

Enhanced Optimization Model for Inverter Short Circuit Prediction Using Machine Learning Techniques

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Abstract. Short circuits are common faults that occur in inverters, which can lead to device damage, safety hazards, and downtime. Early detection of short circuits can help prevent these issues and improve the reliability of inverters. Suggest a machine learning method in this research approach short circuit prediction in inverters. Collected data from various sensors installed in the inverter system, such as voltage, current, and temperature sensors, and used this data to train several machine learning models, such as the Multilayer Perceptron (MLP), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Also utilized artificial intelligence algorithms such as Firefly Algorithm (FA) to optimize the model parameters. One could assess the effectiveness of the models by measuring their performance using different metrics such as accuracy, specificity, and convergence curve, and found that our proposed approach achieved high accuracy and robustness in predicting short circuits. Our results demonstrate the potential of using machine learning and artificial intelligence techniques for early detection of short circuits in inverters, which can contribute to improved system reliability and safety.

1 Introduction

Electric drives, which incorporate an inverter, induction motor, three-phase electrical supply, rectifier, and load, have emerged as the most commonly employed electromechanical conversion equipment in the industrial sector. The rationale behind their widespread adoption lies in their low maintenance costs, simple design, ease of replacement components, and mechanical resilience [1], [2].

A critical component of these electric drives is the power inverter, which converts alternating current (AC) into direct current (DC). Power electronics, such as inverters, are indispensable for managing renewable energy networks and adapting power source patterns. The design of a power inverter dictates its frequency, voltage, and overall power management capabilities, requiring a steady DC power source large enough to support the entire network [3].

The integration of renewable energy sources (RESs) into electricity production is steadily increasing due to their diversity and capacity to support utility systems. However, this widespread adoption presents various challenges in planning, operation, maintenance, and management. Demand-side management (DSM) initiatives, along with regulations imposed by

governments on distributed generation (DG) and distribution system operators (DSOs), have spurred compatibility efforts for generation plants like fuel cells, microsources, solar photovoltaics (PVs), and wind turbines [3].

For a DG system composed of multiple energy resources, proper power electronics are essential for connection at a single bus bar. Grid-connected inverters play a pivotal role in managing these resources efficiently. Additionally, DC-to-DC converters are necessary for controlling the DC power supplied by sources such as fuel cells or PV arrays [3].

The primary objective of a PV energy converter is to maximize electricity transmission from a PV array to the electrical grid. Hence, maximum power point tracking (MPPT) control methods are crucial for optimizing energy generation. The layout of power converters and control techniques is determined by the overall configuration of PV arrays, with string, multi-string, and centralized inverters being the most frequently employed topologies [4]–[6].

Large-scale solar facilities typically employ centralized PV inverters, leveraging PV units coupled in both directions to provide integrated output. Traditional centralized inverters have been utilized for their megawatt-scale conversion capability and power density,

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interfacing giant PV energy plants with the electrical grid. However, the fundamental limitation of centralized inverters lies in their singular MPPT method, which hampers overall efficiency [7], [8].

To address the limitations of centralized inverters, PV multi-string inverters enhanced with DC-DC converters have been developed. These inverters combine the advantages of both centralized and string inverters, offering improved efficiency and flexibility in resource management [7], [8].

String inverters, often configured in solitary or dual-stage structures, are essential for integrating individual PV strings into the power grid. They provide controlled DC bus voltages and MPPT at the DC-to-DC transformation step, with various architectures implemented to address specific requirements and challenges [9].

Solar micro-inverters offer individual MPPT for each PV cell, enhancing monitoring and measurement features compared to string and centralized inverters. However, they face efficiency challenges and technical complexities, particularly in addressing shading issues [10], [11].

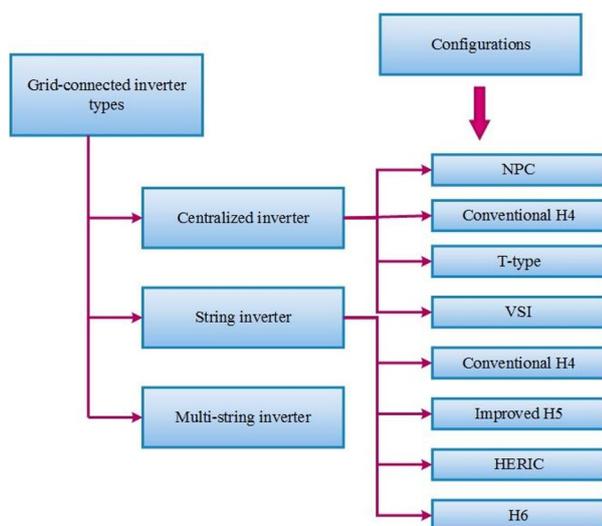


Fig. 1. Grid-connected inverter types and its configurations

The advent of machine learning (ML) and artificial intelligence (AI) techniques has opened new avenues for addressing these challenges. ML, as a data-driven modelling technique, offers promising solutions in situations where traditional mechanisms fall short, such as estimating short-circuit faults in distribution networks [12], [13].

In this context, this research proposes a novel data-driven short-circuit forecasting algorithm for grid-connected inverters, leveraging ML techniques to autonomously map connections between short-circuit power and grid-connected system properties.

2 Related Works

In manufacturing applications, Guerreiro et al. [14] propose a method for detecting incipient short-circuit failures (ISCF) in induction machines (IM). By leveraging discrete wavelet transform (DWT), statistical characteristics, and machine learning techniques, their approach achieves a high true negative rate (TNR) of 100% and reliability of 99.23%. However, it involves a higher computational cost compared to IoT-driven fault-detection systems.

Xiao et al. [15] introduce a methodology using convolutional neural network (CNN) models to detect faults in wind turbine converters. Their enhanced AOC-ResNet50 architecture achieves superior fault identification reliability of up to 98.0%. However, this study does not focus on short-circuit current detection.

Zheng et al. [16] propose a novel data-driven approach for short-circuit power forecasting in distribution networks with inverter-interfaced distributed generators (IIDGs). Despite accurate predictions, computational time remains a concern.

Malik et al. [17] present a smart data-driven deep learning-based approach for fault identification and categorization in one-phase PV inverters. Their method achieves high testing and training reliabilities of 98.3% and 99%, respectively, but its applicability is limited to single-phase inverters.

Behrends et al. [18] propose a machine learning-based method for identifying irregularities in residual current in solar systems. However, the detection process is focused solely on a single type of inverter.

Djamal et al. [19] introduce an automated diagnostic technique for detecting and monitoring switching open-circuit failures in two-stage, three-phase voltage-generating inverters. Despite a high categorization score, the processing time of the model remains a concern.

Skowron et al. [20] propose a CNN-based approach for identifying and classifying defects in the stator circuit of inductive motors. The method demonstrates high accuracy in real-time detection and classification of incipient rotor winding faults but incurs high computational time.

Guo et al. [21] present a DL-based fault categorization approach for small current grounded power distribution networks, achieving accuracy and flexibility in various fault scenarios but limited to fault classification and identification.

Khalil et al. [22] introduce a fault forecasting technique for circuit failures utilizing FFT, PCA, and CNN. Despite high accuracy, the computational cost of the method remains high.

3 Problem Statement

There have been several methods for finding an existing defect. The issue has been then fixed using different approaches like CNN [15], [20], and data-driven

DL [17]. The disadvantage of fault identification was that it degrades inverter effectiveness and results in the loss of specific operations owing to the present problem (because the fault has been rectified after it had previously happened). An earlier forecast of inverter short-circuit remains the solution to this issue in order to decrease faults. As a result, the ML role develops to offer a forewarning. Early short-circuit forecasting has the advantage of assisting fault tolerance techniques in correcting the problem before it manifests, safeguarding inverter operation. Thus, this research aims to develop ML-based approach for short circuit prediction in inverters.

4 Methodology of Inverter Short Circuit Prediction

To develop an inverter short circuit prediction model using machine learning techniques, the first step is to collect a large dataset of inverter operation data including input and output voltages, currents, temperatures, and other relevant variables, as well as the corresponding short circuit occurrence or non-occurrence. The inverter's response during an electric fault is influenced by its controller and hardware capabilities, with variations in the transient and steady-state responses. The controller type can be categorized based on the voltage control approach, with one controller regulating active and reactive power by adjusting the amplitude and angle.

binary classification system (1 for short circuit and 0 for no short circuit). This information can be obtained from inverter testing and monitoring or through simulation of different short circuit scenarios. It important to ensure that dataset is balanced and representative of real-world conditions in which the inverter is operating. The dataset should include various types of short circuits and non-short circuit events to enable the model to learn from a diverse range of scenarios. Once the dataset is prepared, various machine learning algorithms can have used to develop a predictive model. Commonly used algorithms for binary classification tasks include decision trees, logistic regression, random forests, and SVM. Deep learning techniques such as neural networks can also be applied for more complex datasets. The trained model can then be used to predict whether an inverter short circuit is likely to occur based on the input features. This information can be used to implement preventive measures to avoid potential damage to the inverter and associated equipment.

For an actual machine working in a healthy manner, 25,000 samples were taken in total. Additionally, the root domain dataset was built using 5000 fault samples. Therefore, 20% of the specimens in this healthy operating claim that were randomly chosen were set aside for the testing procedure. We looked at three different sorts of beginning, middle, and ending flaws. Overall, the classifiers were trained on 80% of the data, and tested on 20%. Both of the dataset's designs were arbitrarily selected; All of the categorization data shown are average of 20 separate training and testing runs;

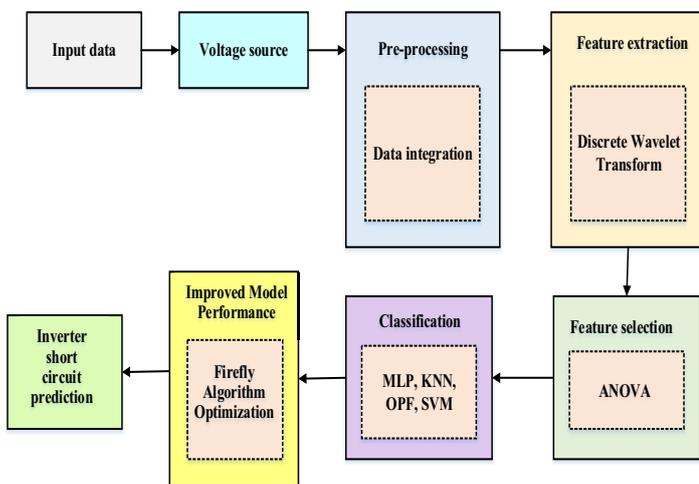


Fig.2. Flow diagram of inverter short circuit prediction.

4.1. Input Data

To develop an inverter short circuit prediction model using machine learning techniques, will need a dataset that contains features and labels. The features will be the input variables that will be used to train the model, while the labels will be the output variable that the model will predict. The dataset should include various types of input features such as current, voltage, power, frequency, temperature, and other relevant parameters. These features can be measured using sensors or collected through simulation software. The labels should indicate whether an inverter short circuit occurred or not, with a

4.2. Voltage Source Induced Short-Circuit Current

In a single line-to-ground (SLG) failure phase y at bus q occurs a power network system with M buses, the negative, positive, and zero-sequence networks are linked in series through bus q, as illustrated in the figure. Before connecting $A_{g,r,p}$, bus impedance matrix for sequence positive network in Figure 2 has to be established.

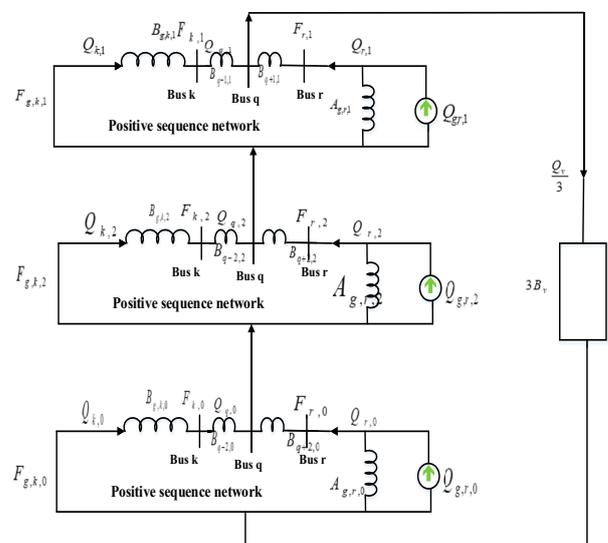


Fig. 3. Architecture of Voltage Source by a Short Circuit Current

When voltage source is connected to a circuit, it creates an electrical potential difference between two points in the circuit, causing current to flow through the circuit. If there is a short circuit in the circuit, the current can bypass the normal current path and take a shortcut, resulting in a large amount of current flowing through the circuit. The architecture of short circuit current by voltage source is typically represented.

$$B_{old}^+ = \begin{bmatrix} B_{g,o,1} & B_{g,o,1} & B_{g,o,1} \\ B_{g,o,1} & B_{g,o,1} + B_{q-1,1} & B_{g,o,1} + B_{q-1,1} \\ B_{g,o,1} & B_{g,o,1} + B_{q-1,1} & B_{g,o,1} + B_{q-1,1} + B_{q+1,1} \end{bmatrix} \quad (1)$$

The final positive-sequence system that contains $A_{g,r,p}$ is as follows using the Kron reduction rule:

$$B_{final}^+ = B_{old}^+ - \frac{B_{old,lj}^+ B_{old,ji}^+}{B_{old,jj}^+ + A_{g,r,1}} \quad (2)$$

where $j = 3$, $l = i = 1$ to j , and $B_{old,lj}^+$ is the component located at the l th row and j th column of matrices. The first step is to compute the bus resistance matrices for the negative- and zero-sequence networks in order to determine the short circuit current at a defective bus or line i .

$$Q_{q,1}^{SLG} = F_v / (B_{qq,0} + B_{qq,1} + B_{qq,2} + 3B_v) = Q_{q,0}^{SLG} = Q_{q,2}^{SLG} \quad (3)$$

$Q_{q,1}^{SLG}$, and $Q_{q,2}^{SLG}$ and $Q_{q,0}^{SLG}$ are the (+) ive, (-) ive, and zero-sequence short-circuit electrical flows that are flowing bus or line that has an error, respectively. $B_{qq,0}$, $B_{qq,0}$ and $B_{qq,2}$ are each of the diagonal components of positive, zero, and negative sequence resistance matrices at column q and row q , respectively, and B_v is fault impedance.

Power source's effects on positive, zero, and negative sequence voltages of bus j are established by:

$$F_{r,012} = [K \quad F_v \quad K]^H - B_{rq,012}, \quad (4)$$

$$B_{rq,012} = [B_0(r, q) \quad B_1(r, q) \quad B_2(r, q)]^H \quad (5)$$

$$Q_{q,012} = [Q_{q,0} \quad Q_{q,1} \quad Q_{q,2}] \quad (6)$$

where $F_{r,012}$ is a 3x1 vector made up of the voltages on bus r 's zero, positive, and negative sequences. The components row r and column q of bus resistance matrix of positive, zero, and negative sequence circuits make up the 3x1 vector $B_{rq,012}$. Here $Q_{q,012}$ is a 3x1 vector of the zero-, positive-, and negative-sequence short-circuit waves, where r is equal to 1, ..., i , ..., N and is the point-by-point multiplying operation. The bus r 's after fault

phase voltages are generated following a failure in bus or line q happens.

$$F_{r,yzw} = H F_{r,012} \quad (7)$$

here $F_{r,yzw}$ denotes the voltages of phase, y , z , and w of bus r , and $r=1$ to N .

4.3. Pre-processing

Data cleaning is the crucial process of identifying and rectifying irrelevant, duplicate, or inconsistent data points to ensure the accuracy and reliability of analysis or prediction tasks. Irrelevant data points, such as missing or null values, are removed as they do not contribute to the analysis. Duplicate data points distort the analysis and are eliminated to avoid skewing results. Inconsistent data points, like outliers, are corrected to align with the expected range of values for a particular variable. For instance, outlier sensor readings significantly deviating from the normal range are removed to prevent analysis distortion.

Data integration, an essential preprocessing step in inverter short circuit prediction using machine learning techniques, involves merging data from diverse sources like sensors, log files, and simulation software into a unified dataset. However, integration may introduce naming conflicts between different data sources, necessitating resolution before merging. Schema conflicts, arising from differences in data types, formats, or units of measurement across sources, must also be resolved by standardizing these aspects. Additionally, data integration may result in missing data, which necessitates handling by imputing values or removing affected data points. Moreover, errors or inconsistencies introduced during data integration should be addressed to maintain data quality, either by validating against known values or comparing with original data sources [23].

4.4. Feature Extraction

4.4.1. Combining DWT with Statistical Features for Signal Analysis

The DWT makes it likely to analyses signal with multiple incidence bands and resolutions. By breaking down the signal into scaled and shifted replicas of a mother wavelet operation, this is accomplished. A signal is represented by the DWT as a multi-level decomposition that is made up of a combination of estimates and details. The division of estimates into successive approximations and details at each higher level enables the calculation of statistical characteristics each frequency sub-band. This broadens feature space's dimensions and makes it easier to eliminate frequency range elements that might compromise categorization. Although there is trade-off between order of wavelet and calculation time, the Daubechies family is a frequently utilized mother wavelet due to its simplicity. Higher-order wavelets are more

efficient and more effective at differentiating between different frequencies, but they take longer to compute.

4.4.2. Feature Selection Using ANOVA (Analysis of Variance)

A hybrid feature selection strategy is used in the study to gradually delete features while analyzing various numbers of decomposition stages. The features are ranked according to their ability to discriminate using the ANOVA F-score, and nested subsets feature is produced and assessed using machine learning algorithms. Each feature's between category variance to within category variance ratio is calculated using ANOVA; a greater ratio denotes superior discrimination ability. After ranking, features are eliminated one at a time until the classification performance starts to deteriorate, which acts as the halting criteria.

4.4.3. Machine Learning Methods for Classification Tasks

In preliminary research, perceptron testing revealed the problem's lack of linear separability. Consequently, more robust classifiers, including Multi-Layer Perceptron (MLP), K-Nearest Neighbors (KNN), Optimum Path Forest (OPF), and Support Vector Machine (SVM), were employed.

MLP, utilizing hidden nodes for non-linear transformation, facilitates pattern differentiation across various classes. The network employs hyperbolic tangent activation functions for neurons and adjusts target values to prevent saturation zones and weight distortion. Parameters like starting learning rate, training epochs, and hidden neurons are optimized through a grid approach.

KNN, leveraging Euclidean distance and grid search, effectively categorizes adjacent data points, serving as a baseline for complex algorithms due to its simplicity and performance.

OPF represents training sets as graphs, assigning each sample to its closest prototype class based on contiguity relations and Euclidean distance. The classifier solely requires the distance metric parameter.

SVM constructs a decision hyperplane based on distance between positively and negatively labeled samples, categorizing new patterns accordingly. Parameters such as aperture (σ) and C are determined through grid search, utilizing an RBF kernel.

These methods collectively address the non-linear separability challenge and offer effective solutions for classification tasks [23].

4.4.4. Firefly Algorithm (FA) Optimization for Improved Model Performance

The Firefly Algorithm (FA) is primarily used for optimization and not typically used in the classification

part of the machine learning model. Used toward optimize the hyper parameters of model, which can improve model's performance in the classification part. Therefore, in the methodology section, it could be mentioned that the FA algorithm use toward optimize hyper parameters of machine learning model before training model on classification task.

Flying bugs called fireflies use a mechanism called biological luminescence, which is chemically created in their lower abdomen, to generate light. Infrared or ultraviolet frequencies are not present in the light that fireflies emit. Fireflies utilize this light to attract mates and prey, as well as to warn off enemies and defend themselves. They flash their lights at night, which is a lovely and natural occurrence.

$$\text{Fitness} = Q_q = f(d_q) \quad (8)$$

Assume there are n fireflies and that d_q represents the response for firefly q. The objective function $f(d_q)$ is connected to the firefly's brightness, q. A firefly's brightness Q is selected to reflect its current fitness value or function objective $f(d)$ location.

$$F(r) = \frac{F_g}{j^2} \quad (9)$$

The amount of another brightness of the firefly q and the separation r_{qr} between the firefly q and the firefly r are what determine the attraction, or brightness, F, of the firefly i on the firefly r.

Each firefly has a unique attraction rating, and the less beautiful one is drawn to and transported to the light one η . Nevertheless, the proportional attraction value depends on how far apart the fireflies are from one another.

$$\eta(r) = \eta_0 e^{-\gamma r^2} \quad (10)$$

where η_0 is the medium light absorbance rate and 0 is firefly attractiveness rating at $r = 0$.

Firefly Movement and Attraction Mechanisms: The equation below explains how a firefly at location d_q moves to a firefly at position d_r that is brighter.

$$d_q(h + 1) = d_q(h) + \eta_0 e^{-\gamma j^2} (d_q - d_r) + \alpha \epsilon q \quad (11)$$

where $\eta_0 e^{-\gamma j^2} (d_q - d_r)$ is caused by the firefly d_q 's attraction and $\alpha \epsilon q$ is a randomization parameter; hence, if $\eta_0 = 0$, it comes out to be a simple random movement.

The firefly algorithm compares a new position against the existing position to determine how enticing it is. The firefly moves to the new spot if it has a higher attraction rating. If not, it stays as it is right now. The algorithm terminates when either a specific fitness value is attained or a predetermined number of iterations have been completed.

The brightest firefly moves according to a mathematical calculation, not at random. The firefly algorithm's equation is based on the separation between

the insects, their beauty ratings, and a randomization element.

$$d_q(h + 1) = d_q(h) + \alpha \varepsilon_q \quad (12)$$

5 Result and Discussion

Performance criteria such as accuracy, specificity, and sensitivity can be utilized to evaluate the effectiveness and reliability of a suggested technique.

5.1. Accuracy

Accuracy expectations given the test results may be calculated by multiplying the whole number of projections by the number of successful projections, providing a proportion of precise projections. Accuracy is an indicator of performance used in classification that quantifies the percentage of instances (or data points) in a dataset that are properly categorized. It is determined by dividing the total number of predictions produced by the model by the number of forecasts that were accurate. A greater accuracy number suggests that the model is more dependable since it is producing more accurate predictions. But accuracy might not always be the greatest measure of a model's performance, particularly when the dataset is unbalanced or when incorrectly categorizing some cases can have serious repercussions.

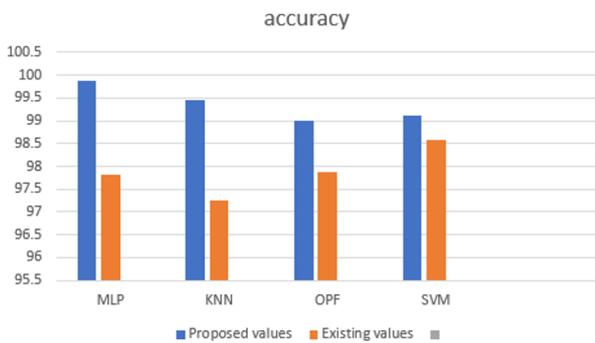


Fig. 4. Accuracy Graph Comparison

Above figure 4 shows the accuracy graph comparison. When compared the existing value our proposed value gives highest accuracy value. The proposed method accuracy value MLP is 99.87, KNN is 99.46, OPF is 98.99, and SVM is 99.12. below table 1 shows the comparison table of accuracy.

Table 1: Comparison Table of Accuracy

Machine learning methods	References	Existing values	Proposed values
MLP	[23]	97.83	99.87
KNN	[23]	97.26	99.46
OPF	[23]	97.87	98.99
SVM	[23]	98.59	99.12

5.2 Specificity

In binary classification issues, the performance parameter known as specificity estimates the percentage of real negative examples that the model properly classifies as negative. In other words, it assesses how well the model can recognize negative instances as such.

The following is the formula for specificity:

$$\text{specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

Where True Negative is proportion negative instances that the model properly classifies as negative, and False Positive is proportion negative cases that model mistakenly classifies as positive. When the cost of false positives is large, like in medical diagnosis or fraud detection, when false positives might result in pointless treatment or investigations, specificity is a valuable statistic.

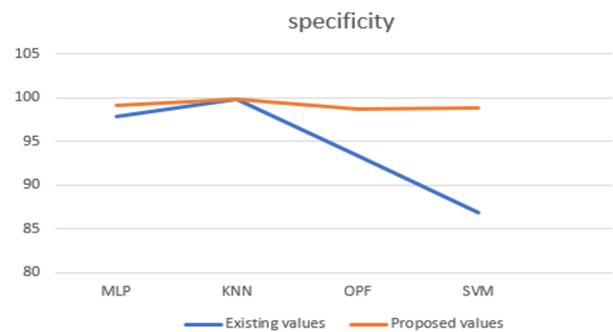


Fig. 5. Specificity Graph Comparison

The above figure 5 shows the comparison graph for specificity. When compared the existing value our proposed value gives highest specificity value. The proposed method specificity value of MLP is 99.12, KNN is 99.9, OPF is 98.7, and SVM is 98.88. below table 2 shows the evaluation table for specificity.

Table 2. Comparison table of specificity

Machine learning methods	References	Existing values	Proposed values
MLP	[24]	97.8	99.12
KNN	[25]	99.8	99.9
OPF	[26]	93.33	98.7
SVM	[25]	86.9	98.88

5.3. Convergence Curve

Figure 6 depicts the convergence graph of the FA, ChOA (Chimp Optimization Algorithm) [27], GTO (Artificial Gorilla Troops Optimizer) [28], and AO (Aquila Optimizer) [29]. Figure 5 indicates that the FA method outperforms the ChOA, GTO, AO algorithms in terms of convergence. The suggested HMWSO algorithm enhances the ChOA, GTO, AO algorithm. The experimental findings with statistical analysis reveal that the FA algorithm excels statistically. As seen by these graphs, FA has the highest convergence rates for the majority of the benchmark functions, followed by ChOA, GTO, AO.

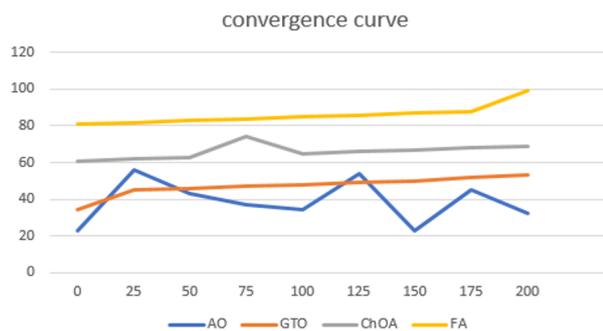


Fig 6. Using convergence curve for find best score

A metaheuristic optimization technique called the Firefly technique was developed in response to the flickering characteristic of fireflies. It is employed to address issues with optimization, like determining the best values for a given collection of variables to minimize or maximize a specified objective purpose. The convergence curve for the Firefly Algorithm shows how fitness value of best solution found so far changes over time, as the algorithm progresses through its iterations. Typically, the convergence curve is plotted as a line graph with the number of iterations or function evaluations on x-axis and fitness value on y-axis. A good convergence curve for the Firefly Algorithm would show a decreasing trend in the fitness value over time, indicating that the algorithm is making progress towards finding the optimal solution. The rate of convergence can also be important a faster convergence indicates that algorithm is efficient and able to quickly find good solutions.

6 Conclusion

Proposed approach using machine learning and artificial intelligence techniques for short circuit prediction in inverters has shown promising results. By collecting data from various sensors installed in the inverter system and using it to train several machine learning models, we were able to achieve high accuracy and robustness in predicting short circuits. Additionally, the utilization of the Firefly Algorithm to optimize the model parameters further improved the performance of the models. Early detection of short circuits in inverters is crucial for preventing device damage, safety hazards, and downtime. By predicting short circuits before they occur, our approach can contribute to improved system reliability and safety. Overall, our study highlights the potential of using machine learning and artificial intelligence techniques for fault prediction in complex systems such as inverters. Future research can focus further improving accuracy and efficiency of the proposed approach and applying it other systems in the power electronics industry.

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