Journal of Engineering Science and Technology
Special Issue on Development of Sustainability Systems - I, 76 - 94

ENHANCED FAULT DETECTION AND CLASSIFICATION IN TRANSMISSION LINES USING FINE-TUNED LSTM MODEL AND DBN TRANSFORM-BASED FEATURE SELECTION

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Abstract

Fault detection and classification in transmission lines is an important problem in power system protection. This paper proposes a novel fault detection and classification approach based on the fine-tuned LSTM model and dbN wavelet transform. Specifically, the selection of the optimal decomposition scale is proposed. An improved Arithmetic Optimisation Algorithm (IAOA) to enhance the accuracy of the LSTM model by optimizing its hyperparameters and reducing model (RMSE) error is implemented. The proposed method makes a significant advancement in the field of fault detection and classification. A simulated version of the model is run through MATLAB using the Three-Phase Series compensation network (735kV, 60 Hz, and 300 km of fault distance) to classify faults. Features are extracted to a depth of three using the dbN, which is modelled as a wavelet function in this investigation. Finally, the IAOA-LSTM model achieves 99.99% accuracy and 0.0010 loss when testing 2545 simulated samples with five different fault types. Maintaining the stability and reliability of power systems relies heavily on fault detection and classification, which is aided greatly by the proposed method. Implementing the IAOA algorithm for hyperparameter optimization and model error reduction has also been shown to enhance the accuracy of the LSTM model further. Therefore, the proposed approach can significantly contribute to developing more advanced and efficient protection systems for power transmission lines.

Keywords*:* dbN wavelet transform, Ground Faults, Improved AOA, LSTM model, Modulus maximum matrix Short-circuit faults.

1. Introduction

Modern society depends heavily on the critical infrastructure that power systems provide. A power system comprises various parts that deliver electricity from power plants to end users, including generators, transformers, and transmission lines. The backbone of the power system is comprised primarily of transmission lines, and any fault in these lines can severely damage the system's ability to function. Therefore, it is essential for maintaining the dependability and safety of power systems that faults in transmission lines are promptly discovered and accurately identified. The conventional approach to fault identification in transmission lines involves using traditional signal processing techniques, which have limitations in detecting and accurately classifying faults. Recently, machine learning techniques such as recurrent neural networks, long short-term memory (LSTM), and CNN networks have shown great promise in fault detection and diagnosis [1].

The application of time series forecasting can be a useful tool for maintenance teams in electric power utilities to predict the possibility of equipment failures [2]. Equipment failures are often closely related to weather conditions, with a higher probability of failures during rainy seasons. Therefore, understanding the patterns of this variation through time series analysis is crucial in this context. Wavelet transform can reduce noise in time series with significant nonlinearity. Since wavelet transform investigates signal energy, high frequencies are not eliminated. Hence, a hybrid deep learning model and Wavelet transform technique may be an effective strategy.

Several studies have explored using LSTM networks for fault identification in transmission lines. [3] proposed a combination of Transfer learning and CNN-based methods for detecting and classifying faults in power systems. This technique uses information from a resource convolutional neural network (CNN) to anticipate a target dataset distinct from the source dataset to diagnose defects for various electrical transmission lengths and characteristic impedance, using Wavelet transform and time-frequency analysis. The simulation outcomes show that employing this combo technique reduces overall training time. [4] introduce a novel method for fault identification and categorization on transmission networks that combines a wavelet transform and a Support vector machine (SVM) classifier. The results of this study suggested that the proposed technique is very efficient and accurate in the case of digital distance protection. [5] proposed a fault diagnosis method using a combination of wavelet transform and LSTM recurrent neural networks. The proposed method used Wavelet transform to extract the fault features and LSTM to classify the fault type. The results showed that the proposed method achieved high accuracy in fault diagnosis. The author presented a combined model of LSTM and an autoencoder for fault classification and detection. In this proposed method, offline data trains the autoencoder for anomaly detection. The LSTM network then classifies autoencoder-predicted errors. According to experimental results, the combined technique accurately diagnoses deviations from expected behaviour and the different glitches within the valuable time.

Naïve Bayes classifier is used to classify faults in transmission lines [6]. This study [6] uses wavelet transformation for feature extraction. By leveraging the multi-resolution property of the wavelet transform, the authors effectively capture and analyse the irregular transient changes that occur during fault events. This allows for accurate identification and classification of different types of faults [7]. Wavelet packet transform detects and classifies the fault within half a cycle [8]. The Wavelet transform is used in [9] to denoise the fault-based current and voltage signals, and the self-attention CNN is used to classify.

However, the hyperparameter tuning is not considered in these above studies. In detecting a motor fault, a PSO-BP (particle swarm optimization-back propagation) based Neural network is employed [10]. However, this study uses Wavelet transform for feature extraction from signals. Similarly, PSO is used for hyperparameter tuning of the SVM model for fault location in transmission lines [11]. Other machine learning algorithms, like KNN [12], are used for fault detection in AC/HVDC lines. Although Wavelet transform is employed, no hyperparameter tuning is considered. However, these studies have not involved hyperparameter tuning, summarized in Table. 1. Similar to [3-5], [6-9] used machine learning models for fault classification but lacked the consideration of hyperparameter tuning. The methods used are summarized in Table 1. Though hyperparameter tuning is used like in [10], the convergence speed is compromised. Based on the discussion above, a summarized table is made based on the method used and whether hyperparameter tuning is used.

Table 1. Review of Studies.

Reference	**Method used**	**Hyperparameter tuning considered. (yes/no)**	**Recommendation or comments**
Fatemeh Mohammadi Shakiba et al. [3]	CNN-based method for classification	No	Transfer learning provides up to 90.11% accuracy for 800km of transmission line. However, the clustering process shows less accuracy. The study constructs the approach robustness regarding training time, which does not comprehend dynamic conditions in the world and other studies.
Manohar Singh et al. [4]	SVM and Wavelet transform	No	The study shows the classification for varying lengths ranging from 50 to 8008%. However, the model should be extended and classified with the location and considering the series of compensated lines.
Pangun Park et al. [5]	LSTM model	No	LSTM model shows improvement over the conventional CNN. However, only one benchmark dataset is used, and it can be recommended to demonstrate various data for fault detection.
Aker et al. [6]	Naïve Bayes	No	The study shows 100% accuracy for Naïve Bayes but less accuracy in the MLP model. This shows inconsistency, and the study is recommended to explore other deep learning models.

Malla et al. [7]	ANN	No	The study used DWT for feature extraction. Based on the results obtained, the authors quoted using pre-processing techniques to speed up the ANN model.
Hong et al. [8]	Taguchi-ANN	No	Like [7], the authors used the ANN model with DWT for feature extraction. However, the model results are compared to the Decision tree model and RBF-based NN.
Fahim et al. [9]	Self-attention CNN	No	The proposed method shows remarkable accuracy. The study does not extensively discuss the potential challenges posed by varying fault severities or imbalanced datasets, which can impact the generalization ability of the classifier.
Lee et al. [10]	PSO-BP	Yes	Like the proposed method, [10] uses PSO to optimize the parameters in Backpropagation NN for fault classification based on the current signals of motors. Other improved optimization algorithms are better and are recommended to be explored.
Parsi et al. [11]	Various WT for feature extraction	No	Unlike the study in [4], authors here in [11] use various other wavelet-based feature extraction and comparison. However, DWT shows better results with automatic operation for reliable results.
Naik and Koley [12]	KNN	No	In this work, it is recommended to explore Deep learning-based approaches
Tang et al. [13]	Normalized CNN	Bayesian-based hyperparameter tuning	Compared to previous studies, in this [13], Bayesian optimization is considered for tuning the CNN model for fault classification. Further, exploring better methods to generalize the model can be recommended.

It is also concluded from the above literature and Table. 1, LSTM effectively captures long-term dependencies in the fault signal. Still, subjective choices in determining the model parameters used for training in realizing the faults can lead to suboptimal performance of the model. Therefore, optimizing the process of fine-tuning the LSTM model parameters will improve the performance, as seen in [10-11, 14]. Moreover, the combination of Wavelet transforms, and LSTM can further enhance the performance of fault feature identification in transmission lines by extracting the relevant features and reducing noise. However, the model's accuracy can be improved by automating the process of finding hyperparameters and optimizing such that the model's error is reduced, as seen in [14].

However, fault detection in transmission lines can be difficult because of the unique characteristics of high-resistance ground faults and arc faults [15]. It's possible that standard techniques for finding and categorizing faults won't be up to the task. In addition, an increase in transition resistance can cause high-frequency signals to become nonlinear and distorted, making it hard to detect and classify short-circuit faults in networks with intricate topologies [16]. However, if the decomposition scale is not carefully selected, information loss or distortion can occur when using the Wavelet transform as a feature extraction technique [17].

In addition, the model's performance may suffer if the training parameters were determined subjectively [14]. Considering these challenges, the paper aims to propose novel approaches for fault detection and classification in transmission lines. Three major contributions can be attributed to the proposed transmission line fault detection method. Primarily, it uses the modulus maximum matrix of the dbN wavelet to construct a fault characteristic matrix from the highest energy values within frequency bands, allowing for optimal selection of the decomposition scale. Additionally, by taking advantage of the model's capability to learn complex patterns and temporal dependencies within the data, using a fine-tuned LSTM shows the efficacy of applying deep learning techniques for fault identification. Moreover, the proposed fault identification system's performance and robustness are improved using the enhanced Arithmetic Optimization Algorithm (IAOA) to optimize hyperparameters. These contributions, taken as a whole, provide a sophisticated and thorough infrastructure for reliable and efficient transmission line fault detection.

2. **Problem Conceptualization**

Fault detection and diagnosis are critical in transmission lines as it is an integral part of power systems, as faults can lead to power outages, equipment damage, and safety hazards [18]. Some of the challenges in the detection of faults in transmission lines are:

- Detecting high-resistance ground faults and arc faults is particularly challenging due to the complex characteristics of these faults [15].
- Traditional fault detection methods may struggle to accurately detect and classify these faults [19] [20].
- An increase in transition resistance causes a sharpening and nonlinearity in high-frequency signals [15]. This nonlinear behaviour can make it challenging to accurately detect and classify short circuit faults in systems with many components and complex network configurations.
- Extraction of features using Wavelet transform is popular. However, Wavelet functions may not always be able to accurately identify the location of a fault in a power system due to factors such as noise and other interferences. If the decomposition scale is not chosen carefully, it can lead to information loss or distortion [17][21] [23].
- However, subjective choices in determining the model parameters used for training in realizing the faults can lead to suboptimal performance of the model [16][22].

Further, the study addresses these issues. Hence, a balance must be struck between reducing harmonic interference and accurately identifying the location of faults in the power system. The authors in [17] use a characteristic matrix $ff1$ to analyze normal and faulty signals based on wavelet decomposition layers and types. This matrix extracts relevant features from the signal and distinguishes between different types of faults. This suggests that a modulus maximum matrix can be utilized to analyze signals and extract relevant decomposition scales to construct the feature matrix. Based on the above discussion, the energy of the feature frequency band is given as [17],

$$E_{d,k} = \sum_{k=1}^{n} \left|d_{i,k}\right|^2 \quad (1)$$

whereas j is the decomposition level and k is the index of wavelet coefficient at the jth decomposition level. Hence, the summation represents the sum of the absolute values of the wavelet coefficients at the jth decomposition level, which corresponds to the signal's energy in the frequency band associated with that decomposition level.

However, in this paper, the modulus matrix [18] is constructed with three fault lines and 6 times the decomposition of the Wavelet. It is given as, M_{36}. In the case of high resistance fault, the elements of the matrix M_{36} represent the maximum absolute value of the wavelet coefficients for the fault mode at each decomposition level and line. Hence, the decomposition level is determined using the condition below,

$$M_{36_{ij}} = max\{|Cd_{j,k}|\} \; for \; i = 1,2,3 \; and \; j = 6 \quad (2)$$

where i corresponds to the line number, j corresponds to the decomposition level, and $|Cd_{j,k}|$ represents the absolute value of the wavelet coefficients at level j and position k. After determining the scale, the energy value is calculated using Eq. (1). The maximum energy value is considered for forming a feature matrix, F_{ij}. Where i is the fault line, and j is the decomposition scale.

3. Proposed Methodology

In the interest of resolving the issues which are highlighted in the above section, this paper proposes a deep learning-based method. For the classification of faults, the research suggests an LSTM model. However, the model's optimization was accomplished by resorting to mathematical definitions. The LSTM network's error is a fitness function, and the main task of AOA is to find the optimal set of hyperparameters to minimize this error.

The input data, which is a line-ground fault, line-to-line fault, two-lines-to-ground fault, and three-phase fault, are generated from the fault breaker setup in the transmission line. This input signal is broken down using wavelet transform, and features are extracted. The training samples from the data are fed to the Enhanced LSTM model in which the hyperparameters are optimized using the Improved Arithmetic Optimisation Algorithm. The process flow is detailed in Fig. 1. The methodology is divided into three parts: input data and feature extraction and Model training, including the LSTM model tuned using IAOA. These methods employed are explained in detail in the next sections.

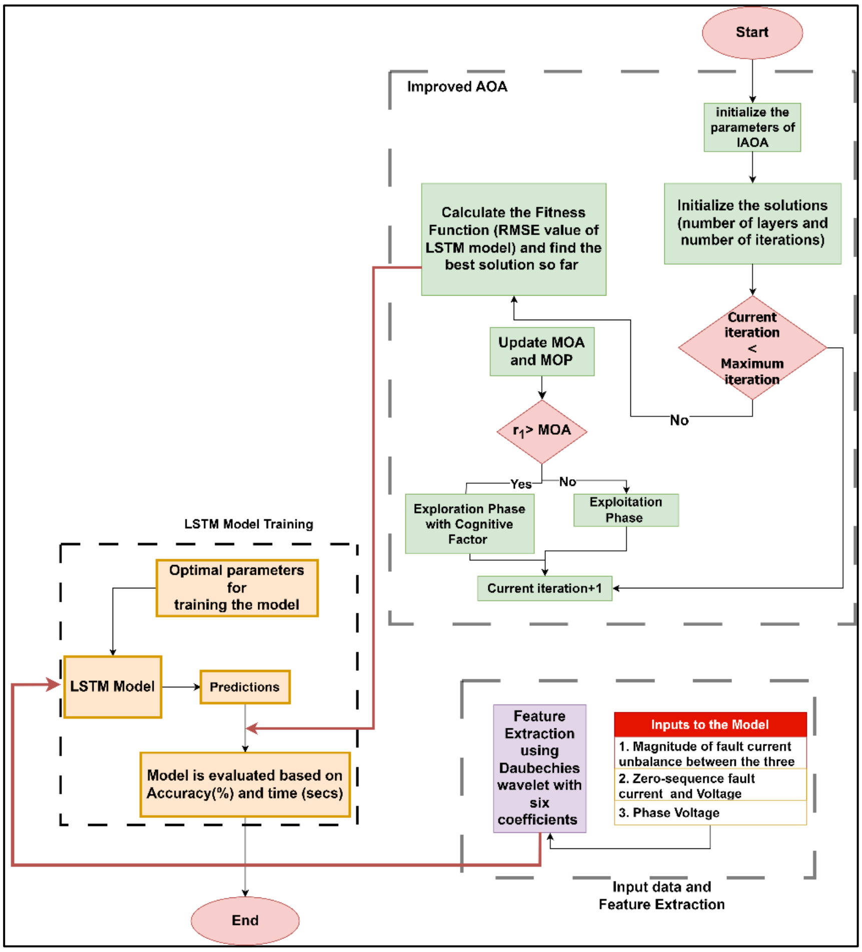


Fig. 1. Process Flow.

3.1 Input data and feature extraction

When considering the faults in 735 kV transmission lines (TL) [24], the fault transient component during a transient process is typically much higher than the steady component. As a result, this paper studies fault transient electrical to identify single-phase ground faults and short circuit faults.

The three-phase compensated network is considered here, which consists of 6 350 MVA generators as expressed in [25]. However, TL is split into two halves (each of $300km$) and is connected to the buses (B1, B2, B3). The three-phase block to the circuit discussed in [24] is given in [25] and is considered in the study as simulations. The fault breaker unit is connected to the Series Compensation (unit 1). As the fault is introduced, after the simulation, the fault is studied at B2 [25]. The compensator is shown in Fig. 2. In this study, the faults (line-ground fault, line-to-line fault, two-lines-to-ground fault, and three-phase fault) are applied at line 1 and parameters are specified using MATLAB toolbox as in [25]. A line-ground fault, also known as a single-line-to-ground fault, is a type of electrical fault that occurs when one of the three phases, *A*, *B*, and *C*, as seen in Fig. 2, of a three-phase power system encounters the ground or any other conductive object that is connected to the ground. In this type of fault, the current flows from the phase conductor to the ground [26], which can cause damage to electrical equipment and pose a safety risk to people in the vicinity.

Whereas line-to-line fault results in short circuit faults and occurs when two phases of the three meet each other [12]. A two-lines-to-ground fault is a type of electrical fault that occurs when two phases of a three-phase system meet the ground. In this type of fault, two of the three phases contact the ground, causing a short circuit between them. The third phase remains unaffected and continues to operate normally [12]. This type of fault is also called a Phase-to-Phase-ground-fault.

The three-phase fault is considered one of the most severe and can result in high short-circuit current levels [12]. Hence, these faults are considered and modelled using MATLAB by applying the fault current of $10\ kA$ at the series compensation subsystem at line 1 and measured at Bus $B2$. The duration of time considered from $t =\ 0.01\ to\ 0.1$ that the system is in the settling mode [26]. The Line-to-ground fault is seen in Fig. 3 (a).

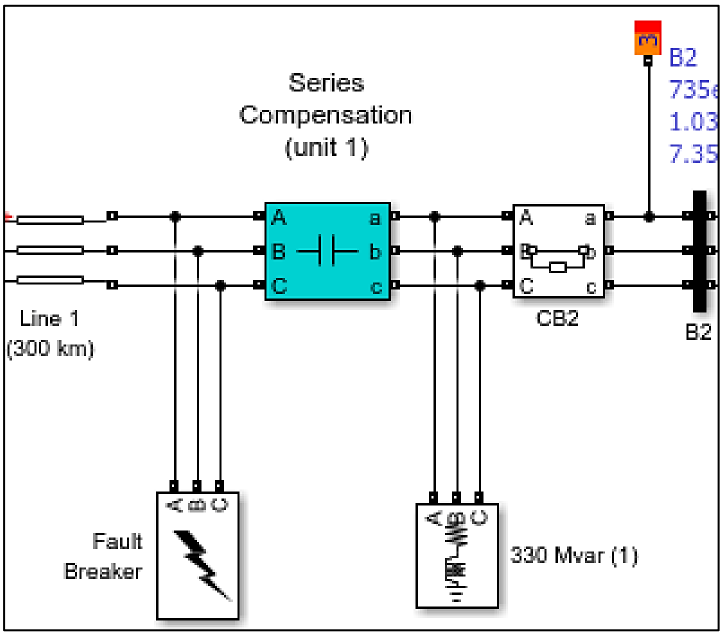
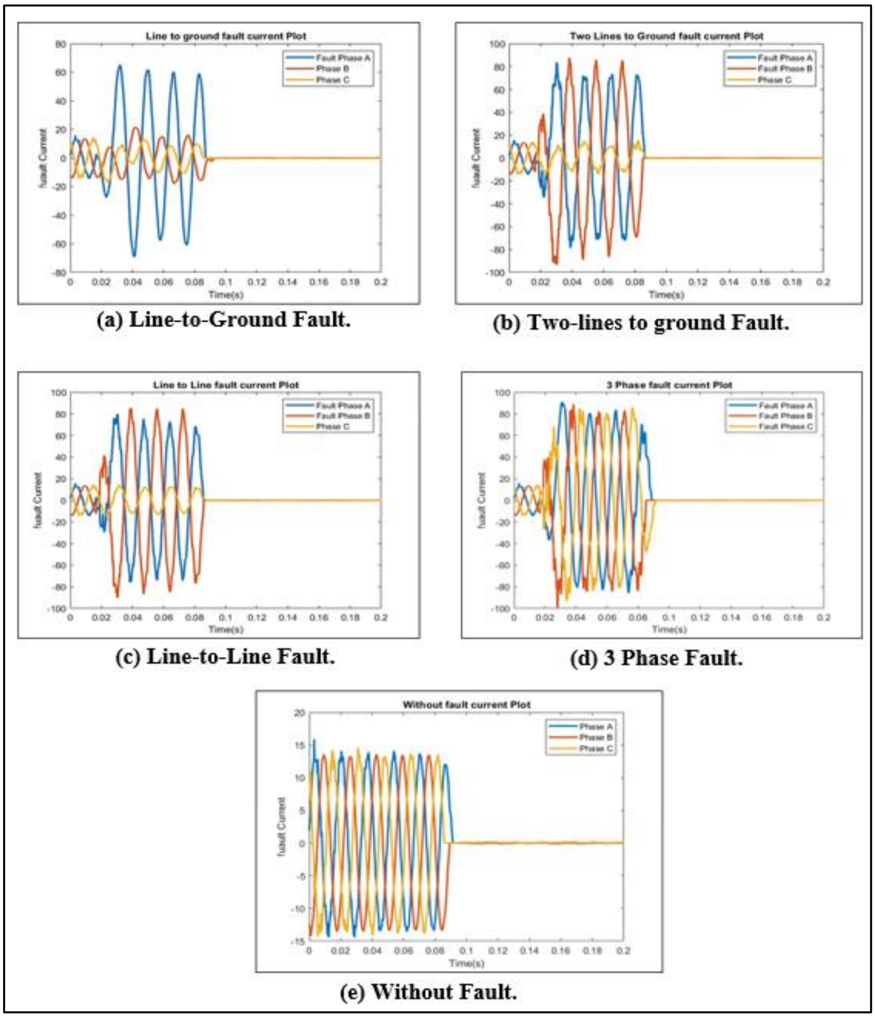


Fig. 2. Fault Breaker [26].

Based on Fig. 3 (c), when the fault to Phase A and B Phase C has a phase difference of 180 $degrees$. In this case, the fault current for the fault Phases increases suddenly, which is over 15 (as seen in Fig. 3 (e)) compared to the no-fault condition. Similarly, as seen in Fig. 3 (b), the fault on phases A and B records a high fault current during the fault time compared to phase C from MATLAB. This explains the Two lines to Ground fault. Further, when the 3-phase fault occurs, the fault current spikes out of the limit, a high-short circuit fault, as seen in Fig. 3 (d).



(a) Line-to-Ground Fault.

(b) Two-lines to ground Fault.

(c) Line-to-Line Fault.

(d) 3 Phase Fault.

(e) Without Fault.

Fig. 3. Fault current variation.

3.2 Wavelet transforms for feature extraction of the faults.

The approach utilized in the paper involves using Wavelet transforms for breaking down the zero sequences current signal of a fault simulated at $B2$ as seen in Fig. 2 [27]. This method is effective in dealing with abrupt and nonlinear signals. To maintain the fault information's accuracy following the decomposition process, the paper employs the modular maximum matrix (Eq. (2)) to identify the appropriate decomposition scale. Additionally, the energy value, i.e., Eq. (1), is employed to compute the energy value of each frequency band and develop a fault characteristic matrix (F_{ij}). This matrix represents the unique features of four types of faults, thus aiding in their precise identification.

In this study, db6 is considered a wavelet function, and features are extracted to 3 levels. The idea of wavelet transform is considered from Multilevel 1-D discrete wavelet transform. The input current is divided into components ($CA1, CA2$) and further divided into 3 levels ($CA3$) as seen in Fig. 4. If s is the input signal and analyzed till j level the following tree is generated.

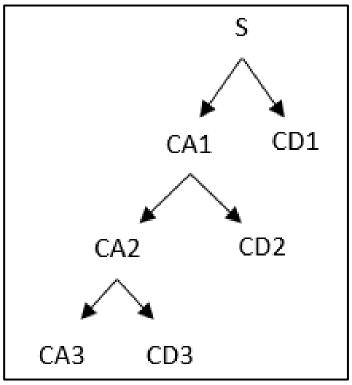


Fig. 4. Structure of Wavelet Decomposition

Finally, the approximation coefficient from Fig. 4 is considered as a feature. Considering this, the original signal dimension is 4001, and after decomposition, up to 3 levels, the approximation coefficient is 509 (features). These features are trained using IAOA-optimized LSTM.

3.3 Optimizing LSTM model parameters using an improved arithmetic optimization algorithm (IAOA)

The proposed model for training in this work is the LSTM. This recurrent neural network (RNN) type is designed to process data sequences with long-term dependencies [28]. Unlike traditional RNNs, which can suffer from problems with vanishing or exploding gradients, LSTM models include input, forget, and output gates that control the flow of information through the network, as seen in Fig. 1. Mathematical representation and working are seen in [28]. As discussed above, it is suggested that if the subjective choices made in determining the LSTM model parameters are not optimal, then the model's performance in detecting faults may also be less effective. The meta-heuristics algorithm improved- AOA (IAOA) is considered for finding the optimal model parameter value to reduce the error of the LSTM model.

The improved Arithmetic Optimization Algorithm (IAOA) is used to optimize the hyperparameters of an LSTM network to minimize the network's error, which is measured using the root mean square error as seen in Fig. 1. The generic view of LSTM can be given as, The LSTM takes in a sequence of input values, denoted by $x(t)$ or the output of a convolutional neural network (CNN). Both $h(t-1)$ and $c(t-1)$ come from the LSTM used in the preceding timestep. For this timestep, the LSTM's output is denoted by $o(t)$. The LSTM also produces the $c(t)$ and $h(t)$ that the subsequent time step LSTM will use as input.

The forget gate can be explained as,

$$f_t = \sigma_g(W_f * x_t + U_f * h_{t-1} + b_f) \tag{3}$$

The input gate and the output gate are explained as,

$$i_t = \sigma_g(W_i * x_t + U_i * h_{t-1} + b_i) \quad (4)$$

$$o_t = \sigma_g(W_o * x_t + U_o * h_{t-1} + b_o) \quad (5)$$

The cell state and Hidden state is given as,

$$c'_t = f_t.c_{t-1} + i_t.c'_t \quad (6)$$

Whereas $c'_t = \sigma_c(W_c * x_t + U_c * h_{t-1} + b_c)$ (7)

$$h_t = o_t.\sigma_c(c_t) \quad (8)$$

In these equations, sigmoid and tanh is given as σ_g and σ_c. The weights and bias matrices are given as $W_f, W_i, W_o, W_c, U_f, U_i, U_o, U_c$ and b_f, b_i, b_o, b_c.

The optimized hyperparameters include the number of hidden layers, epochs, and learning rates. During the algorithmic exploration phase, the IAOA algorithm employs a cognitive factor (a), in addition to multiplication and division strategies as seen in Eq. (4), to improve the spread of solutions and boost global search. This prevents the algorithm from being prematurely convergent, hindering its search for the optimal solution. The mathematical formulation of IAOA is given as the coefficient Math Optimizer Accelerated (MOA) is given as in [27].

$$MOA(t_c) = min + t_c \times (\frac{max - min}{t_m}) \quad (9)$$

whereas t_c is the current iteration and t_m is the maximum iteration, as seen in Fig.1. Max and Min denote the accelerated function of maximum and minimum value.

The exploration phase is improved, as seen in Eq. (10),

$$h_{i,j}(t_c + 1) = \begin{cases} a \times \left(best(h_j) \div MOP + \epsilon\right) \times ((UB_j - LB_j) \times \mu + LB_j)) \\ \quad +(1 - a) \times \left(best(h_j) - local(j)\right), \; if \; r_2 < 0.5 \\ best(h_j) \times \left((UB_j - LB_j) \times \mu + LB_j\right) \times MOP, else \end{cases} \quad (10)$$

Whereas MOP is given as,

$$MOP(t_c) = 1 - \frac{t_c^{\frac{1}{\alpha}}}{t_m^{\frac{1}{\alpha}}} \quad (11)$$

where $x_{i,j}(C_{iter} + 1)$ defines the ith solution in the next iteration, $x_{i,j}(C_{iter})$ denotes the jth position of the ith solution at the current iteration, UB_j and LB_j denotes the upper bound and lower bound value of jth position. The exploitation phase is explained in [29].

However, as seen in Fig.1, when the condition is satisfied ($t_c > t_m$), the optimal parameters are generated and fed to the model for training. The parameters obtained (best solution obtained) are fed through the fitness function to continue the predictions until the process is converged. The Pseudo code for IAOA is explained in Appendix A. Finally, the model is evaluated based on the prediction accuracy and time taken for training for a different setting of fault distances and phase angles.

4. Results and Evaluation

The effectiveness of the proposed method has been demonstrated through simulations using MATLAB, and the transmission line is modelled as [24][25].

4.1 Simulation environment

This is a single-line of a $735\ kV$, three-phase, $60\ Hz$ power system that transfers energy from a power plant with $6\ 350\ MVA$ generators to an equivalent system located 600 kilometers away. Buses $B1, B2$, and $B3$ are connected to the transmission line via separate $300\ km$ lines. The transmission line parameters are seen in Table 2 [25]. Based on the simulated transmission line, the four faults are analyzed.

Table 2. Parameter Specification of Three-phase Series Compensation Network.

Parameter	Value
Shunt compensation	300 Mvar
Shunt Reactance	330 Mvar
Transformer	300 MVA, 73 5/230 kV
Tertiary Winding	25 kV
Load	230 kV, 250 MW
Series Capacitor	Included in each phase of the series compensation module
Generator Model	Simplified Synchronous Machine block
Transformer Model	Universal transformer blocks (two-windings and three-windings)
Saturation	Implemented on transformer connected at bus $B2$
Measurement Locations	B1, B2, and B3 blocks
Type of Faults	Line-to-ground fault, line-to-line fault, Two-line-to-ground fault, three-phase Fault, and No-fault condition

4.2 Simulation of LSTM model with IAOA technique

The input to the network is a sequence of features represented by a $sequenceInputLayer$. The number of hidden units in the LSTM layer is set by $Best\_P(1)$, which is defined as 183 in this case. The output of the LSTM layer is connected to a fully connected layer, which maps the LSTM output to the number of output classes. The output of the fully connected layer is then fed to a $softmaxLayer$ for classification. The parameters are detailed in Table 3.

Table 3. Hyper-parameter specification of LSTM Model

Parameter	Value
Best from IAOA	[183, 0.001, 2000]
Num Hidden Units	183
Mini batch Size	128
Learning rate	0.001
Max epoch	2000

The experimental results demonstrate the effectiveness of the proposed IAOA-LSTM model for fault detection and classification. After feature extraction, 509 samples were available for each fault condition, including the non-fault condition, resulting in a dataset of 2545 samples. Among these samples, 2036 (80%) were used to train the model, while the remaining samples were used for validation. After feature extraction, there were 509 samples for each fault (including the non-fault condition), as seen in Table 2. Which is 2545 samples, out of which 2036 samples are considered for training the IAOA-LSTM model (80%), and the remaining samples are considered for validation. The simulated model for 2000 epochs is evaluated based on accuracy and loss, as shown in Fig. 5.

The performance of the IAOA-LSTM model was evaluated over 2000 epochs, focusing on accuracy and loss metrics. Fig. 5 illustrates the model's training progress, showcasing the accuracy and loss values across 1400 iterations. Notably, a high learning rate can lead to the problem of exploding gradients, causing difficulties in effectively training the model and impacting accuracy. However, the proposed IAOA algorithm (Appendix A) effectively addresses this concern by providing optimal hyperparameters for the LSTM model, as shown in Table 3.

As observed in Fig. 5, the IAOA-LSTM model consistently achieved an accuracy of 99.9% throughout the training process. This remarkable accuracy demonstrates the model's capability to effectively detect and classify different types of faults in the power transmission system. Moreover, the loss value remained negligible at 0.0010, indicating minimal discrepancies between the predicted and actual values.

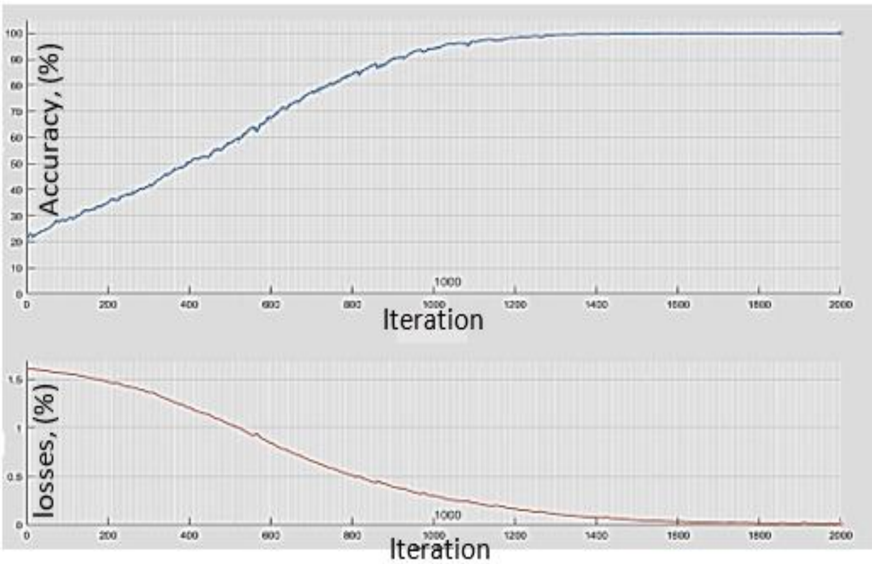


Fig. 5. Progress of LSTM model based on Accuracy and Loss.

In the case of LSTM models, a high learning rate can also cause the gradients to explode, leading to the problem of exploding gradients [30]. This can make it difficult to train the model effectively and cause accuracy to suffer. Hence, IAOA is employed in this paper to provide the optimal hyperparameter of the LSTM model, as seen in Table 2. Due to this, the output in Fig. 5 shows the training progress over 1400 iterations and maintains an accuracy of 100% and negligible loss of 0.0010. Eventually, the accuracy and loss will be reasonable as the training iteration converges.

The convergence of accuracy and loss metrics over the training iterations signifies the robustness and stability of the IAOA-LSTM model. It can be inferred that the model has successfully learned the underlying patterns and features of the dataset, leading to reliable fault detection and classification performance. The high accuracy and negligible loss values demonstrate the model's ability to generalize well to unseen samples and make accurate predictions.

The quantitative analysis of the results further supports the effectiveness of the proposed approach. Significant performance improvements were achieved by leveraging the IAOA algorithm to optimize the LSTM model's hyperparameters. The model's accuracy reaching 99.99% indicates its capability to correctly identify and classify various faults in the power transmission system. The negligible loss value further highlights the model's accuracy in predicting fault conditions accurately.

In conclusion, the experimental evaluation results demonstrate the IAOA-LSTM model's superiority in fault detection and classification. The model consistently achieved high accuracy, and the negligible loss values indicate its ability to handle the complexities of the power transmission system effectively. The proposed approach provides a robust and reliable solution for detecting and classifying faults, thereby reducing downtime and losses in industrial applications.

4.3 State-of-the-art Comparison of Proposed with Various Studies

Based on Table 4, the proposed model has achieved the highest accuracy of 99.99% with the lowest loss of 0.0010 among all the listed models. However, it is important to note that the fault distance in the proposed model is the furthest among all the models at 300km, and the IAOA method is employed for the optimal selection of hyperparameters, which could contribute to its higher accuracy. As seen in [31], the paper suggests using Grid search CV for a similar purpose. However, compared to [31], the proposed model shows a 0.03% improvement in accuracy with higher fault distance.

Compared to the model [32], the proposed model shows an improvement of 2.33% in accuracy and a decrease in the loss by 2400. while compared to the model [33], the proposed model has improved accuracy by 1.85% without providing information about the loss. In Table 4, 0.54% and 0.55% of improvement in accuracy is seen when compared to Model [34][31]. The fault distance of the models in [34][31] is less when compared to the proposed model. The proposed model is a competitive state-of-the-art method for fault diagnosis, particularly for faults occurring at long distances.

Table 4. Comparative Analysis of Various Studies.

Author	Method used	Fault distance	Samples	Accuracy (%)	Loss	Comparison
Current model	Wavelet decomposition for feature extraction and IAOA-LSTM for fault classification.	300 km	2545 samples	99.99	0.0010	Provides high accuracy compared to other models
Appaih et al. [31]	A machine learning model is used for Transmission line Fault classification. 4-level wavelet decomposition is applied for feature extraction, and Grid-search CV is applied for finding optimal hyperparameters.	99 km	-	99.46	-	The proposed model shows 0.03% of improvement in accuracy with higher fault distance.
Ou et al. [32]	The extracted features from the LSTM are then fed into a SoftMax regression classifier for fault diagnosis.	-	2240 cases of Line-to-line fault, 1961 samples of Hot spot fault and 1866 samples of normal condition	97.66	0.025	The proposed model shows a 2.33% of improvement in accuracy and 0.24 reduction in loss with more samples than [32]
Elmasry and Wadi [33]	Fitness Proportionate Selection of Binary Particle Swarm Optimization and Entropy (FPSBPSO-E) algorithm and a bagging ensemble system are deployed from three different deep learning which include LSTM+RNN and Double PSO (Particle Swarm Optimization is used for hyperparameter optimization).	Electric grid operating at 50Hz	8712 samples	98.14	-	Compared to the model [33] the proposed model has achieved an improvement in accuracy of 1.85% with 0.001 of loss.
Rafique et al. [34]	LSTM model is implemented for end-to-end classification of the fault and tested on WSCC-9 bus system	25 km	27000 samples	99.45	-	The proposed model shows a 0.54% improvement in accuracy with a 0.001 loss.

5. Conclusions

The proposed approach using the fine-tuned LSTM model and dbN wavelet transform for fault detection and classification in transmission lines has shown to be a promising and effective method. The MATLAB simulation results demonstrate the proposed method's high accuracy, quick identification, and robust adaptability in identifying five types of faults. Implementing the IAOA algorithm for hyperparameter optimization and model error reduction has also demonstrated its ability to improve the accuracy of the LSTM model further. Therefore, the proposed approach can contribute significantly to developing more advanced and efficient protection systems for power transmission lines, ultimately ensuring the stability and reliability of power systems.

Further studies can explore the potential of the proposed method on a larger dataset with more complex scenarios and investigate its applicability in real-world power systems. Future studies can explore the potential of the proposed method on a larger dataset encompassing more complex scenarios, allowing for a comprehensive evaluation of its performance. Additionally, investigating the applicability of the proposed approach in real-world power systems would provide valuable insights into its practicality and scalability.

To quantify the main research findings, it is essential to present specific performance metrics such as accuracy, precision, recall, or F1-score for each fault type. These metrics would provide a quantitative evaluation of the proposed method's efficacy and allow for a direct comparison with existing approaches in the field.

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Appendix A

Pseudocode

Algorithm 1: Pseudo code of IAOA

Start IAOA parameters β, σ, set of values for $number\ of\ hidden\ layer$, $Mini\ batchsize, learning\ rate\ and$ max $Epoch$.
Start the outcomes position arbitrarily.
($best\ Outcomes$ (y): $number\ of\ hidden\ layer$, $Mini\ batchsize, learning\ rate\ and$ max $Epoch$).
While (current iteration< maximum iteration):
For the provided solution calculate the evaluation function.
Get the ideal response.
Applying Eq. (9), modify the math optimizer acceleration (MOA) value.
Applying Eq. (11), modify the math optimizer probability (MOP) value.
For ($i = 1\ to\ Outcomes$) do
For ($j = 1\ to\ Location$) do
Make a random range of values within [0,1] ($r1, r2, and\ \ r3$)
If $r1 > MOA$ then
// Exploration phase
If $r2 > 0.5$ then
Employ the Division procedure (D " $\div$ ")
Update the *i*th outcome location by employing first rule in equation (9)
Else
Employ the multiplication procedure (M " $\times$ ").
Upgrade the *i*th outcome location utilizing the second rule in equation (11)
End if
Else
//Exploitation phase
If $r3 > 0.5$ then
Employ the Subtraction procedure.
Upgrade the ith outcome location utilizing $1st$ rule equation (10)
Else
Employ the addition procedure (A "+").
Upgrade the ith outcome location utilizing the $2nd$ rule equation (10)
End
End for
$C_{Iter} = C_{Iter} + 1$
End while
Return to possible best outcome (y)