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Original Article

A Novel Quantum-Behaved Future Search Algorithm for the Detection and Location of Faults in Underground Power Cables Using ANN

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Abstract
This article introduces a novel Quantum-inspired Future Search Algorithm (QFSA), an innovative amalgamation of the classical Future Search Algorithm (FSA) and principles of quantum mechanics. The QFSA was formulated to enhance both exploration and exploitation capabilities, aiming to pinpoint the optimal solution more effectively. A rigorous evaluation was conducted using seven distinct benchmark functions, and the results were juxtaposed with five renowned algorithms from existing literature. Quantitatively, the QFSA outperformed its counterparts in a majority of the tested scenarios, indicating its superior efficiency and reliability. In the subsequent phase, the utility of QFSA was explored in the realm of fault detection in underground power cables. An Artificial Neural Network (ANN) was devised to identify and categorize faults in these cables. By integrating QFSA with ANN, a hybrid model, QFSA-ANN, was developed to optimize the network's structure. The dataset, curated from MATLAB simulations, comprised diverse fault types at varying distances. The ANN structure had two primary units: one for fault location and another for detection. These units were fed with nine input parameters, including phase- currents and voltages, current and voltage values from zero sequences, and voltage angles from negative sequences. The optimal architecture of the ANN was determined by varying the number of neurons in the first and second hidden layers and fine-tuning the learning rate. To assert the efficacy of the QFSA-ANN model, it was tested under multiple fault conditions. A comparative analysis with established methods in the literature further accentuated its robustness in terms of fault detection and location accuracy. this research not only augments the field of search algorithms with QFSA but also showcases its practical application in enhancing fault detection in power distribution systems. Quantitative metrics, detailed in the main article, solidify the claim of QFSA-ANN's superiority over conventional methods.

Keywords
novel quantum-inspired future search algorithm, QFSA, artificial neural networks, ANN, underground power cables, fault detection, fault location, optimization, quantum mechanics, benchmark functions, algorithm comparison, MATLAB simulations.

I. INTRODUCTION

Underground power cables play a crucial role in modern power distribution systems, ensuring a reliable and efficient electricity supply [1]. However, faults in these cables can cause significant disruptions and financial losses [2]. Accurate and efficient fault detection, and Location are essential for minimizing the impact of these faults on the power distribution network [3]. Artificial intelligence (AI) represents an effective solution to introduce successful fault analysis, with various AI techniques mentioned in the literature [3], such as artificial neural networks (ANN) [4], random forests [5], fuzzy logic [6–8], and adaptive-neuro fuzzy [7]. The ANN is one of the earliest and most influential AI techniques in fault analysis. ANNs draw inspiration from biological neural systems, comprising interconnected processing nodes that mimic the function of neurons. These networks are adept at recognizing intricate patterns, making them invaluable when fault symptoms are subtle or embedded within a larger dataset. Many scholars have detailed their successful applications, emphasizing their adaptability and precision in diagnosing a wide array of faults. On the other hand, Random Forests are an ensemble learning technique primarily used for classification and regression tasks. They operate by constructing many decision trees during training and outputting the mode of the classes for classification or mean prediction for regression. Their strength lies in their ability to handle large amounts of data with higher dimensions, providing insights into features of paramount importance and reducing the risks of overfitting. Fuzzy Logic systems introduce a different perspective by dealing with uncertainties inherent in many real-world applications. Unlike traditional binary logic systems, fuzzy logic operates on the principle that truth values can exist between absolute truths and absolute falsehoods, thus offering a nuanced approach to fault detection. By embracing the vagueness of real-world systems, fuzzy logic provides a complex system of s with an inherent degree of uncertainty. Lastly, the Adaptive-Neuro Fuzzy systems combine the strengths of neural networks and fuzzy logic. These hybrid systems encapsulate the learning capability of neural networks and the reasoning capability of fuzzy logic. Their synergy allows for an adaptable system that can learn from data while incorporating human-like reasoning, making them particularly potent in scenarios where both pattern recognition and nuanced judgment are required. In this context, ANN-based fault detection and Location could improve power system distribution lines with overhead or underground power cables by introducing optimal fault detection or location [4, 9, 10]. Optimization; tracing algorithms can improve the ANN's prediction performance by searching for ideal ANN parameters [11, 12]. Numerous optimization algorithms have been introduced, each with unique characteristics inspired by diverse natural phenomena. Genetic algorithms (GA) are based on Darwinian Theory [13], particle swarm optimization (PSO) mimics the social behavior of birds or fish during searching for food [14], and differential evolution (DE) is based on possibly nonlinear and non-differentiable continuous space functions [15]. The electromagnetism-like mechanism (EM) is inspired by the attraction-repulsion mechanism [16], while cat swarm optimization (CSO) is created by observing cat activities; tracking and tracing seeking mode are the two sub-models that are included in this model. Both of these modes are used to replicate cat behavior [17]. On the other hand, the problem of the solution getting stuck in local minima is a significant limitation of these algorithms [18]. To alleviate this issue, numerous different algorithms have been devised, including firefly optimization algorithm (FA) [19], charged system search (CSS) [19], dolphin echolocation algorithm (DEA) [20], lightning search algorithm (LSA) [21, 22], and future search algorithm (FSA) [23]. The FFA is inspired by the lifestyle of the firefly insect when attracting mating partners and searching for potential prey. The CSS utilizes two laws of physics and mechanics, the Newtonian rules of mechanics and the fundamental law of electrostatics, the Coulomb law. The DEA is based on echolocation, the biological sonar used by dolphins. The LSA is inspired by the movement of lightning toward the ground. The FSA mimics a person's life when searching for the best life and trying to change the lifestyle by imitating successful individuals. However, not all optimization algorithms provide satisfactory solutions, leading to the need for introducing new algorithms and improving existing ones. However, s this paper proposes a quantum-inspired use search algorithm (QFSA) combined with an ANN for detecting and locating faults in underground power cables. The QFSA is inspired by the classical FSA and quantum mechanics theories [18], improving the exploration and exploitation capabilities of the FSA to find the optimum solution. The ANN is used to discover and locate faults in the power cables, allowing for rapid and accurate identification. This approach aims to address the limitations of traditional methods and provide a more advanced technique for fault analysis in power distribution systems. The research focuses on developing an accurate and efficient fault locator for power using Artificial Neural Networks for power distribution and transmission systems to analyze 3-phase voltages and currents, zero sequence components, and voltage angles during negative sequence during different fault conditions to quickly and accurately identify and isolate faults. ANN-based fault locators are more effective than other methods like expert fuzzy systems and can be used by individuals without extensive power system experience. This user-friendly approach aims to improve the reliability and efficiency of power systems, ensuring a continuous electricity supply. However, many researchers are developed quantum-like algorithms. Malossini, Blanzieri, and Calarco 2008 have developed a quantum version of GA called QGA, which utilizes quantum parallelism to evaluate multiple solutions at once and quantum mutation to explore new solutions efficiently [24]. Abbas and Aftan 2014 have developed a quantum version of ABC called QABC, which leverages quantum principles to search the solution space more efficiently and effectively [25]. Li et al. 2014 have developed a quantum version of BFO called QBFO, which leverages quantum principles to search the solution space more efficiently and effectively [26]. Soleimanpour-

Moghadam, Nezamabadi-Pour, and Farsangi 2014 to enhance its performance and prevent premature convergence to local optima. The proposed algorithm combines classical GSA with the principles of quantum mechanics, providing a powerful strategy to diversify the population and improve the algorithm's performance. QIGSA has shown promising results in various optimization problems, including feature selection, image processing, and classification [27]. Abd Ali, Hannan, and Mohamed 2015 developed the (QLSA) by utilizing theories from quantum mechanics to produce it. The QLSA makes it easier for each step leader to find the optimal position for a projectile by improving the searcher searching dictionary learning method through trial and error is unnecessary, thanks to the QLSA, which produces adaptive input and output membership functions instead [18]. in the field fault detecting and locating faults, this brief literature review can focus light on some previous work Garima Tiwari 2019 [28]: Tiwari proposed using a hybrid of ANN, fuzzy systems, and DWT for improved fault detection in underground cables. The method utilized DWT for feature extraction and an ANFIS training system. Klomjit and Ngaopitakkul 2020 [29]: Authors evaluated PNN, BPNN, and SVM for fault classification in hybrid transmission lines. SVM was found to be the most accurate. Naidu, Ali, et al. 2020 [30]: paper introduced a PSO-optimized ANN for fault impedance estimation in distribution networks, using DWT and cross-product analysis for feature extraction. Ahmad and Hanafi 2021 [31]: Authors developed a fault detection system for underground cables using wavelet analysis and ANN, which was tested on an IEEE bus system. Samet, Khaleghian, et al. 2021 [32]: paper proposed a new algorithm for incipient fault detection in underground cables, emphasizing the unique characteristics of electric arcs. Swaminathan, Mishra, et al. 2021 [33]: Authors advocated a deep learning approach, specifically a CNN-LSTM model, for fault classification in underground cables. Tiwari and Saini 2022 [34]: paper used an ANN model, trained on MATLAB Simulink data, to detect faults in underground cables. Aqamohammadi et al. 2023 [35]: Authors introduced a Fault Detection Method for microgrids, showcasing high computing efficiency and accuracy. Wan et al. 2023 [36]: paper proposed a deep learning method using deep belief networks for cable fault identification in smart grid systems. Alabbawi et al. 2023 [37]: Authors designed an intelligent protection relay using ANN for securing power infrastructure, emphasizing the effectiveness of the Levenberg-Marquardt training technique.

II. PROPOSED QFSA

A. Classical FSA

The Future Search Algorithm (FSA) is a computational model simulating human behavior in the quest for improved life conditions. It uses both local and global search methods, representing individual efforts and learning from successful individuals, respectively. The FSA's key features include no requirement for parameter tuning, low computational complexity, rapid convergence, and resistance to local optima. Benchmark tests and comparative studies indicate that the FSA outperforms other established methods in finding optimal solutions efficiently and quickly [23].

B. Quantum-Behaved Future Search Algorithm

QFSA design for optimal ANN fault detection and location of faults Recent work in the field of research has resulted in the development of novel optimization strategies, which will play an important part in future research. FSA is one such strategy, and it was suggested by Elsisi 2019 as an alternative, as was discussed in [23]. The FSA is a heuristic optimization algorithm that mimics human behavior in searching for the best life around the world. The algorithm's solutions space is represented by individuals, where each individual represents a potential solution to the optimization problem. The FSA algorithm begins with a randomly generated population representing possible solutions. These individuals move around the search space in each iteration, where they are attracted to the best individuals in their local neighborhoods. The best individual in each neighborhood represents the optimal local solution. In addition to local search, the FSA algorithm also incorporates a global search strategy. The algorithm maintains a record of the best individuals encountered, representing the global optimal solutions. The algorithm then uses this global information to guide the search toward the better areas of the search space. The FSA algorithm updates the local solutions in each iteration and selects the best overall iterations, representing the global solution. This allows the algorithm to converge the optimal solution faster than other heuristic optimization algorithms, such as GA and particle swarm optimization. This study is performed using an enhanced QFSA based on quantum mechanics. However, QFSA is an extension of the FSA, in which a new position is searched to obtain the best position for the step population. QFSA is developed to increase the searching capacity by utilizing the mean of the best positions of the global step population. denotes the best step population that can obtain the minimal value of. QFSA determines the attraction and convergence of each step population with a global minimal and searches for the best position of the step population Where Mbest t_j^t is the mean best position for the step leaders and is calculated as follows:

$$\begin{aligned} Mbest\ t_j^t &= \frac{1}{N}\sum_{i=1}^{N} P_{ij}^t \\ &= \left(\frac{1}{N}\sum_{i=1}^{N} P_{i1}^t, \frac{1}{N}\sum_{i=1}^{N} P_{i2}^t, \frac{1}{N}\sum_{i=1}^{N} P_{i3}^t, \ldots\ldots, \frac{1}{N}\sum_{i=1}^{N} P_{ij}^t\right) \end{aligned} \tag{1}$$

To optimize the convergence speed, the tuned contraction expansion coefficient (β) is computed as follows

$$\beta = \beta_0 + (T - t) \cdot \frac{\beta_1 - \beta_0}{T} \tag{2}$$

where β_0 is the initial value of β, β_1 is the final value of β, t is the present iteration, and T is the maximum number of iterations—the detailed settings of β_0 and β_1 for generating an acceptable algorithmic performance. The position of the step population is updated based on the best position of each Pt of the step population.

The Monte Carlo method is a stochastic optimization technique used to improve the efficiency of search algorithms. It involves generating random samples from a problem space and evaluating each solution using an objective function. This approach allows for a probabilistic exploration of the search space, reducing the risk of getting stuck in local optima. Adaptive sampling and importance sampling strategies can be used to enhance the convergence and efficiency of the search algorithm. Adaptive sampling adjusts the sampling distribution based on previously obtained results, while importance sampling focuses on areas of the search space with higher probabilities of yielding optimal solutions.

- Using the Monte Carlo method, we can obtain the j^{th} component of position Pi at iteration $(t+1)$ as follows:

$$p_{ij}^{t+1} = p_{ij}^{t} \pm \beta \mid MeanBest_j^t - P_{ij}^t \mid \ln(1/u_{ij}^{t+1}) \tag{3}$$

Where p_{ij}^t is the best position of the step leader and u_{ij}^{t+1} is the uniformly distributed number between (0,1)

C. Work of QFSA

Now combine the two methods to get the following:

1. Population initialization:

$$S(i,:)_L = (LS(i,:) - S(i,:)) * rand \tag{4}$$

2. Updating beta value:

$$\beta = \beta_0 + \frac{(\mathrm{T} - t)(\beta_1 - \beta_0)}{\mathrm{T}} \tag{5}$$

3. Computing average D-point (C):

$$C_{1,nn} = \frac{\sum_{i=1}^{n} S_{i,nn}}{n} \tag{6}$$

4. Updating the position (S) using the best global solution, best local solution, and beta value:

$$S_i = S_i + (-S_i + \mathrm{best}) \cdot \mathrm{rand} + (-S_i + Lbe_i) \cdot \mathrm{rand} + \beta \cdot |C_1 - S_i| \cdot \left(\log \frac{1}{\mathrm{rand}}\right) \tag{7}$$

5. Updating the solution positions (S_i) based on the best global solution and the best local solution:

$$Si_i = \frac{(\mathrm{rand} \cdot Lbe_i + \mathrm{rand} \cdot \mathrm{best})}{(10 \cdot \mathrm{rand})} \tag{8}$$

where S: Solution,
d: Dimensions of problem.
Ub: Upper limit bounds,
i: Current solution of population size,
Lb: Lower limit bounds,
rand: Uniformly distributed pseudo-random numbers.

Here are the steps for the QFSA represented as a table in Table I:

TABLE I.
CODE STEPS METHODOLOGY, FOR THE QFSA

Step	Description
1	Start
2	Initialize Parameters
2.1	Population size (n)
2.2	Maximum number of iterations
2.3	Number of runtimes (r_time)
2.4	Number of dimensions (d)
2.5	Lower bounds (Lb)
2.6	Upper bounds (Ub)
3	For each runtime (r):
3.1	Initialize the population/solutions (S)
3.2	Evaluate the fitness of each solution (Fitness)
3.3	Find the initial best global solution and best local solutions.
4	Main global loop: For each iteration (t)
4.1	Update the beta value.
4.2	Compute the average D-point (C)
4.3	Main local loop: For each solution (i)
4.3.1	Update the position (S)
4.3.2	Evaluate the fitness of the new solution (Fnew)
4.3.3	Update the local best solution.
4.3.4	Update the current global best solution if necessary.
4.4	Initial update loop: For each solution, (i)
4.4.1	Update the solution positions (Si)
4.4.2	Evaluate the fitness of the new solutions (Fitness)
4.4.3	Update the local best solution if necessary.
4.5	Update the global best solution and fitness value if necessary.
4.6	Store the best fitness value for each iteration (fgbest)
5	Display the best solution and minimum fitness value for each runtime.

TABLE I.
CODE STEPS METHODOLOGY, FOR THE QFSA (*Continued*)

6	Store the best solution and minimum fitness value for further analysis.
7	Identify the overall best solution and minimum fitness value across all runtimes.
8	Display the overall best solution and minimum fitness value.
9	Plot the semilogarithmic plot of the best fitness value for each iteration in the best runtime.
10	End

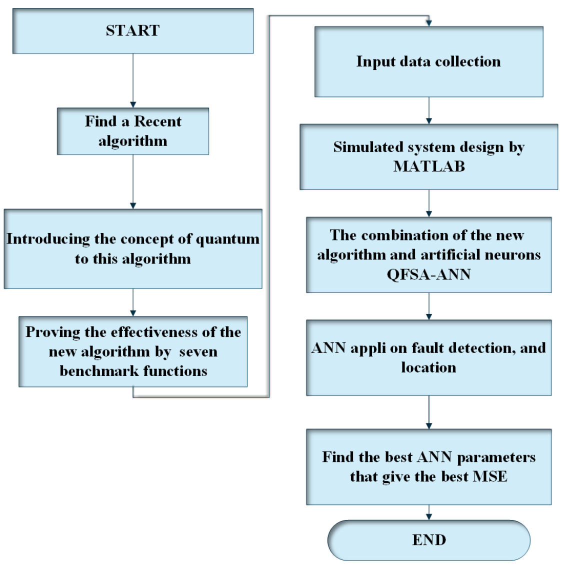
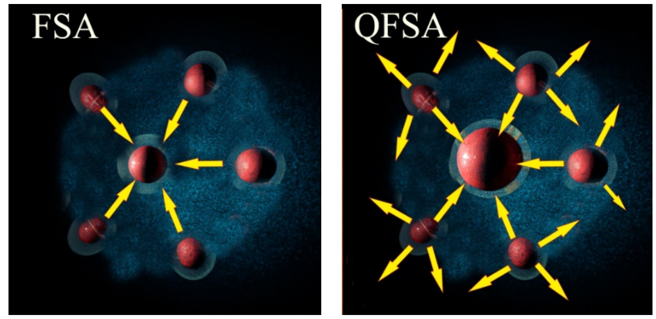


Fig. 1. The general research path flowchart

The overall trajectory of this research follows a structured and comprehensive path, encompassing several key stages aimed at reaching the study's objectives. as shown in as a flowchart step.

Fig. 2 illustrates the behavior of individuals in the search process using the (FSA). The algorithm starts with a population of randomly generated individuals, and each individual represents a potential solution to the optimization problem. The ball in the center represents the global position, and the other balls denote the other individuals. The arrows around the other ball's circles indicate the individuals' possible movement directions. In the original FSA algorithm, each moves directly toward the best individual in their local neighborhood and does not search or wait to obtain a new global best position.



(a) (FSA) behavior (b) (QFSA) behavior

Fig. 2. The behavior of individuals in the search process

This behavior is shown in Fig. 2a. However, in the (QFSA), individuals around the global best position are allowed to move in any direction to obtain the best new position, as illustrated in Fig. 2b. This approach enables a more thorough search space exploration and potentially better optimization results. Therefore, using the QFSA algorithm with Quantum-Inspired techniques, we can enhance the search process by enabling individuals to explore the search space more thoroughly and potentially find better solutions to the optimization problem.

D. Verification of the Proposed QFSA Method

To evaluate the performance of the proposed QFSA, we used seven benchmark functions with varying complexities. The QFSA was compared with five well-known algorithms to assess its reliability and efficiency. The results showed that the proposed QFSA outperformed the other algorithms in terms of solution quality and convergence speed, demonstrating its potential for solving complex optimization problems. And all details in Table II

$$F_1(x) = \sum_{i=1}^{d}\left(\sum_{j=1}^{i} x_j\right)^2 \tag{9}$$

$$F_2(x) = \sum_{i=1}^{d-1}\left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\right] \tag{10}$$

$$F_3(x) = \sum_{i=1}^{d} i\, x_i^4 + random(0,1) \tag{11}$$

$$F_4(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i\, x_2)}{b_i^2 + b_i\, x_3 + x_4}\right]^2 \tag{12}$$

TABLE II.
BENCHMARK FUNCTION DETAILS

Function	d	s	F_{min}	Type
F1	100	[-100, 100]	0	Unimodal
F2	30	[-30,30]	0	Unimodal
F3	30	[-1.28,1.28]	0	Unimodal
F4	4	[- 5, 5]	0.0003075	Multimodal
F5	2	[-5, 10] × [0, 15]	0.398	Multimodal
F6	3	[0, 1]	- 3.86	Multimodal
F7	6	[0, 1]	- 3.32	Multimodal

$$F_5(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10 \tag{13}$$

$$F_6(x) = -\sum_{i=1}^{4} c_i \ \exp\left(-\sum_{j=1}^{3} a_{ij}\left(x_j - p_{ij}\right)^2\right) \tag{14}$$

$$F_7(x) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{6} a_{ij}\left(x_j - p_{ij}\right)^2\right) \tag{15}$$

Where (s) refer to the ranges of their search space, (d) refers to the dimension of each function, and (F_{min}) refers to the minimum value of each function.

III. ARTIFICIAL NEURAL NETWORKS (ANN) FOR FAULT DETECTION AND LOCATION

A. Fundamentals of ANN

ANN are computer models that take their inspiration from the biological neural networks found in the human brain. They are made up of a network of interconnected artificial neurons or nodes. which process and transmit information. ANNs have been widely used for various applications, including pattern recognition, data classification, and prediction, due to their ability to learn from data and adapt to changes in the environment [38, 39].

B. Structure and Components

This study employed a feedforward ANN with two hidden layers for fault detection and Location. The ANN has nine input nodes, representing the currents and voltages taken from each phase and the current and voltages in zero sequences. The output layer consists of one node corresponding to each block task's fault detection or location.

C. Problem Formulation

This research aims to build an ideal network of artificial neural cells (ANN) capable of fault detection and location in subterranean power cables that is accurate and effective. The optimization problem involves choosing the number of neurons placed in the first and second hidden layers and figuring out the ANN's learning rate.

IV. IMPLEMENTATION OF THE QFSA-ANN

A. Fault Location Methodology

This part of the study aimed to evaluate the effectiveness of using ANN in MATLAB for fault detection and location in a buried underground power line with a voltage of 11 kilovolts. To accomplish this task, we used the following methodology were used: Data collection: to collect data from the power distribution line, a long 21 km line with three bus bars and two sources. This data included measurements of various electrical parameters, such as the voltage and current of 3 phases, the voltage and current of zero sequences, and the angle of the negative sequence. They started with Data preprocessing. Before using the data to train the ANN model, preprocessed it by normalizing the values to a standard range and dividing it into training, validation, and testing sets in a ratio of 70:15:15, respectively, the total number of data used to train ANN in this part was 4650 cases. This step ensures the model can generalize well to new data. Model design and configuration: MATLAB Simulink was used to design and configure the ANN model. This involved selecting the number and size of hidden layers and neurons and the optimization algorithm for training. In this case, the Levenberg-Marquardt algorithm is used for training. After that, start Model training: use the training data to train the ANN model using the selected optimization algorithm. This involved iteratively adjusting the weights and biases of the model to minimize the error between the predicted and actual values. Mean Squared Error (MSE) was used as the performance indicator to evaluate the training procedure.

B. ANN Structure Optimization

The proposed QFSA optimized the ANN structure, searching for the optimal number of neurons in the hidden layers and the appropriate learning rate. The QFSA-ANN was then trained using the collected data to obtain the best-performing model.

C. Simulink and Modeling System

The model comprises a source feeder (11 KV, 30 MVA, 50 Hz, 3-phase) and three buses (BUS-BAR), where voltage and current measures are obtained with other input parameters, and a fault block that is applied to the distribution line. It uses a step-down transformer rated at 11 KV/ 0.4 KV and a connected load. After the model has been used to generate the fault data and account for the simulation of the ANN that has been trained, the selection to employ the distribution line Simulink model is made based on the model's specification. This study used the scheme shown in Fig. 3 and Fig. 4 .

D. Mean Squared Error

MSE was used as the performance indicator to evaluate the training procedure. The equation for MSE can be written as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{16}$$

The equation is the formula for MSE used in statistics and machine learning. It is a standard metric used to evaluate the performance of regression models. Here's what each component in the equation represents:

- n: the total number of data points in the dataset.
- yi: is the true (observed) value of the i-th data point.
- $\hat{y}i$: is the predicted (estimated) value of the i-th data point, as output by the regression model.
- $(yi - \hat{y}i)$: is the difference (or error) between the true and predicted values of the i-th data point.

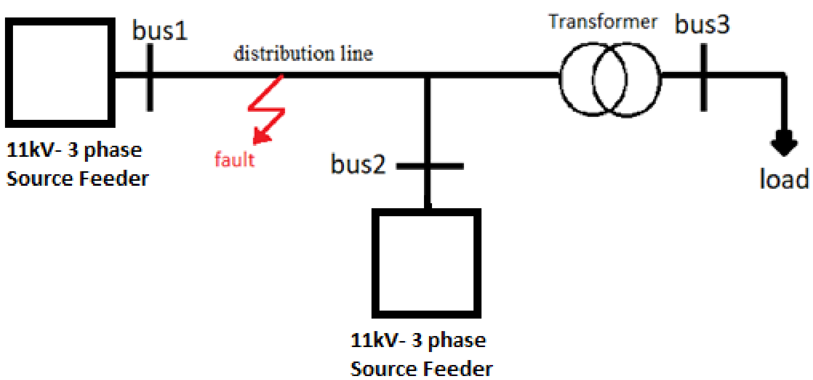


Fig. 3. Simplified schematic of the utilized power system design

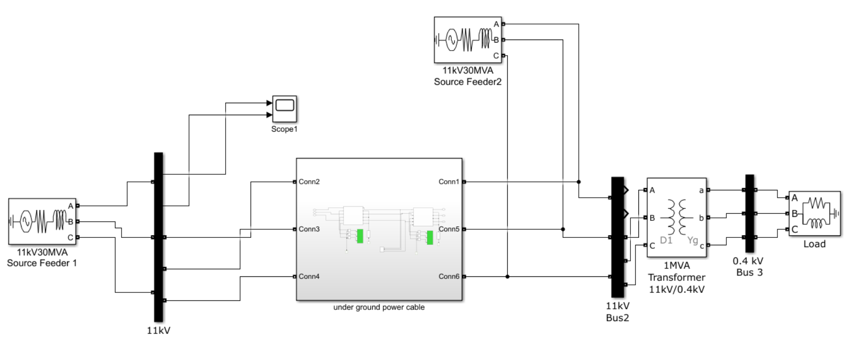


Fig. 4. MATLAB- simple Simulink model of a 3phase system with underground power cable line

- $(yi - \hat{y}i)^2$: is the squared error (or loss) for the i-th data point.
- $\sum$: denotes the summation operator, meaning we add the squared errors for all n data points.
- Finally, the sum of squared errors is divided by (n) to obtain the MSE

The lower the value of MSE, the better the performance of the regression model, as it indicates that the model's predictions are closer to the actual values.

V. RESULTS AND DISCUSSION

During the training process of the ANN for fault detection in cables, the output was consistently one of two results: either a fault was detected, or no faults were found, as shown in Table III. The Levenberg-Marquardt algorithm was used to train the ANN using 720 samples to automate the training process and 4650 models for fault location.

A. Quantum-Behaved Future Search Algorithm Results

In the context of benchmark functions and optimization algorithms, the fitness with iterations Fig's is a line graph showing how the optimization algorithm's fitness changes over time as the algorithm runs for a certain number of iterations. The fitness value, which indicates the level of quality of the solution discovered by the algorithm, is often defined by the benchmark function being applied. The number of iterations is represented along the x-axis of the graph, while the fitness value is shown along the y-axis. As the algorithm runs, the fitness value is updated at each iteration, and the chart shows how the fitness value changes over time. The fitness with iterations Figure is a helpful tool for comparing the performance of different algorithms on a given benchmark function. The fitness with iterations Figures typically includes a line for each compared algorithm. The line for each algorithm will show how the fitness value changes over time as the algorithm runs. By comparing the lines, it is possible to see which algorithm performs better in finding the optimal solution for the benchmark function.

Fig. 5 shows a comparative analysis between two algorithms, FSA, represented by the red line, and QFS, A, depicted by the blue line, in the benchmark function F1.

TABLE III.
DIGITAL OUTPUT OF THE FAULT DETECTION

No	Type	Output
1	Faults	1
2	No fault	0

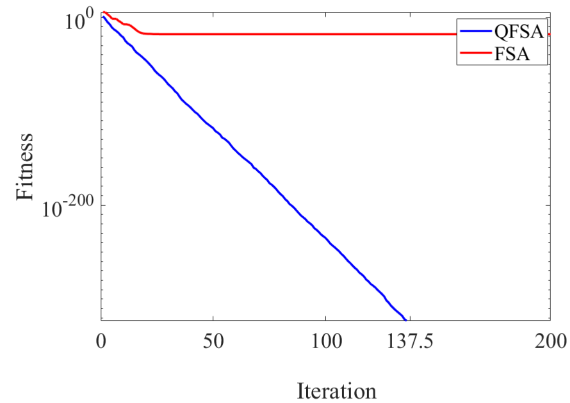


Fig. 5. Convergence characteristics in F1

The study was conducted by performing 10,000 iterations, and the results highlight the superior performance of the QFSA algorithm in achieving the minimum fitness value with the lowest number of iterations. On the other hand, the FSA algorithm exhibits a consistent level of performance regardless of the increase in the number of iterations.

Fig. 6 presents a comparative analysis of the performance between two algorithms: FSA and QFSA, specifically on the Benchmark function F2. The experiment was limited to 50 iterations. Results indicate that within this constraint, QFSA exhibited a more pronounced ability to achieve a minimal fitness value. Conversely, the FSA algorithm demonstrated an fitness level in just 26 iterations and stopped at that point. The analysis was capped at 50 iterations due to the observed stability and lack of significant changes in the results beyond this point.

Fig. 7 shows the comparison between FSA-taking the red line and QFSA-taking the blue line, in the 3rd benchmark function (F3), by taking 10,000 iterations. It shows the QFSA algorithm's superiority in reaching the min fitness with the least number of iterations.

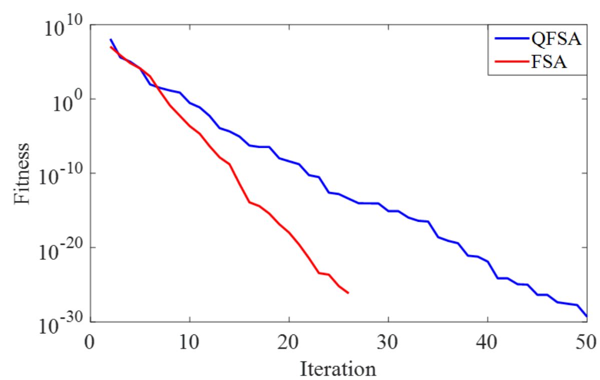


Fig. 6. Convergence characteristics in F2

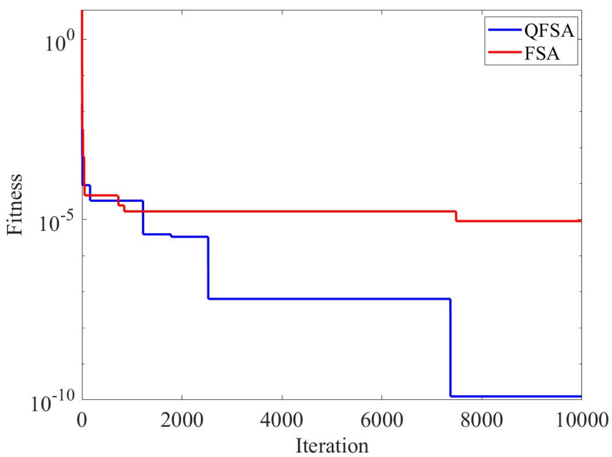


Fig. 7. Convergence characteristics in F3

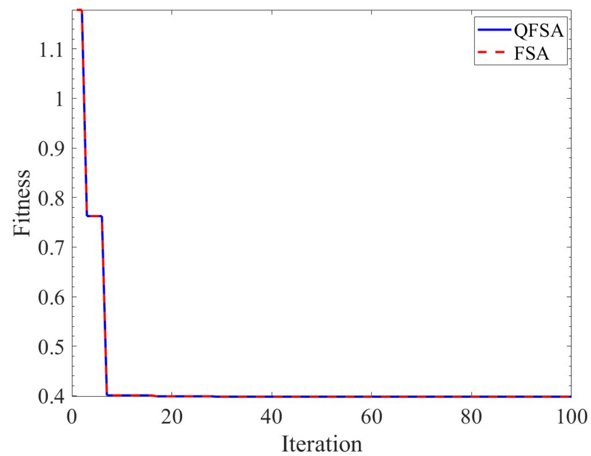


Fig. 9. Convergence characteristics in F5

In the context of analyzing the FSA and QFSA algorithms, it's worth noting that both methods achieved results that seem close, as shown in Fig. 8. The QFSA algorithm slightly outperformed the FSA algorithm when applied to the 4th benchmark function F4. This result suggests that the QFSA algorithm is more efficient than the FSA algorithm for functions with certain characteristics and complexities.

Fig. 9 depicts two lines, one in blue and the other in dashed red, which may be perceived as a single line. However, the results obtained from the QFSA outperform those obtained from the FSA. The QFSA algorithm yields a result of 0.3979, which is closer to the optimal value for the F5 equation compared to the FSA algorithm's result of 0.3978, depicted in dashed red.

QFSA and FSA are two optimization algorithms that use different approaches to find the minimum of a function. Based on the results provided, QFSA appears to have performed slightly better than FSA in this particular instance, as shown in Fig. 10. By analyzing the results of the two algorithms. The QFSA result is -3.86002, while the FSA result is -3.862. When applying F6. However, based solely on the results, it appears that QFSA performed slightly better than FSA, obtaining a slightly better objective function value.

In Fig. 11 Convergence characteristics in F7, we observe the convergence characteristics of the seventh benchmark function, showcasing a smooth and superior performance in reaching the optimal value. The Figure effectively demonstrates the applied algorithm's robustness and efficiency in navigating the problem's complex search space.

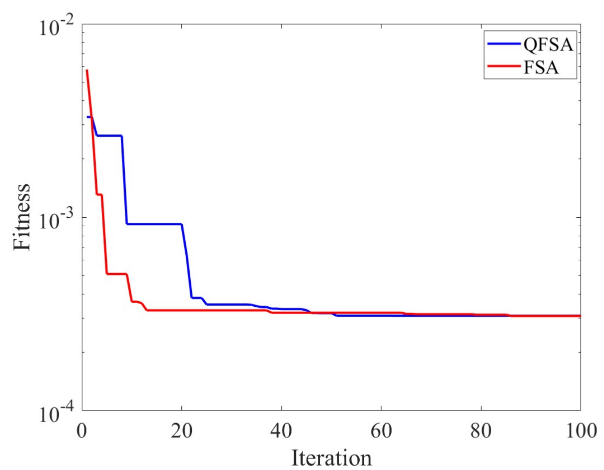


Fig. 8. Convergence characteristics in F4

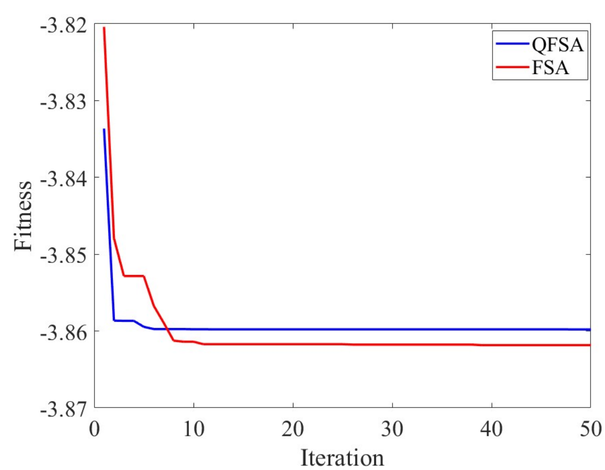


Fig. 10. Convergence characteristics in F6

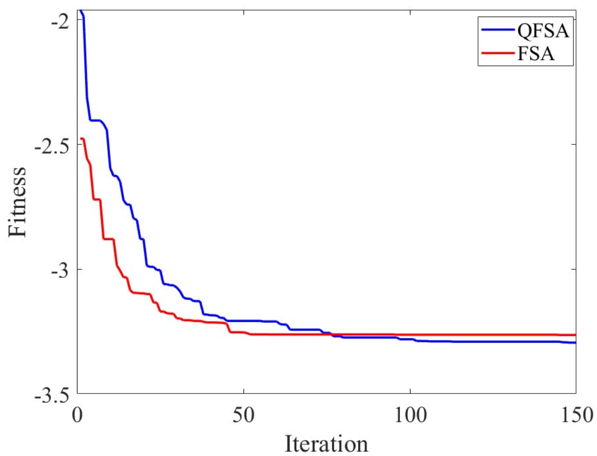


Fig. 11. Convergence characteristics in F7

The rapid convergence towards the optimal value indicates that the algorithm can mitigate the effects of local minima and effectively exploit the available information to guide the search process.

It is worth noting that the smoothness of the convergence curve suggests a balanced trade-off between exploration and exploitation, which is a key aspect of successful optimization algorithms. This balance enables the algorithm to efficiently locate promising regions within the search space while still maintaining a sufficient degree of diversity among the candidate solutions. Consequently, the algorithm's superior performance on the seventh benchmark function highlights its potential applicability to a broad range of optimization problems, both in academia and industry.

According to a comparative analysis of optimization algorithms on seven benchmark functions, the QFSA algorithm has demonstrated superior performance over other optimization algorithms such as FSA, LSA, GA, PSO, and Firefly Optimization Algorithm. The algorithms were compared based on the optimization metrics for the benchmark functions. The comparison results revealed that the QFSA algorithm had outperformed the FSA algorithm on all benchmark functions. Notably, the FSA algorithm outperformed the GSA, which indicates that the QFSA algorithm has surpassed all other algorithms in terms of performance. Therefore, the QFSA algorithm can be considered the leading optimization algorithm for the given benchmark functions. The comparative results of the optimization algorithms are presented in Table IV Below. The Quantum-Behaved Future Search Algorithm (QFSA) has emerged as a remarkable contender in the arena of optimization algorithms, especially in the context of the given benchmark functions. This conclusion is not made random but is the result of meticulous testing, performance assessment, and comparison with other optimization techniques. The comparative results of the optimization algorithms are presented in the Table IV while most other algorithms results taking from [23].

B. Performance Evaluation of the QFSA-ANN

The QFSA-ANN demonstrated high accuracy in detecting, locating, and classifying faults in underground power cables. The model's performance was found to be robust and stable under various fault conditions, indicating its suitability for practical applications. The study explores the use of QFSA for optimizing the structure of ANN in terms of hidden layer neurons (N1, N2) and learning rate (LR), as shown in Table V. QFSA initializes a quantum state, applies quantum operations, and adjusts based on fitness evaluations for a predefined number of iterations. The approach was tested for 100 iterations and outperformed manual selection in terms of accuracy and lower MSE in fault detection and Location. The graphs demonstrate the application of QFSA for determining the optimal ANN structure through 100 iterations and other details in Table VI.

This research determined that the search for optimal parameters would be conducted within predetermined ranges. The number of neurons in the neural network architecture was incremented or decremented by a value of one at each step, as it must be an integer.

The first parameter, "MSE goal," indicates the target MSE the ANN-QFSA model aims to achieve. In this case, the goal is set to 0, implying that the model aims to achieve perfect accuracy. "ANN iterations" specifies the number of iterations for the training of the ANN.

TABLE V.
LOWER AND UPPER LIMIT OF SEARCH

	Upper N1, N2	Lower N1, N2	Upper L. R	Lower L. R
Detection and Location	15	5	0.98	0.02

TABLE VI.
PERFORMANCE METRICS FOR AN ANN-QFSA MODEL

MSE goal	0
ANN iterations	300
QFSA iterations	100
number of populations	20
Run time	3

TABLE IV.
THE COMPARATIVE OUTCOMES OF THE VARIOUS OPTIMIZATION ALGORITHMS

Function	QFSA	FSA	LSA	FA	PSO	GA
F1	9.881e-324	1.14e-18	9.201365586	716.4716944	0.59714	0.717
F2	4.94e-30	6.95e-27	0.560036507	27.85966457	7.2414	0.5024
F3	1.25e-10	9.12e-06	0.016268885	0.008299594	0.0042529	0.9137
F4	0.000307501	0.000308226	0.000307486	0.000443132	0.00030749	3.1625e-04
F5	0.3979	0.3978	0.3978	0.3978	0.3978	0.3978
F6	-3.86002	-3.862	- 3.862	- 3.862	- 3.862	- 3.862
F7	-3.32	-3.273	- 3.322	- 3.322	- 3.322	- 3.3219

In this case, the model is trained for a total of 300 iterations. ”QFSA iterations” denotes the number of iterations for the optimization process conducted by the QFSA algorithm. The model is optimized for 100 iterations using the QFSA algorithm. ”a number of populations” refers to the size of the population of particles used in the QFSA algorithm. The model employs a population size of 20 particles.

Fig. 12 shows Quantum-behaved Future search algorithm (QFSA) results to find the optimal structure for the fault detection task; it requires 13 neurons in the first hidden layer and 13 neurons in the second hidden layer, with a learning rate of 0.776825, achieving an extremely low MSE of 1.19061e-15 as fm. However, fault detection is not considered the major importance of this research, as much as determining the location of the fault is the essential thing that fd on in this research.

Through the (QFSA), the optimal structure for fault location has been discovered to consist of 15 neurons in each hidden layer, with a learning rate of 0.908593This optimized structure exhibits exceptional performance, achieving a remarkably low MSE of 5.65994e-05, as illustrated in Fig. 13. Such an achievement serves as a testament to the efficiency and efficacy of the QFSA algorithm in the task of fault detection and location in underground power cables. The optimized ANN structure provides a powerful tool for accurately identifying and locating faults in an efficient manner, enabling prompt and effective intervention to prevent potential power outages.

The results presented in Fig. 13 are a remarkable feat in the domain of fault location detection, and they provide a solid foundation for further exploration and refinement of the ANN-QFSA model. With continued development, this model has the potential to revolutionize the field of power cable maintenance and contribute to enhancing energy delivery systems worldwide.

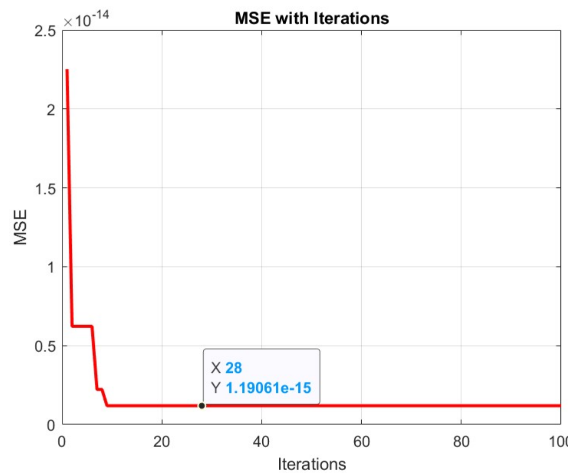


Fig. 12. QFSA-ANN of fault detection

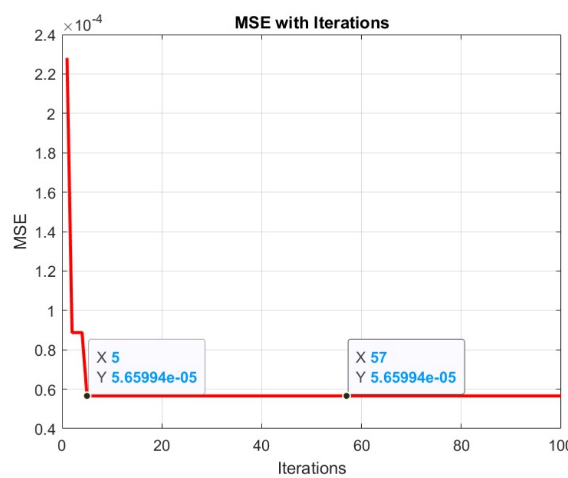


Fig. 13. QFSA-ANN of fault location

Fig. 14 presents a scatter plot representing the interplay between LR, N1, and N2. This Figure illustrates the exploration of the algorithm across the search space, represented in three dimensions. From a visual analysis, the algorithm appears to have comprehensively covered most of the search area.

The scatter plot suggests an effective distribution of data points, indicating that the algorithm has successfully navigated through the complexities of the multi-dimensional space. The dense coverage of points may suggest a balance between exploitation and exploration, a key feature in ensuring the robustness of an algorithm.

Fig. 15 is a two-dimensional scatter plot illustrating the relationship between N1 and N2, with data points colored according to their corresponding MSE values.

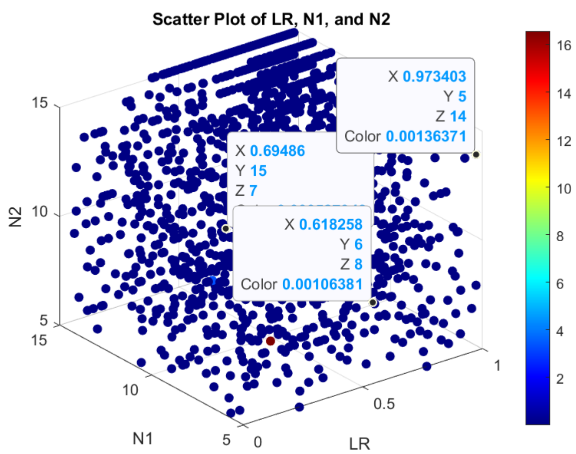


Fig. 14. Scatter plot of LR, N1, and N2

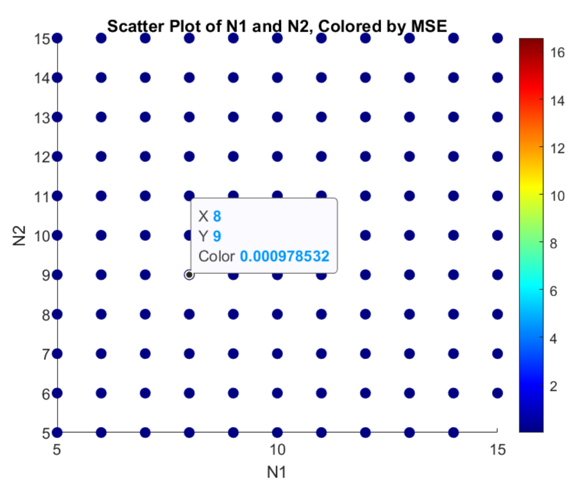


Fig. 15. Scatter plot of N1 and N2, colored by MSE

Fig. 16 presents a scatter plot depicting the variation of MSE with respect to the iteration number. This plot offers insights into the convergence behavior and performance of the algorithm over iterative cycles.

The use of color provides an additional dimension of information on this 2D plot, allowing us to visualize the effect of N1 and N2 on the MSE.

The findings can serve as a valuable reference for researchers and practitioners interested in developing more accurate and efficient solutions for fault detection and other related applications. With continued development and refinement, the ANN-QFSA model has the potential to revolutionize the field of power cable maintenance, resulting in significant improvements in energy delivery and reliability worldwide.

Table VII observes the optimal ANN structure obtained using QFSA. The table meticulously presents the various components of the ANN architecture, including the number of hidden layers, the number of neurons in each layer, and the learning rate. In ANN structure of 2 hidden layers is used for detection, location, and classification, according to the data collected.

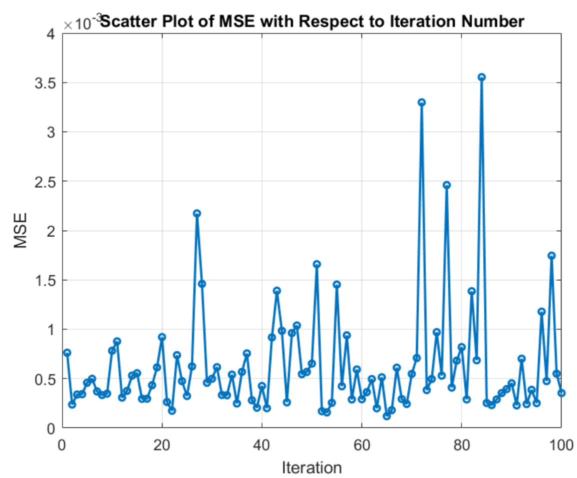


Fig. 16. Scatter plot of MSE with respect to iteration number

TABLE VII.
QFSA OPTIMAL ANN STRUCTURE

	N1	N2	L.R	MSE	Iterations
Detection	15	15	0.908593	fmin= 5.6599e-05	100
Location	13	13	0.776825	fmin= 1.19061e-15	100

C. Comparative Analysis with Other Solutions

The performance of the QFSA-ANN was compared with other solutions reported. The results showed that the proposed QFSA-ANN outperformed existing methods, highlighting the effectiveness of the quantum-inspired optimization approach in enhancing the ANN's performance.

(PSO) and Quantum-behaved Particle Swarm Optimization (QPSO) [40] are swarm intelligence-based algorithms used in complex optimization problems. For instance, both algorithms are applied in the optimization of multi-modal functions, with PSO often demonstrating faster convergence. Ant Colony Optimization (ACO) [41] is another instance of a bio-inspired algorithm, often used in path-finding problems such as the traveling salesman problem. (FA) mimics the behavior of fireflies and is used in various optimization tasks like function optimization and clustering.

The Cuckoo Search (CS) algorithm, which gets its name from the brood parasitism used by some species of cuckoos [41], has been implemented in diverse fields, such as structural design optimization. FSA is a recently developed algorithm that considers the future state of the search space for optimization, showing potential in dynamic optimization problems. The Grey Wolf Optimizer (GWO), inspired by the hierarchical leadership and hunting behavior of grey wolves [42], has demonstrated efficient performance in various optimization tasks, such as feature selection and neural network training.

Finally, Quantum Future Search Algorithm (QFSA) is an advanced version of FSA that incorporates quantum mechanism principles. QFSA demonstrated the best MSE among the tested algorithms, as shown in Table VIII. This was primarily due to its enhanced exploration and exploitation capabilities, which were derived from the superposition and entanglement properties of quantum mechanics. As shown in Fig. 17, the convergence characteristic curves for multiple algorithms in finding the optimal structure of Artificial Neural Network (ANN) for fault location can provide a comprehensive perspective on the effectiveness and efficiency of these algorithms. Fig. 18, the box and whisker plot for each algorithm, provides a visual representation of the distribution of results for each algorithm.

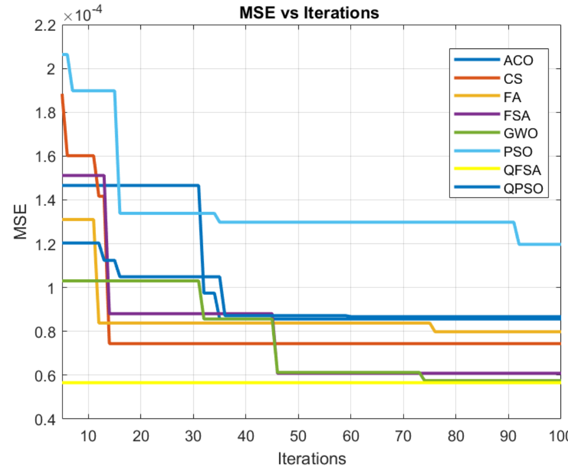


Fig. 17. Convergence characteristic curves for multi-algorithm in finding the optimal structure of ANN fault location

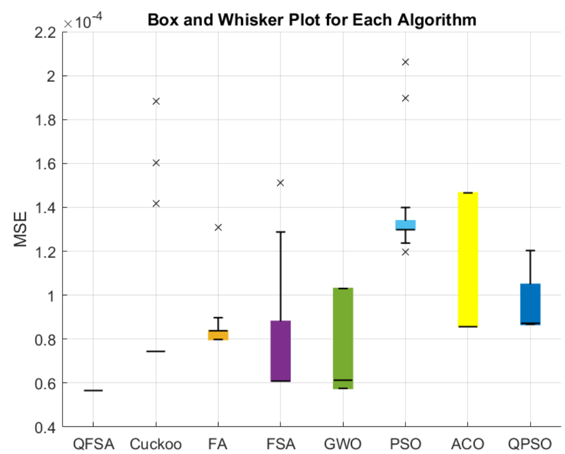


Fig. 18. Box and whisker plot for each algorithm

TABLE VIII.
MULTI-ALGORITHM OPTIMAL RESULT OF ANN STRUCTURE IN FAULT LOCATION

PSO	0.00011973
QPSO	8.67e-05
ACO	8.56e-05
FA	7.98e-05
CS	7.44e-05
FSA	6.09e-05
GWO	5.76e-05
QFSA	5.66e-05

However, that algorithm performance can vary significantly depending on the specific nature and requirements of the problem at hand. Therefore, despite QFSA's impressive performance, other algorithms may be more suitable for different types of problems or constraints.

The convergence characteristic curves in Fig. 17 depict the rate at which each algorithm approaches its optimal solution over iterations. These curves provide insights into the speed, stability, and reliability of each algorithm in finding the optimal structure:

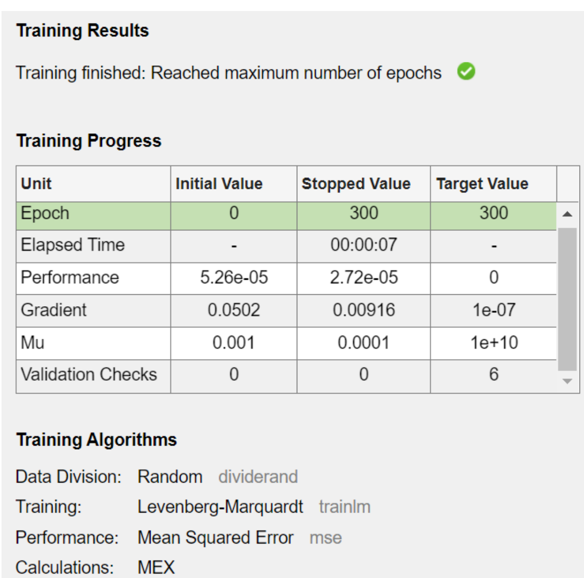
- Stability: An algorithm that shows minimal fluctuation in its curve is more stable.
- Speed: Algorithms that reach their optimal or near-optimal values in fewer iterations are faster.
- Reliability: If an algorithm consistently reaches the same (or very close) values upon multiple runs, it's considered reliable.

From the provided data, QFSA appears to perform impressively, but a detailed examination of Fig. 17 would elucidate the comparative performance further.

D. Fault Location Training Results

Fig. 19 provides an overview of the neural network and includes a screenshot of the training window generated using the ANN Toolbox in Simulink.

It is noteworthy that the training process performance in terms of MSE was deemed satisfactory upon completion of the training. The result has gotten after the optimal structures were known and tested after a few tries.



Training Results

Training finished: Reached maximum number of epochs

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	300	300
Elapsed Time	-	00:00:07	-
Performance	5.26e-05	2.72e-05	0
Gradient	0.0502	0.00916	1e-07
Mu	0.001	0.0001	1e+10
Validation Checks	0	0	6

Training Algorithms

Data Division: Random dividerand
Training: Levenberg-Marquardt trainlm
Performance: Mean Squared Error mse
Calculations: MEX

Fig. 19. Neural network training result of the location block

The neural network's training performance plot is displayed in Fig. 20. As can be observed, 5.26e-05represents the best validation result in this case in terms of MSE at the conclusion of the training phase. It is evident that there is a significant correlation between the two. This shows that the ANN's performance in terms of accurate fault location system is satisfactory. Fig. 21 shows the Error Histogram and exhibits a good degree of performance, further proving this.

Fig. 22 depicts a neural network with the best linear regression fit between its outputs and targets. This network has one neuron in its output layer, nine neurons in its input layer, and 15 neurons in each of its hidden layers. (9-15-15-1). In this particular instance, the correlation coefficient R-value was determined to be 1, which is the optimal value.

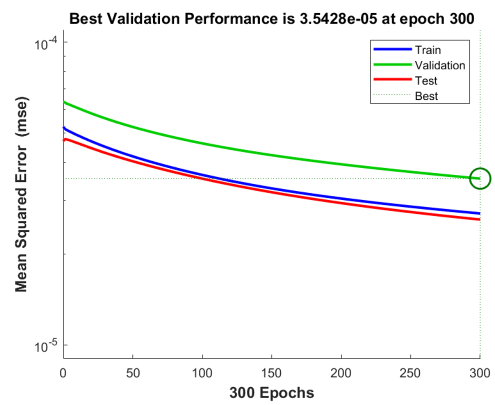


Fig. 20. Training ANN performance for the location with MSE

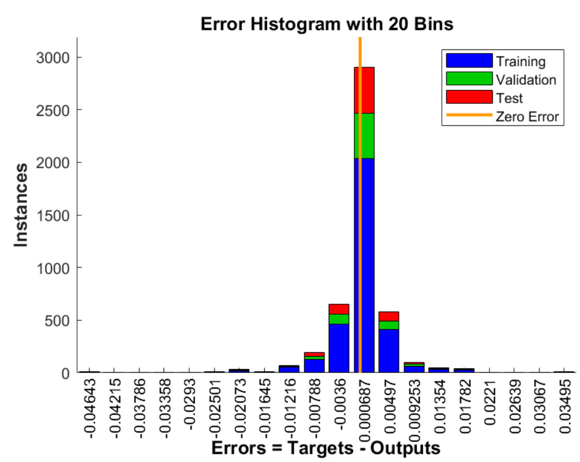


Fig. 21. Error histogram, training ANN for location - with 20 bins

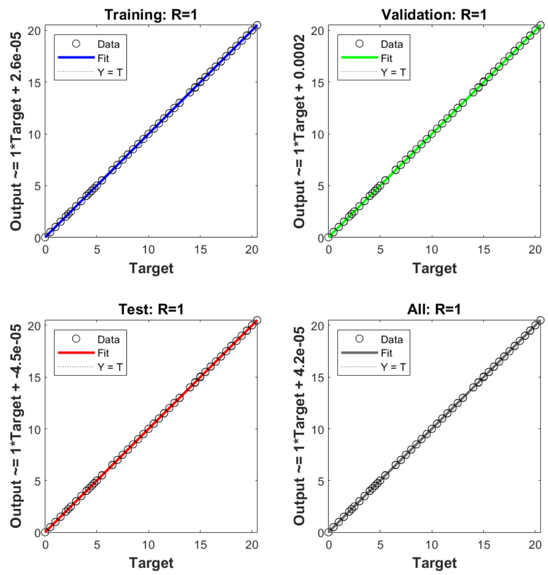


Fig. 22. ANN regression chart of location training

E. Faults Location Estimated by ANN

The following tables present the actual and estimated locations of faults determined through the ANN. These faults are classified based on the lines where they were detected, per the nomenclature used in power system analysis. The tables 'A', 'B', and 'C' refer to the three phases of a three-phase system. AND 'G' represents the ground or the neutral line. 'AG' means a fault in the connection between phase A and the ground, 'B-G' refers to a fault in the connection between phase B and the ground, and so on.

Table IX displays the actual locations of these faults in kilometers and the corresponding fault locations estimated by the ANN. By comparing the actual and estimated values, the effectiveness of the ANN in detecting and locating the faults can be evaluated. In analyzing

Table IX, which illustrates the disparities between the actual fault locations and those estimated by an ANN, several factors merit consideration. Firstly, the quality and volume of training data play a pivotal role. An inadequacy in either dimension could compromise the ANN's ability to generalize, particularly for certain fault types. The architecture of the neural network itself might also be a contributing factor. If not adequately designed to encapsulate the intricacies of various fault manifestations, the ANN might not offer precise location estimates. External influences, such as data noise or temporal and environmental conditions under which faults occur, might also skew predictions if the ANN hasn't been primed to account for them. It's also plausible that there exists a mismatch between the distributions of training and testing datasets for specific fault types, leading to suboptimal predictions.

Fig. 23 of the scatter plot and marker graph obtained from

TABLE IX.
FAULTS LOCATION ESTIMATED BY ANN

Actual faults location	Faults location estimated by ANN										
(km)	AG	B-G	C-G	A-B	A-C	B-C	ABG	ACG	BCG	ABC	ABCG
0.5	0.427	0.657	0.593	0.801	0.757	0.204	0.462	0.492	0.409	0.56	0.56
1	0.937	1.165	1.095	1.278	1.237	0.689	0.968	0.982	0.945	0.969	0.969
2	1.955	2.143	2.087	2.24	2.206	1.665	1.943	1.965	1.923	1.93	1.93
3	2.968	3.142	3.082	3.213	3.183	2.648	2.939	2.951	2.943	3.005	3.005
4	3.978	4.14	4.076	4.196	4.168	3.636	3.935	3.94	3.958	3.995	3.993
5.5	5.485	5.637	5.564	5.686	5.659	5.128	5.429	5.428	5.474	5.486	5.484
6.25	6.236	6.385	6.308	6.438	6.409	5.877	6.176	6.173	6.231	6.234	6.234
7.75	7.735	7.881	7.796	7.95	7.917	7.381	7.671	7.668	7.74	7.735	7.735
8	7.985	8.13	8.044	8.202	8.169	7.633	7.921	7.917	7.991	7.984	7.986
9.25	9.23	9.374	9.284	9.47	9.432	8.891	9.167	9.166	9.246	9.24	9.241
10.5	10.474	10.616	10.525	10.739	10.697	10.15	10.414	10.417	10.501	10.497	10.497
11.75	11.717	11.857	11.767	12.008	11.962	11.41	11.661	11.669	11.757	11.754	11.753
12	11.966	12.105	12.015	12.262	12.215	11.662	11.911	11.92	12.008	12.004	12.005
13	12.96	13.096	13.01	13.273	13.224	12.668	12.909	12.922	13.014	13.009	13.008
14.25	14.203	14.333	14.255	14.532	14.482	13.923	14.158	14.175	14.274	14.264	14.263
15.5	15.447	15.567	15.501	15.781	15.734	15.174	15.408	15.427	15.537	15.515	15.514
16.75	16.693	16.801	16.748	17.016	16.977	16.419	16.659	16.676	16.803	16.762	16.762
17	16.943	17.047	16.997	17.262	17.224	16.667	16.91	16.926	17.057	17.011	17.011
18.5	18.442	18.524	18.495	18.72	18.698	18.149	18.415	18.42	18.582	18.501	18.502
19.75	19.695	19.752	19.744	19.913	19.912	19.374	19.673	19.659	19.858	19.733	19.733

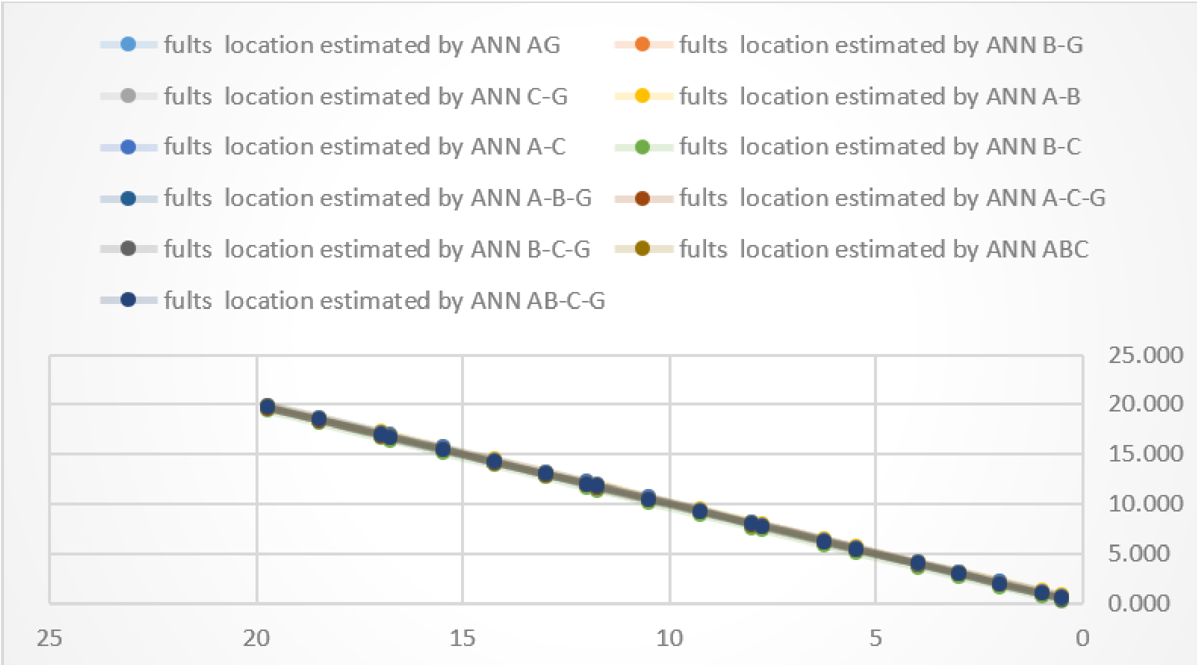


Fig. 23. Scatter with a straight line and marker graph of a fault location result

the fault location analysis illustrate the proposed methodology's effectiveness. The plot features several different lines, each representing another type of fault. Despite the fault types' variations, all plotted lines align closely as if they were one line. This alignment with the actual fault locations significantly indicates the results' accuracy. Furthermore, the convergence of the plotted lines is an important observation. The 12 distinct lines planned initially demonstrate a high degree of alignment, which suggests that the proposed methodology can precisely identify the fault location. This proposed convergence strongly indicates the effectiveness of the approach and its ability to deliver precise and accurate results. It is important to note that the accuracy of the results is not only due to the proposed methodology but also due to the integration of the (ANN) into the process. As described earlier, selecting the optimal ANN structure allows for precise identification of the fault location and its type. Integrating the ANN with the proposed methodology was a crucial factor in achieving the high degree of accuracy observed in the results.

VI. Discussion

A. Potential Challenges

1. Complexity: The integration of quantum mechanics theories into classical algorithms might introduce complexities that can be computationally demanding or challenging to debug.
2. Data Sensitivity: For the QFSA-ANN model to accurately detect faults, it relies heavily on the quality of the input data. Faulty or noisy data can lead to inaccurate results.
3. Resources or specific hardware capabilities that aren't always readily available.

B. Future Directions/Recommendations

1. Hybrid Models: Integrate QFSA with other machine learning and optimization algorithms to create hybrid models that can leverage the strengths of multiple approaches.
2. Real-world Testing: Transition from MATLAB simulations to real-world testing for fault detection in underground power cables to understand practical challenges and constraints.
3. Expand Applications: Explore the utility of QFSA in other fields beyond power systems, such as finance, healthcare, or logistics.
4. Enhance Quantum Theories Integration: Delve deeper into quantum mechanics theories to explore other principles that can be fused into classical algorithms for more efficient problem-solving.

C. Importance of These Studies

1. Innovation: Studies like these push the boundaries of what's possible, merging disparate fields like quantum mechanics and optimization algorithms to create groundbreaking solutions.

2. Efficiency: As systems grow in complexity, traditional algorithms may falter or take exceedingly long to produce results. Quantum-inspired algorithms like QFSA offer a pathway to faster, more efficient solutions.

3. Safety & Reliability: In the context of power distribution systems, early and accurate fault detection is crucial. It can prevent potential hazards, reduce downtimes, and ensure the reliability of power supply.

4. Economic Benefits: Reducing faults and downtimes can lead to significant economic savings for power companies and consumers alike.

5. Foundational for Future Technologies: As we inch closer to the era of quantum computing, understanding and leveraging quantum principles in today's algorithms prepare us for the technologies of tomorrow.

VII. Conclusion

This article presented an innovative quantum-based future search algorithm (QFSA) combined with an ANN for detecting and locating faults in underground power cables. The proposed QFSA-ANN demonstrated superior performance compared to other algorithms and solutions, offering a promising approach for accurate and efficient fault management in power distribution systems. Future work may explore further improvements to the QFSA-ANN, such as incorporating additional features or adapting the model for real-time fault detection and location. The QFSA algorithm's ability to find the optimal global solution represents a significant advantage over other optimization algorithms that may only find local solutions.

Conflict of Interest

The authors of this paper do not have any conflicts of interest that are relevant to this article.

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