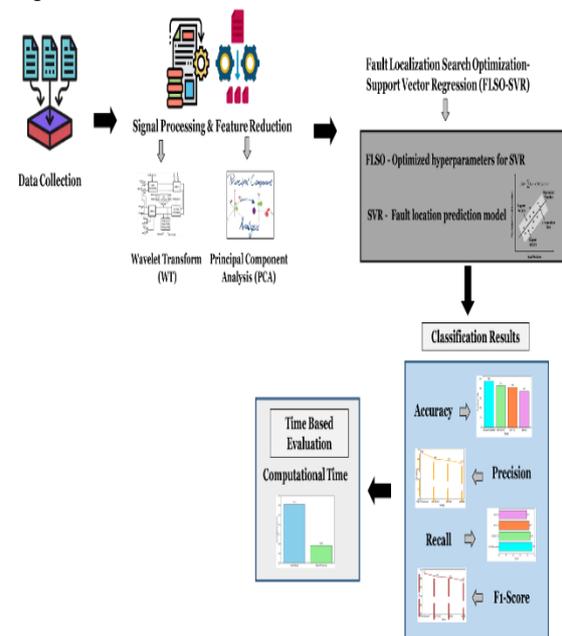


Figure 1: Process flow of the proposed methodology.

#### 3.1 Wavelet transform

Wavelet Transform (WT) is an effective signal processing tool which provides multi-resolution analysis capability where it is applicable to analyze nonstationary signals in time as well as frequency domain. This renders it

especially appropriate in the analysis of transient faults in power systems. In this research, voltage and current signals were decomposed into three levels (D1, D2, D3 and A3) using discrete WT with Daubechies-4 (dB4) as the wavelet and the statistical features were extracted to classify the features are shown in figure 2.

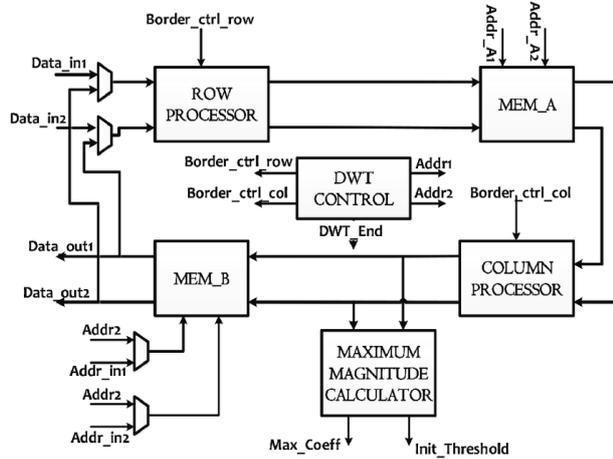


Figure 2: Wavelet transform

In the present instance, the wavelet basis function employed in the fault localization evaluation was dB4. dB4 is a wavelet type function commonly applied in fault localization, as it can extremely capture smooth and sudden variations of signal. Its small support and great localization in the time frequency domain allow an effective localization of brief faults in overhead lines. The properties of dB4 wavelet enable clear decomposition of the fault signals and therefore fault localization and fault location can be conducted accurately. The signal might be decomposed into a set of detail (c) and approximate (b) coefficients which are associated with high and low-frequency bands, respectively. Wavelet Transform is a mathematical tool that analyzes signals at different frequencies to carry out fault localization in overhead lines. Wavelet Transform decomposes fault signals into different frequency components along with fault-related characteristics in the context of overhead lines. In conjunction with a rapid fault localization and location method, it makes possible real-time fault localization in overhead lines through the localization of anomalies in the signal. Such a technique offers high accuracy in quickly pinpointing both the kind and location of faults. It helps in furthering the reliability of fault localization since it captures both low and high-frequency signatures of faults. Its application minimizes diagnostic time, thereby making possible prompt maintenance and short grid downtime.

The Discrete Wavelet Transform (DWT), given a voltage signal  $U(s)$  from the power supply, is described as

$$DWT(U, N, M) = \frac{1}{\sqrt{N}} \int_{-\infty}^{\infty} U(s) \Psi\left(\frac{s-M}{N}\right) ds \tag{1}$$

The wavelet basis function is denoted by  $\Psi$ , and the dilation and translation variables are denoted by  $N$  and  $M$ . Finally, WT in the discrete form as,

$$DWT(U)[n] = \sum_{l=-\infty}^{\infty} U(l) \Psi\left(\frac{n-lN_0^j}{N_0^j}\right) \tag{2}$$

$N$  and  $M$  are substituted with  $N_0^j$  and  $lN_0^j$ , respectively, and  $l$  is a single integer (i.e., sample index of the signal). The scaling function in the initial phase is represented as the sum of the subsequent phase and it could be expressed as follows,

$$\varphi(s) = \sum_{m=-\infty}^{\infty} g(m) \sqrt{2} \varphi(2s - m) \tag{3}$$

The primary voltage signal can be expressed through the previous equation.

$$U(s) = \sum_{l=-\infty}^{\infty} a_j(l) 2^{J/2} \phi(2^J s - l) + \sum_{j=J}^{\infty} \sum_{l=-\infty}^{\infty} d_j(l) 2^{j/2} \varphi(2^j s - l) \tag{4}$$

represents the scaling function's coarse modification parameter. Where,  $J$  is the lowest resolution level.  $a_j(l)$  is the scaling coefficient and  $d_j(l)$  is the wavelet coefficient at level  $J$ .  $\phi$  and  $\varphi$  are the scaling and wavelet functions respectively. The detail and approximate coefficients are expressed as follows,

$$b_o(l) = \sum_{n=-\infty}^{\infty} b_{o+1}(n) g(n - 2l) \tag{5}$$

$$c_o(l) = \sum_{n=-\infty}^{\infty} d_{o+1}(n) g_1(n - 2l) \tag{6}$$

Where  $o$  is the decomposition level and  $g(n - 2l)$ ,  $g_1(n - 2l)$  are low-pass and high-pass wavelet filters respectively.

After applying 3-level wavelet decomposition using the dB4 wavelet, statistical features were extracted from the resulting sub-bands. From each sub-band, the following seven features were computed: mean, standard deviation, energy, entropy, kurtosis, skewness, and root mean square (RMS). This resulted in a 28-dimensional feature vector per signal instance (4 sub-bands  $\times$  7 features). PCA was subsequently applied to reduce the dimensionality of these feature vectors. Based on the cumulative explained variance, six principal components were retained, capturing over 95% of the original variance. These six-dimensional vectors served as the input for training the FLSO-SVR model.

### 3.2 Principal component analysis

Principal Component Analysis (PCA) is a well-liked dimensionality reduction method for data compression and analysis. The method works by finding a small set of symmetric linear combinations that include the beginning variables that have the maximum variance. This sets the limit for the number of linked variables. The modification specifies that the initial principal element is the linear combination of the initial elements with the highest variance; the subsequent principal element is the linear combination of the initial elements with the largest deviation, parallel to the initial principal component; and so on. Many data sets' top few principal components capture the majority of the original data set's differences, enabling the balance to be discarded with minimal variance loss when data dimensions are lowered. PCA streamlines analysis by breaking down high-dimensional data into small, uncorrelated components. When running diagnostics on overhead lines, PCA improves problem localization accuracy by helping to spot patterns in system variables like voltage and current. Blending PCA with rapid fault localization methods enables accurate defect localization and type identification. To find problems with overhead electricity lines, this method reduces the complexity and processing time required. In general, it makes power grid maintenance more efficient and reliable, and it assists with fault management. Below is the flow of the transition:

Every observation in the given collection of observations  $W_1^t, W_2^t, W_m^t$  is represented by a single vector of length  $W_{m \times n}$  in the data, which is expressed by a matrix  $n$ . Each  $w_i \in \mathbb{R}^n$  is a row vector of the matrix.

$$W_{m \times n} = \begin{bmatrix} w_{11} & \dots & w_{1n} \\ w_{21} & \dots & w_{2n} \\ \dots & \dots & \dots \\ w_{m1} & \dots & w_{mn} \end{bmatrix} = \begin{bmatrix} W_1^t \\ W_2^t \\ \dots \\ W_m^t \end{bmatrix} \tag{7}$$

The average observation is described as

$$\mu = \frac{1}{m} \sum_{j=1}^m w_j \tag{8}$$

The difference from the average is defined as

$$\Phi_j = w_j - \mu \tag{9}$$

The sample CM of the data set can be described as

$$D * = \frac{1}{m} \sum_{j=1}^m (w_j - \mu)(w_j - \mu)^T = \frac{1}{m} \sum_{j=1}^m \Phi_j \Phi_j^T = \frac{1}{m} B B^T \tag{10}$$

Where  $B = [\Phi_1, \Phi_2, \dots, \Phi_m]$  which represents the matrix of centered column vectors,  $\mu$  is the sample mean vector.  $\Phi_j = (w_j - \mu)^T$  represents the centered column vector of sample  $j$ .

When doing principal component analysis (PCA) on CM sample  $D$ , the Singular Value Decomposition (SVD) method is typically used to find the eigenvalues and eigenvectors. Think about the fact that the  $CM_{sampleD}$  contains eigenvalues and eigenvectors in pairs, denoted as  $(\lambda_{_1,v_1}), (\lambda_{_2,u_2}), \dots, (\lambda_{_n,v_n})$  together with  $n$ . We select the  $l$  eigenvectors in a way that maximizes their eigenvalues. It is reasonable to assume that the residual  $(n-l)$  dimensions are usually filled with noise because of the presence of strong eigenvalues and that the intrinsic dimensions of the signal-regulating subspace are  $l$ . Subspace  $k$ 's dimensions can be assessed.

$$\frac{\sum_{j=1}^l \lambda_j}{\sum_{j=1}^n \lambda_j} \geq \alpha \tag{11}$$

Where the variable  $\alpha$  stands for the ratio of the variance in the subspaces to the total variation in the starting space. The eigenvectors serve as the columns of the  $n \times l$  matrix  $V$  that we construct. Data representation using principal components allows for expression into the  $l$ -dimensional subspace.

$$z_j = V^S(w_j - \mu) = V^S \Phi_j \tag{12}$$

To reduce the dimensionality of the wavelet-derived feature vectors, PCA was applied. Prior to PCA, each signal instance was represented as a 28-dimensional vector, composed of statistical features extracted from the four wavelet sub-bands. After PCA transformation, six principal components were engaged, conserving over 95% of the collective modification. These six-dimensional feature vectors were utilized as input to the SVR classifier for training and testing.

### 3.3 Fault localization search optimization-support vector regression (FLSO-SVR)

In this research, the FLSO approach is integrated with SVR, which provides FLSO-SVR for effective fault localization in the overhead lines. To increase the accuracy of fault localization, FLSO-SVR combines SVR with the FLSO algorithm. In this framework, SVR serves as the regression engine for modeling fault location, while FLSO is used to optimize SVR's hyperparameters, including the penalty parameter  $C$ , the epsilon-insensitive loss  $\epsilon$ , and kernel-specific parameters (e.g.,  $\gamma$  for RBF kernel). The integration improves performance by enabling better

generalization and faster convergence. Quantum-inspired features in FLSO enhance search diversity and reduce training error, thereby improving overall fault localization precision.

**FLSO (Fault Localization Search Optimization)**

With its foundation on quantum bits and rotation gates, FLSO not only provides a higher search capability but also a faster convergence rate. In contrast to the standard Localization Search Optimization (LSO), which uses a galaxy's velocity as well as location to express its state, the FLSO uses a quantum bit and an angle. These words are defined further down. The FLSO integrates a quantum-inspired encoding scheme, where solution states are modeled using probability-based binary representations. This enhances the diversity and adaptability of the search process, enabling faster convergence and better fault localization. Although quantum principles inspire the design, it operates on classical computing platforms. The influence of this component would be further analyzed through ablation experiments in future work.

- A pair of integers characterize the smallest FLSO component, a quantum bit.

$$r_{ij}(x) = [\alpha_{ij}(x), \beta_{ij}(x)]^T \tag{13}$$

The probability that a quantum bit is in states 0 and 1, respectively, is provided by its modulus  $\alpha_{ij}(x)$  as well as  $\beta_{ij}(x)$ , and both of these conditions must be met.

$$\frac{|\alpha_{ij}(x)|^2 + |\beta_{ij}(x)|^2}{1} = 1 \tag{14}$$

A quantum bit individual, which is the component that comprises a string of quantum bits, is described as

$$r_i(x) = \begin{bmatrix} \alpha_{i1}(x), \dots, \alpha_{ij}(x), \dots, \alpha_{im}(x) \\ \beta_{i1}(x), \dots, \beta_{ij}(x), \dots, \beta_{im}(x) \end{bmatrix} = [r_{i1}(x), \dots, r_{ij}(x), \dots, r_{im}(x)] \tag{15}$$

Where each  $r_{ij}(x) = [\alpha_{ij}(x), \beta_{ij}(x)]^T$ . Every possible outcome can be expressed linearly by a quantum bit due to its probability definition. Thus, entirely  $2^m$  kinds of people can be described using combinations of different quantum bit levels. When it comes to ensuring population diversity, this quantum bit design outperforms other descriptions. In the case where three individuals with two sets of amplitudes and three quantum bits are present, for instance,

$$\begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{2} & \frac{1}{\sqrt{2}} \\ \cdot & \cdot & \cdot \\ \frac{1}{\sqrt{2}} & \frac{\sqrt{3}}{2} & \frac{-1}{\sqrt{2}} \end{bmatrix}$$

$$\tag{16}$$

Subsequently, the individual's state vectors can be shown as

$$\left\{ \frac{1}{4}|000\rangle, \frac{-1}{4}|001\rangle, \frac{\sqrt{3}}{4}|011\rangle, \frac{1}{4}|100\rangle, \frac{-1}{4}|101\rangle, \frac{\sqrt{3}}{4}|110\rangle, \frac{-\sqrt{3}}{4}|111\rangle \right\} \tag{17}$$

The preceding result shows the probability that stands for the different states, which are 0 and 1. An individual quantum bit contains data made up of eight separate states.

- The normalization criteria allow for the representation of the quantum angle as

$$\begin{cases} |r_{ij}(x)\rangle = \cos\theta_{ij}(x)|0\rangle + \sin\theta_{ij}(x)|1\rangle \\ \theta_{ij}(x) = \arctan\left(\frac{\beta_{ij}(x)}{\alpha_{ij}(x)}\right) \end{cases} \tag{18}$$

The quantum angle can be utilized for representing the individual quantum bit.

$$\begin{matrix} \vec{r}_i(x) = [r_{i1}(x), \dots, r_{ij}(x), \dots, r_{im}(x)] \\ \downarrow \qquad \qquad \qquad \downarrow \qquad \qquad \qquad \downarrow \downarrow \\ \theta_i(x) = [\theta_{i1}(x), \dots, \theta_{ij}(x), \dots, \theta_{im}(x)] \end{matrix} \tag{19}$$

Here,  $r_{ij}(x) = [\alpha_{ij}(x), \beta_{ij}(x)]^T$

Quantum bits and angles are changed because of the basic FLSO updating process, and the modified quantum bits have to satisfy the normalization criteria. One might calculate the quantum rotational gate updating equation using,

$$\Delta\vec{\theta}_i(x+1) = \omega \cdot \Delta\vec{\theta}_i(x) + \varphi \cdot q_1 \cdot [\vec{\theta}_{pb} - \vec{\theta}_i(x)] + \eta \cdot q_2 \cdot [\vec{\theta}_{gb} - \vec{\theta}_i(x)] \tag{20}$$

Where  $\omega$  is the inertia weight ( $\omega = 0.72$ ),  $\varphi, \eta$  represents the parameters (i.e.  $\varphi = 1.65, \eta = 1.81$ ), the random numbers  $q_1$  and  $q_2$  are in the range (0, 1),  $\Delta\vec{\theta}_i(\cdot)$  is the change of the angle,  $\vec{\theta}_i(\cdot)$  represents the present angle,  $\vec{\theta}_{pb}$ , and  $\vec{\theta}_{gb}$  represents the personal and global best angles.

The quantum bit as well as the rotation gate model has precocious convergence issues, despite its better population diversity characteristics. Assuming the world's finest individual stays the same throughout generations, two quality barriers such as concentration and affinity emerge once we find the evolutionary solution. Individuals' affinity values reflect how well they solve issues, whereas concentration tells what proportion of the

population is quantum. The optimized hyperparameters determined by FLSO are then used in the SVR model to perform the final regression and fault location. SVR uses kernel functions to transform the input space into a high-dimensional space where linear regression becomes more effective.

### Support Vector Regression (SVR)

To account for these outliers, a non-linear Membership Degree (MF) is employed to map the initial Input Space (IS) which is usually non-linearly linked to the predictor variable onto a higher-dimensional Feature Space (FS). For the SVR, this is an essential principle. As an extra IS, the FS which has been encoded in the kernel's matrix could be used to resolve the regression problem (refer to Figure 3).

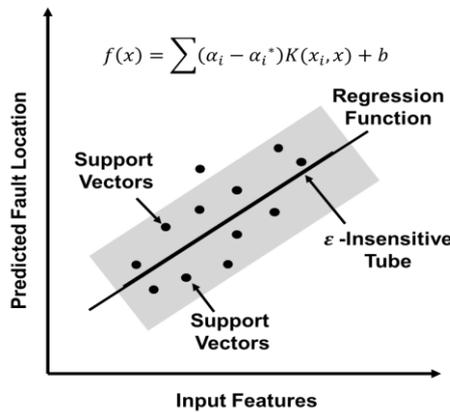


Figure 3: Support Vector Regression

SVR model predicts a continuous output based on a set of learned support vectors and a kernel function. The regression output is given in the figure 3. In this expression,  $f(x)$  represents the predicted value for a new input  $x$ , such as the estimated fault location in a power distribution network. The summation runs over all support vectors, which are specific training samples that have a non-zero influence on the final regression function. The terms  $\alpha_i$  and  $\alpha_i^*$  are Lagrange multipliers obtained during the training process. The kernel function  $K(x_i, x)$  measures the similarity between the new input  $x$  and each support vector  $x_i$ . The term  $b$  denotes the bias or offset, which is also learned during training.

Let  $H(M \times N)$  be the data set and  $z_j \in Q$  be the output vector. Using the provided data set  $T$  as a basis, SVR attempts to identify a multivariate regression function  $e(h)$  that would forecast the intended output characteristic of an unidentified object. A thorough description of the SVR equations is provided. As a result, we would express the SVR equation as follows,

$$e(h) = \sum_{j,i=1}^M (\alpha_j - \alpha_j^*) \langle \phi(h_j), \phi(h_i) \rangle + a \tag{21}$$

Where  $D$  is a regularization constant that establishes a balance between the training error and model effectiveness, and  $\alpha_j$  and  $\alpha_j^*$  represents the LM achieving constraint  $0 \leq \alpha_j, \alpha_j^* \leq D$ . The initial position of the regression function  $e(h)$  is represented by parameter  $a$ , and the MF is represented by component  $\phi$ . It is challenging to identify the non-linear mapping  $\phi(h)$  because it is typically unknown previously. Frequently, a KF is used to calculate the mapping term  $\langle \phi(h_j)\phi(h_i) \rangle$  in Equation (22).

$$L(h_j, h_i) = \langle \phi(h_j), \phi(h_i) \rangle \tag{22}$$

We can easily manage the non-linear interactions in the data according to this kernel modification. Variance-covariance, polynomial, RBF-based kernels, PUK, and RBF are among the KFs that are appropriate to handle non-linear regression issues. We have demonstrated that the PUK KF might act as a robust alternative for the polynomial, RBF-based KFs, and variance-covariance that are frequently used.

By the time the KF is run, Equation (23) is equivalent,

$$e(h) = \sum_{j=1}^m (\alpha_j - \alpha_j^*) L(h_j, h) + a \tag{23}$$

The non-linear IS is typically transformed through the KF, into a high-dimensional FS where the solution to the issue can be described as a straight linear issue. Through employing QP to solve the altered regression issue, the  $\alpha_j$  and  $\alpha_j^*$  values are found. As a result, they are referred to as support vectors since the input objects belonging to the non-zero LM  $\alpha_j$  and  $\alpha_j^*$  contribute to the last regression design.

The FLSO-SVR technique is a novel approach to diagnosing and finding problems with overhead electricity lines. This method seeks to revolutionize fault localization in power transmission networks by combining ideas from quantum computing with fault location. Traditional methods of fault localization often have problems with accuracy and performance, especially in complicated network settings. By incorporating quantum-centric calculations, this method takes advantage of the massive processing capacity along with the scalability of quantum systems, simplifying and speeding up the evaluation of

fault data. The addition of FLSO improves the technique's efficacy. Inspired by ideas from celestial navigation, this optimization method finds errors in massive datasets with pinpoint precision. Through SVR-assisted learning and adaptation, the model progressively improves its diagnostic abilities. By decreasing latency, increasing grid reliability, and accurately diagnosing and localizing issues in overhead power lines, the approach leads to a strong electrical network. The suggested model's pseudocode is represented by Algorithm 1.

**Algorithm 1: FLSO-SVR**  
**Input:** SVR  $P = \{X, Y\}$ , where  $X = \{features\}$ ,  $Y = \{fault\ locations\}$   
**Output:** Fault location prediction

1. Divide the dataset  $P$  into a training set ( $P_{train}$ )
2. Preprocess the dataset (Categorical Encoding,  $n$ )
3. Train an SVR model utilizing FLSO with PUK kernel
  - a. Perform 5
    - fold grid search ( $C \in [0.1-100]$ ,  $\gamma \in [0.001-1]$ ,  $\epsilon \in [0.001-0.1]$ ) to optimize hyperparameters.
    - b. Train the SVR model utilizing the optimized parameters.
4. Assess the trained model on  $P_{test}$ :
  - a. Forecast the fault location for each instance
  - b. Compute performance metrics (accuracy, precision, recall, F1-score)
5. Return the fault location prediction for the test set

In this research, localized distributed power generation is used in the data collection process. By using principal component analysis, the data is preprocessed. The wavelet transform is used to decompose the fault signals into different frequency components along with fault-related characteristics in the context of overhead lines. In conjunction with a rapid fault localization and location method, it makes possible real-time fault localization in overhead lines through the localization of anomalies in the signal. SVR is used for training data, identifying the irregularities in quantum bits, and identifying overhead lines. The optimization process can be done by using FLSO. The proposed model FLSO-SVR is used to identify the overhead lines in the distributed network.

## 4 Results and discussions

The IEEE 118-bus system was used as a testing environment to evaluate the proposed Fault Location Accuracy (FLA) under realistic power grid conditions. The system offered a wide range of fault scenarios, including changes in bus voltage, current flow, line impedance, and fault severity, enabling a systematic valuation of the algorithms.

The simulations were performed in Python 3.10 on a 64-bit Windows 11 platform. The libraries version

used were as follows: model training and validation Scikit-learn 1.3.0, numerical operations NumPy 1.24.2, visualization Matplotlib 3.7.1 and Seaborn 0.12.2. The fault data utilized was synthetically generated and taken out of the IEEE 118-bus system modeling single-phase and three phase faults at different load and generation conditions. Twenty random lines at various voltage levels were selected and faults were introduced on these lines: five fault types were represented, namely, single line-to-ground (SLG), double line-to-ground (DLG), line-to-line (LL), three-phase (LLL), and open conductor faults. All conditions were emulated at varying DER penetration rates and load variations to mirror real-life circumstances of disturbances. A 2000 labeled samples were gathered, stratified and divided into 80 percent training and 20 percent testing to get balanced classes and sound evaluation. In fault localization, FLSO optimizes SVR model through tuning of hyperparameters, whereas, SVR considers a kernel function (e.g., RBF) to carry out regression-based fault location. The suitability of the massive power network automation by the proposed algorithms was evidenced by their ability to run experiments on the IEEE 118-bus system and demonstrated the ability to deal with complex fault scenarios. The performance of the two algorithms was evaluated based on four useful measures:

- Accuracy: The proportion of accurately detected fault locations (FL) in a distributed network
- Precision: The percentage of true positive predictions among all positive predictions, denoting the relevance of fault localization.
- Recall: The proportion of true positives discovered out of all actual positives, reflecting the sensitivity of the algorithms.
- F1-score: The harmonic means of precision and recall, offering a balanced measure of performance.

The suggested FLSO-SVR were evaluated against several previous methods such as Variational mode decomposition Teager Energy Operator (VMD-TEO) [18], Adaptive extended Kalman filter (AEKF) [19], War Strategy Optimization (WSO) [20] to determine their efficacy. FLSO-SVR's comparison metrics are accuracy, precision, recall, and F1-score.

Table 2: Comparison of FLSO-SVR with Existing Techniques

Technique	Accuracy (%)	Precision	Recall	F1-score
FLSO-SVR [Proposed]	95	0.92	0.94	0.91
VMD-TEO [18]	85	0.80	0.88	0.84
AEKF [19]	82	0.77	0.85	0.81
WSO [20]	74	0.72	0.78	0.75

To ensure the robustness of the FLSO-SVR model, variance analysis was conducted by running the experiments ten times with different random splits. The average performance metrics and standard deviations were calculated to assess consistency. The model achieved an average accuracy of  $95.1\% \pm 1.2$ , precision of  $0.91 \pm 0.03$ , recall of  $0.93 \pm 0.02$ , and F1-score of  $0.90 \pm 0.02$ . These results confirm the model’s stability and reliability across different data configurations. Such variance analysis is critical for validating ML models, as single-run metrics can lead to misleading conclusions about performance. The findings in Table 2 clearly show that the proposed FLSO, which uses an SVR, surpasses conventional methods on all metrics tested. The high recall value of 0.94 shows its resilience in accurately determining fault locations, whereas the F1 score of 0.91 emphasizes its balanced efficiency in terms of precision and recall. This enhancement demonstrates the efficacy of combining the FLSO output with sophisticated fault severity evaluations and isolation tactics. Despite their popularity, rule-based and heuristic approaches lag because of their restricted adaptability to dynamic fault scenarios. These comparisons emphasize the better results of the proposed intelligent algorithms in fault localization and isolation, establishing a new benchmark for power grid automation systems. Figure 4 represents the graphical representation of the accuracy.

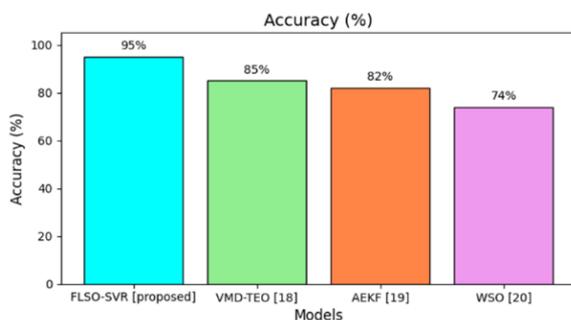


Figure 4: Accuracy Comparison of FLSO-SVR with existing techniques

The graph explains that the proposed FLSO-SVR has the highest accuracy (95%) because the SVM classifier can model complex relationships between input features and fault locations. Unlike conventional methods, SVM efficiently differentiates classes with a well-defined margin, even in high-dimensional spaces, resulting in better fault localization accuracy. Figure 5 depicts the graphical illustration of the precision over methods.

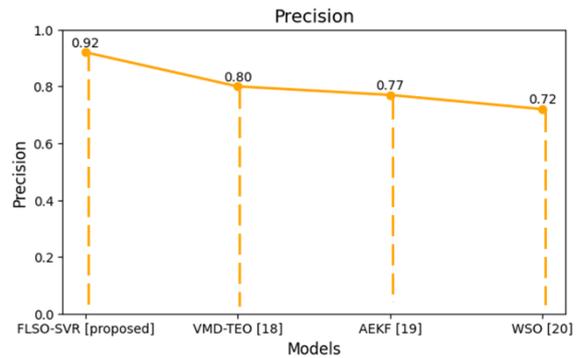


Figure 5: Precision comparison of FLSO-SVR with existing techniques

Figure 5 compares the precision of four fault localization models. The proposed FLSO-SVR method achieves the highest precision (0.92), outperforming traditional methods. This indicates that FLSO-SVR has superior capability in correctly identifying fault instances. Figure 6 explicitly mentions the pictorial representation of the recall over various methods.

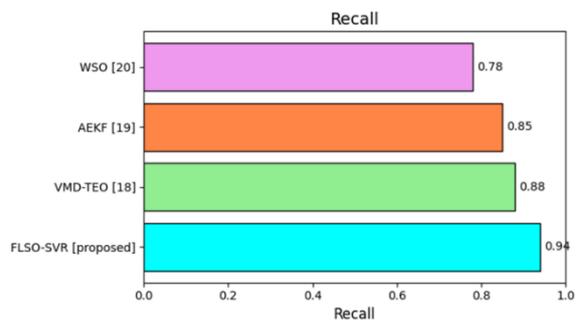


Figure 6: Recall Comparison of FLSO-SVR with existing techniques

Figure 6 shows the FLSO has the highest recall (0.94), suggesting that it is efficient in detecting almost all actual fault locations. SVRs resilience against data imbalance and its ability to manage nonlinear fault patterns contribute substantially to this efficiency. Figure 7 represents the F1-Score Comparison of proposed approach with Existing Techniques.

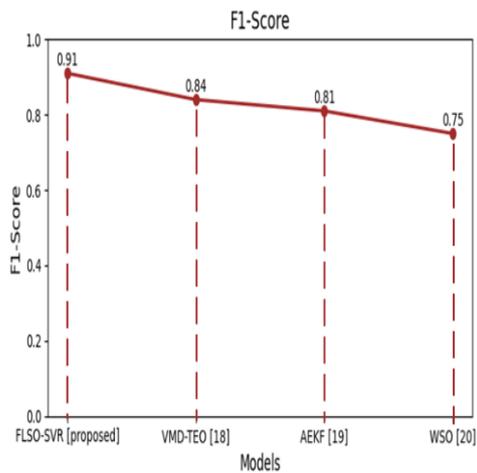


Figure 7: F1-Score Comparison of FLSO-SVR with existing techniques

Figure 7 demonstrates that the FLSO-SVR model has an F1-score of 0.91, which means that the model performs similarly in precision and recall. It proves that it is consistent in keeping both accurate and large fault localization.

In comparison with rule-based or threshold methods, the FLSO-SVR adapts itself dynamically to various fault situations and thus, is more accurate. The suggested algorithms were more accurate, precise, recall, and F1 score than the traditional approaches due to the smart utilisation of the SVR classifiers and robust fault handling strategies. The ability of FLSO-SVR to fit complicated fault patterns and flexibility in isolation actions offer better reliability and performance in automation of power grids compared to the past methods, which makes superior substitutes.

**Computational time**

The computational complexity of models can be a determining factor in their usefulness particularly in real-time or resource limited systems. Table 3 presents a comparison of computational time for the existing PSO-SVM model and the proposed FLSO-SVR technique. The proposed approach is designed to update processing and reduce computational overhead during implementation. Enhanced efficiency not only accelerates prediction but also improves scalability across larger datasets and complex problem domains.

Table 3: Comparison of computational time over method.

Metrics	Computational Time
PSO-SVM [21]	5.341s
FLSO-SVR [proposed]	5.298 s

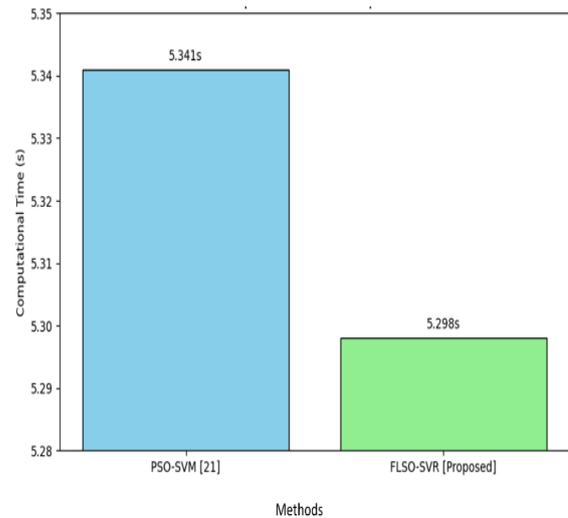


Figure 8: Graphical representation of the computational time performance.

As observed, the proposed FLSO-SVR method achieves a marginally lower computational time (5.298 seconds) compared to PSO-SVM (5.341 seconds), indicating an improvement in efficiency while maintaining predictive performance. Figure 8 illustrates the visualization of the time evaluation performance.

**4.2 Ablation research**

To understand the individual and combined impact of each component in the proposed fault localization framework, the ablation research was conducted. The core modules evaluated included the integration of PCA, WT, and FLSO-SVR. Each combination was tested for classification accuracy, recall, precision and f1-score. The results demonstrated in table 4 enhance the fault localization performance with the integration of all three modules.

Table 4: Performance comparison of ablation results over metrics.

Model Configuration	Accuracy (%)	Precision	Recall	F1-Score
SVR only (baseline)	86.3	0.84	0.80	0.82
WT + SVR	89.7	0.87	0.84	0.85
PCA + SVR	90.4	0.88	0.85	0.86
PCA + WT + SVR	92.2	0.89	0.87	0.88
<b>PCA + WT + FLSO-SVR (Proposed Method)</b>	<b>95.0</b>	<b>0.92</b>	<b>0.91</b>	<b>0.94</b>

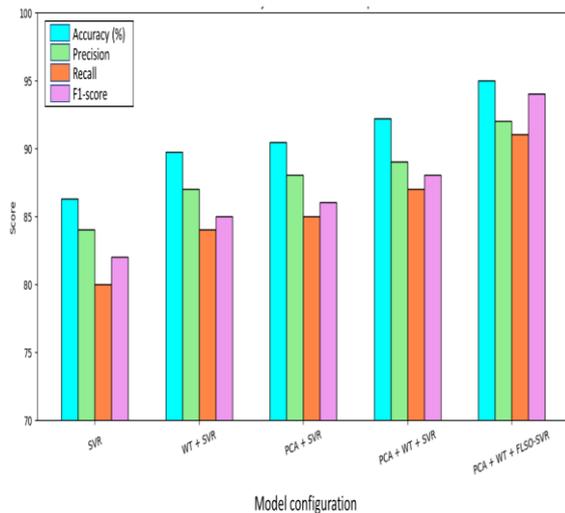


Figure 9: Graphical illustration of ablation results

Figure 9 validates the contribution of each module to the overall performance. The incorporation of FLSO enables optimal parameter tuning in SVR, resulting in significantly improved localization accuracy. Such modular analysis ensures the transparency and reproducibility of the proposed model and highlights the importance of signal decomposition and dimensionality reduction in high-voltage fault localization.

### 4.3 Discussion

Fault location in modern power distribution networks has become a significant research focus due to the increasing integration of DERs. Several existing approaches like, Researches such as [10] fail to consider the changing complexity of high-penetration renewable DGs, which may make it inapplicable to the contemporary smart grids. Co-optimization outage recovery framework presupposes the presence of timely available and deployed mobile power sources which might be infeasible in the case of large-scale disturbances. In addition, there is an issue of the computational load in real time [12]. The approaches of [18] and [19] provide high accuracy fault localization based on traveling wave technique but under the assumption of dense sensors and ideal signal scenario which hinders application in practice. Such an algorithm as the War Strategy Optimization Algorithm [20] is innovative but not broadly comparatively validated and not tested in noisy realistic conditions. To address these types of limitations, the present research introduces a novel hybrid model based on FLSO-SVR. This approach combines the generalization ability of machine learning with the flexibility of fuzzy logic and the adaptability of metaheuristic optimization. Unlike conventional methods, the proposed model effectively handles non-linear relationships in the network and performs reliably even under noisy and uncertain operational conditions.

## 5 Conclusion

The proposed approach outperforms traditional methods by incorporating SVR classifiers and sophisticated fault severity assessments, thereby improving grid dependability and stability. This research proposes a machine learning-based method for fault localization in distributed networks which has been validated using a custom dataset and the IEEE 118-bus system. While the current framework does not explicitly integrate rule-based decision-making, such mechanisms are envisioned as part of future hybrid approaches. Research's limitations include the lack of potential dataset constraints, and challenges in scaling to larger and more complex grid environments. Future research can focus on extending the FLSO-SVR model for real-time operation in decentralized smart grid environments. This can involve adapting the model for streaming data, implementing real-time optimization mechanisms, and validating performance using live sensor data from distributed energy resources. Additionally, incorporating IoT-based fault monitoring and adaptive self-learning mechanisms can further strengthen the model's effectiveness, making it a valuable step toward intelligent and automated smart grid infrastructure.

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