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Optimizing fault diagnosis in variable load conditions: A machine and deep learning approach for voltage source inverters

Vaishali R. Sonawane,[1,2*] Sanjay. B. Patil,[3] Omprakash S. Rajankar,[4] Seema Idhate[5]

[1]Sinhgad college of Engineering, Vadgaon, Pune. India. [2]Department of E&TC, Smt Kashibai College of Engineering, Vadgaon, Pune. India. [3]Rajgad Dnyanpeeth's Shree Chhatrapati Shivajiraje College of Engineering, Dhangwadi, Pune. India. [4]Dhole Patil College of Engineering, Pune. India. [5]School of Computer Engineering and Technology, MITWPU Pune. India.

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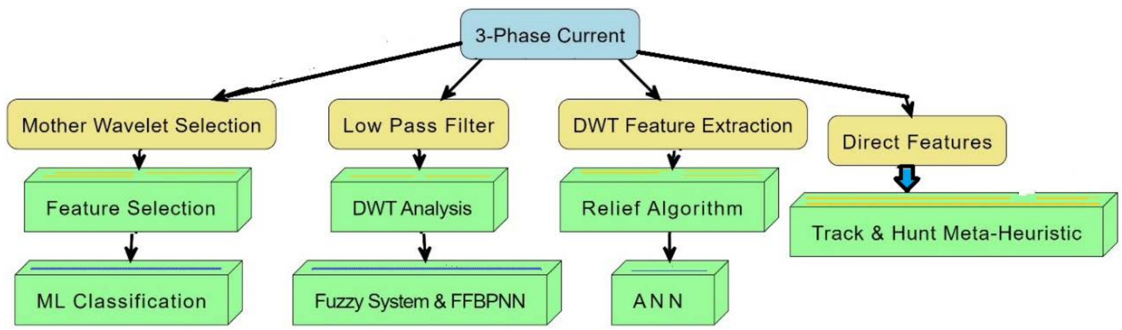
Article

ABSTRACT



This study investigates industrial three-phase voltage source inverters (VSI) diagnostics. The system assesses and suggests a novel approach. The research finishes with developing a novel problem-detection tool that identifies individual and multiple open switches and adjusts to various loads. This approach utilizes feature selection and machine learning algorithms to classify issues based on load conditions, aiming to enhance intelligence and performance by leveraging historical data and real-time operational conditions. An in-depth analysis of VSI fault diagnostics is conducted, encompassing preventive measures and sophisticated control techniques to enhance reliability. The utilization of DWT analysis for feature extraction and machine learning classifiers is recommended to identify challenges encountered in three-phase induction motors. The thesis concludes with implementing the Track and Hunt optimization-based Deep Neural Network. The methodology demonstrates a greater ability to anticipate faults than existing diagnostic approaches under various load circumstances. The simulation findings confirm the efficiency of the suggested system in precisely identifying faults, even in dynamic operational circumstances.

Keywords: Deep Neural Network, DWT, Fault diagnosis, Track and Hunt optimization, Voltage Source Inverter

INTRODUCTION

In industrial applications, fault detection for three-phase Voltage Source Inverters (VSIs) is essential for electrical system dependability. We discover and rectify faults before they affect VSI performance and durability, protecting industrial operations and reducing downtime.[1] The study will compare three-phase VSI fault diagnostic systems. It provides a new diagnostic approach that can identify open switches in all three stages of a VSI and readily react to varying loads to overcome present method shortcomings. The study solved variable load concerns, rendering fault identification methods useless. Load conditions affect problem detection and classification in the recommended fault diagnostic technique. The old method struggled to adjust threshold values to load circumstances, but the new one does. Due to industrial load changes, diagnosis of real-world issues requires adaptability. Switching device open switch failure diagnosis methods are reviewed in the study. Diagnostic methods are evaluated for effectiveness, resistance, detection time, implementation issues, and threshold dependence. This evaluation reveals that an easy-to-implement system that detects single- and double-switch Open Circuit (OC) failures independent of threshold is essential.[2]

The motivation behind this research stems from the critical need to enhance the reliability and intelligence of fault diagnostics in industrial three-phase VSIs, which are integral to various industrial applications. Traditional diagnostic methods often fall short in dynamic operational environments and diverse load conditions. This study introduces a novel approach that leverages Discrete Wavelet Transform (DWT) for feature extraction and machine

*Corresponding Author: Vaishali Sonawane, SCOE, Vadgaon.
Tel: +91-9881431811; Email: vaishali.baste@gmail.com

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learning classifiers to identify and categorize faults accurately. Incorporating a Track and Hunt optimization-based Deep Neural Network further distinguishes this method by significantly improving fault anticipation capabilities. This innovative approach adapts to different load conditions and demonstrates superior performance in simulation tests, marking a substantial advancement over conventional diagnostic techniques.

LITERATURE SURVEY

A Convolutional Neural Network (CNN) model to detect failures in industrial cascaded Multilevel Inverters have been implemented earlier studies.[3] The faults' precise localization is achieved using SIFT, a two-stage PDE segmentation technique, and the Adaptive Hilbert-Huang Transform. A CNN classifier adjusted for CSA is used. The technique have been tested with single-, multiple-, and SC MLI faults. The CSA-CNN approach is compared to existing classifiers. Simulations show 99.84% classification accuracy using CSA-CNN. Since it accurately detects MLI difficulties, the CSA-CNN method is suited for industrial applications.[3] The VSI can be used for detecting three-phase VSIOC faults. Troubleshooting entails finding the problem. Power converter defect diagnostics uses Discrete Wavelet Transform, Park's Vector Transform, Artificial Neural Networks, and Fuzzy Logic. These methodologies are necessary for training a machine learning algorithm to extract and select features.[4]

Converter flaws are detectable in numerous ways. Traditional fault diagnostic methods, such as manual examination and professional knowledge, are costly and time-consuming. With AI's development, data-driven methods are common. This study categorized home wind turbine converter issues using diode rectifiers to convert AC to DC. A boost stage, uncontrolled three-phase rectifier, and wind emulator analyze MATLAB model data, including normal mode defects. Python linked input-output parameters. Wind turbines must be optimized as renewable energy grows, and downtime must be decreased. Over 30% of wind turbine failures are due to converter and semiconductor device failures.[5] A cost-effective solution is needed.

Due to their durability and inexpensive maintenance, induction motors are essential in nuclear and radiological facilities and industrial drive systems. Though reliable, the systems need occasional maintenance. One issue is the building's unreliable electricity system. Unstable HVAC systems can endanger operations and cause other disasters. Air instability in the HVAC system worries the radiopharmacy business. Safety and regulation require controlled environments. Maintaining air quality and radioactive material safety requires constant attention. The study used simulated electric data to produce motor condition datasets. Better dependability and lower risks necessitate fault diagnosis. This study uses machine learning to introduce a cost-effective, reliable, user-friendly induction motor defect classifier.[6]

MMC-HVDC fault detection and classification are difficult. A single SoftMax classifier and two deep learning algorithms (CNN and AE-based DNN) identified and categorized defects. This article recommends using raw current sensor data to identify and categorize MMC-HVDC problems. PSCAD/EMTDC simulations show that all three approaches have detection accuracies > 99.7%. The CNN is somewhat less accurate than the solo SoftMax classifier, which scores 100. Three efficient techniques with low variability and high classification precision. The SoftMax classifier tests more quickly and accurately than CNN, despite CNN having the shortest training time.[7]

This paper provides a unique Model-View-Controller (MVC) framework based on Multi-Class Support Vector Machine (MCSVM) for fault localization and classification in research nuclear reactors. ATP/EMTP simulates many faults with different locations and conditions to create input data. The combination of DFRFT, SVD, and MCSVM improves the effectiveness of the classification and localization procedures. The classification efficiency is influenced by the rotation angle of DFRFT, which varies based on its value. We classified using RBF, SVM linear, and quadratic kernels. The quadratic kernel is the most cost-effective since it effectively separates classes on the quadratic plane. DFRFT factors suggest quadratic and linear kernels work best with 0.5 factors. Execution time is mostly affected by kernel complexity. The fastest and most efficient kernel is the linear kernel, at 0.01 seconds and 99.8%. It is capable of handling faults at various beginning angles, resistances, and locations. The maximum fault location error, inception angle, and fault resistance at the MVC receiving end are 0.525789%, 900 degrees, and 200, respectively. Advanced fault locators that are dependable and fast may employ MCSVM.[8]

Existing studies have advanced fault detection methods for various industrial systems, such as CNN models with sophisticated feature extraction for multilevel inverters and machine learning for VSI OC faults. Nevertheless, they frequently necessitate human involvement and are not consistently cost-efficient or adaptable to changing load conditions. In addition, although techniques such as SoftMax classifiers and deep learning for MMC-HVDC systems demonstrate excellent levels of accuracy, they may not comprehensively tackle the intricacies of diverse operational conditions. Therefore, there is a need for a comprehensive and adaptable diagnostic tool for three-phase VSIs that can effectively handle various load circumstances and offer exceptional fault foresight. This study addresses this deficiency by combining DWT for feature extraction with a Track and Hunt optimization-based DNN, providing a more intelligent, adaptable, and dependable solution.

PROPOSED DESIGN

Three-phase VSIs can be fault-diagnosed using four ways in the described system.

OC Fault Diagnosis in VSI using DWT and ML Approach

This process uses machine learning and the DWT to identify OC problems in VSIs accurately. Due to their susceptibility to failure, industrial VSIs that convert direct current (DC) to alternating current (AC) require precise fault diagnosis (FD) through the use of current signal analysis.[9] It is essential to use knowledge-based fault diagnosis techniques (K-FDMs), which combine qualitative and quantitative methods. Expert-based approaches offer subjective perspectives as opposed to quantitative methods.

System performance is reduced by non-crashing OC failures (OCFs). The Park's Vector Transform (PVT) identifies Orthogonal Component Frames (OCFs) through the analysis of Alternating Current (AC) vectors.[10] Under varying levels of stress, the diagnosis of OCF can be achieved by many methods. Utilizing real-time monitoring with DWT may effectively detect instances of OCF and pinpoint the issue. Expertise is necessary for formulating and validating hypotheses in FD.[11] The advantages and disadvantages of automated fault detection systems such as CSA, PCA, PVT, DWT, FL, and ANN differ.[12] Figure 1 depicts the application of machine learning for diagnosing OC faults.

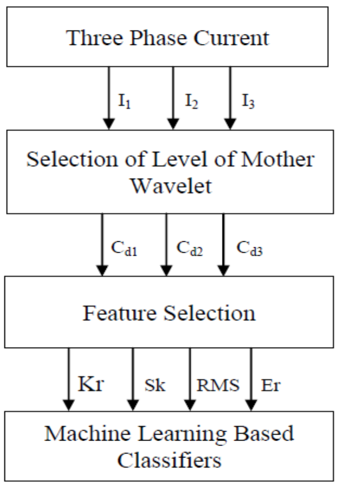


Figure 1. Methodology for OC Fault Diagnosis using ML algorithm

The Wavelet Transform is a useful tool for detecting flaws in signals that are not constant over time, such as currents. It excels in extracting features from signals with varying statistical properties compared to Ordinary Fourier analysis.[13] The Wavelet Transform can adjust its time-frequency resolution by modifying the dilation and translation of the basic band-pass function, which is a capability that the STFT lacks. The ability to adapt and change makes it a very effective tool for detecting defects in electrical systems through dynamic signal analysis.[14]

The literature examines several methods for analyzing signals in the frequency domain. The many mother wavelets of DWT enable users to analyze the same data from several perspectives. This facilitates the process of selecting the mother wavelet. The DWT using the Daubechies (DB) mother wavelet effectively addresses problems related to switching devices. The mother wavelet is capable of providing frequency-domain Detail Coefficients.[15,16] The mother wavelet offers distinctive features for the ultimate analysis. Characteristics Fault diagnosis utilizes characteristics. Machine learning techniques have effectively assessed classifiers for fault diagnosis.[17]

Open Switch Fault diagnosis in 3ΦVSI using ANN and FIS

These fault detection systems determine the impact of open switch failures on inverter performance and enable corrective measures.[18] The Wavelet Transform is utilized in contemporary fault diagnostic systems to extract characteristics, employing Fuzzy Logic (FL) and Artificial Neural Networks. The study investigates the impact of mother wavelet and decomposition levels on fault identification utilizing time domain waveforms, specifically focusing on WT-FL and WT-ANN FDSs.

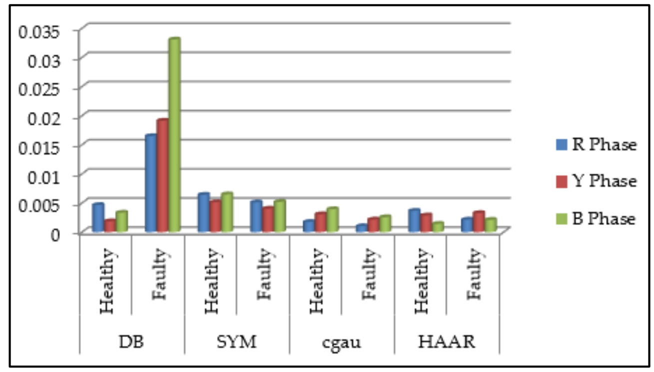


Figure 2. Analysis of Waveform using DB 2 at level 2

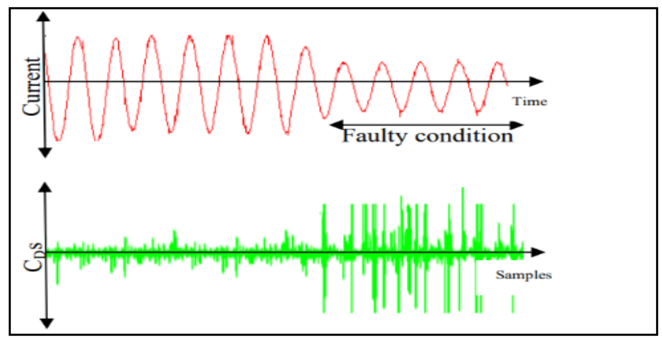


Figure 3. Analysis of Waveform using DB 2 at level 2

Defect detection entails identifying flaws without understanding their cause. DWT is used in modern vibration and current analysis. In order to find defects, the DWT converts 1D non-stationary signals into 2D using high-frequency and low-frequency components.[19,20] Many wavelet kernels emphasize the parental wavelet and determine breakdown. Decomposition depends on data quality and mother wavelet properties. DWT and other innovative technologies are needed to diagnose complex signals for issue detection.[21,22] Figure 4 shows a broken three-phase VSI output waveform.

Figure 4. Detail Coefficients at different faulty conditions

FL-FD effectively manages intricate system uncertainty. Rule-based Fuzzy Logic Controllers (FLCs) utilize heuristics or expert knowledge to handle signals. Uncertainty is increased when clean inputs produce fuzzy values.[23] The fuzzy rules of the inference engine provide the system's diagnostic. Applying the process of defuzzification to this output can assist in identifying problems in complex and dynamic systems.

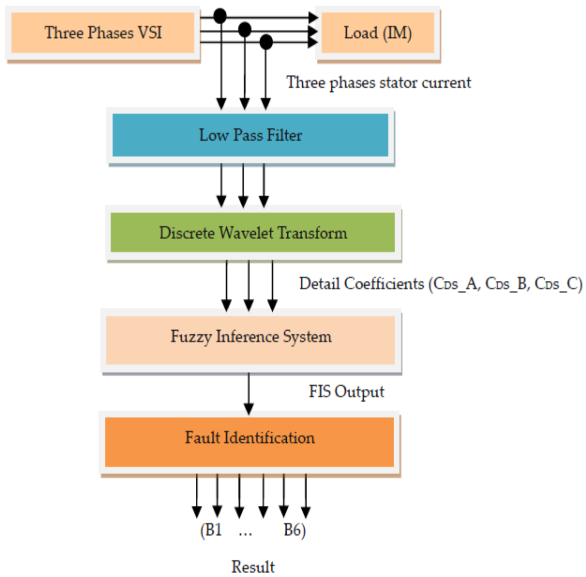


Figure 5. Block diagram of FL-FD system

Figure 5 illustrates the block diagram of the FL-FD system. The technique utilizes advanced artificial neural networks. Neural network block diagrams establish connections between different layers. The input layer receives signals from the system. Data processing includes intricate algorithms, concealed layers, and weighted linkages. During training, weights and biases are adjusted to enhance performance. Patterns aid in the categorization or diagnosis of the output layer. The provided block diagram illustrates the neural network's independent learning and decision-making process, highlighting NN-FD as a robust tool for defect diagnosis. We utilize the "6-25-6" artificial neural network. The network's input layer comprises six neurons, which receive six variables as input. The system performs intricate computations and extracts data using a network of 25 neurons. The complexity and ability to recognize patterns of this hidden layer are evidenced by its fifty-five neurons. Six neurons in the final layer provide attributes, groupings, and categorizations for six dimensions.

Current Signature Analysis of OC Fault Diagnosis in 3Φ VSI under Variable Load Conditions

This study uses Artificial Neural Networks (ANN) to investigate the dynamics of altering load current waveforms. The performance of an ANN classifier is contingent upon selecting an appropriate Mother Wavelet (MW) and using Relief F for feature selection.[24,25] The process of diagnosing faults segment-by-segment considers the factors of signal, sampling, and segment length. Reliable analysis is guaranteed. Including detail coefficients in feature extraction facilitates the training and evaluation of artificial neural networks.[26]

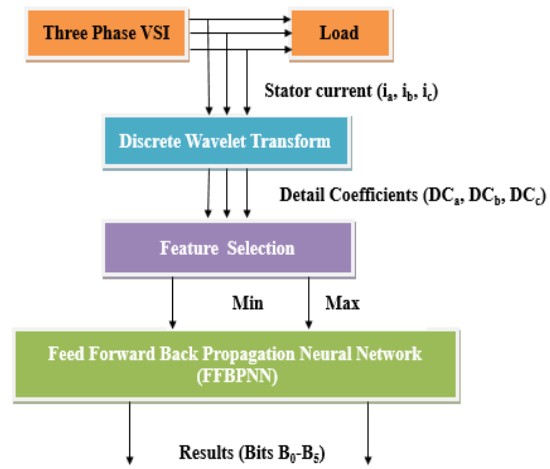


Figure 6. Block diagram of NN-FD system

Table 1: Pilot Experimentation Input Conditions

Conditions	IGBTs
Healthy	All IGBTs Healthy
Single Switch OCFs	T1, T2, T3, T4, T5 and T6
Double Switch OCFs	T1-T3, T1-T6,
Phase OCFs	T1-T4

Table 1 presents the pilot study settings for the fault diagnostic model of a three-phase VSI system. After the "Healthy Condition" stage, single and double switches and phases experience failures due toOCs. By modifying failure situations, we may evaluate the accuracy and resilience of the model.

Proposed Track and hunt met heuristic-basedDNN-based fault diagnosis model for the VSI under varying load conditions

This approach employs DNNs and the Track and Hunt metaheuristic to diagnose VSIs in dynamic load conditions. A hybrid algorithm extracts characteristics from intentionally generated faults. The model's load-adaptability is assessed by testing accuracy, precision, recall, F1 measure, and mean squared error. The research is significant because of the hybrid algorithm's ability to balance exploration and exploitation, resulting in reliable defect prediction. Figure 7 illustrates the block diagram of the defect detection system that relies on DNN.

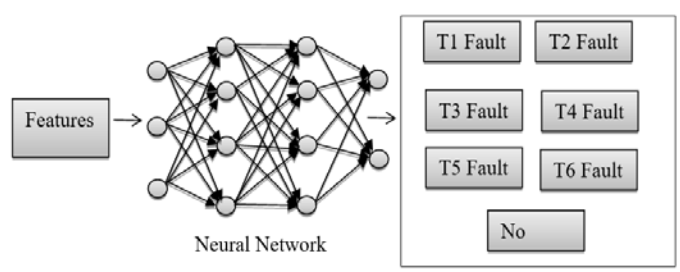


Figure 7. DNN for fault prediction

- Social grading: The alpha, beta, delta, and omega canis species are classified using fitness solutions. The alpha, beta, and delta canis direct the hunting process under the proposed optimization, with the omega canis taking the last position in the pack following the first three canis.

- Surrounding: The method of hunting involves surrounding the prey, and the equations (1) and (2) below represent how the canis behaves when it is in its immediate environment,

$$\vec{K} = |\vec{O}.\vec{J}_e(T) - \vec{J}(T)| \quad (1)$$

$$\vec{J}(T+1) = \vec{J}_e(T) - \vec{L} \cdot \vec{K} \quad (2)$$

- Hunting: Prey position identification led by alpha canis. Alpha canis directs hunting in the pack. Beta and delta canis seldom join the hunt. Mathematical modeling aids in finding optimum solutions.[27] Alpha represents the decision-making candidate. Beta and delta have better knowledge. The top three agents canis influence omega in the pack

$$\vec{K}_\alpha = |\vec{O}_1 \cdot \vec{J}_\alpha - \vec{J}|, \vec{K}_\beta = |\vec{O}_2 \cdot \vec{J}_\beta - \vec{J}|, \vec{K}_\delta = |\vec{O}_3 \cdot \vec{J}_\delta - \vec{J}| (3)$$

$$\vec{J}_1 = \vec{J}_\alpha - \vec{L}_1 \cdot (\vec{K}_\alpha), \vec{J}_2 = \vec{J}_\beta - \vec{L}_2 \cdot (\vec{K}_\beta), \vec{J}_3 = \vec{J}_\delta - \vec{L}_3 \cdot (\vec{K}_\delta) (4)$$

$$\vec{J}(T+1) = \frac{\vec{J}_1 + \vec{J}_2 + \vec{J}_3}{3} \quad (5)$$

The precise coordinates of alpha, beta, and delta canis can determine where the prey is captured in the foraging area. This site is investigated within a randomly selected set of houses arranged in a circular pattern. Furthermore, the position is determined by the guidance of the alpha, beta, and delta canis members within the pack, who are close to the prey.

- Capturing prey: Canis attempt to catch prey when it remains stationary. The mathematical model uses coefficient vectors with components. The fluctuation range of the coefficient vector is decreased by reducing the value of 'w.' Random value 'w' lies within the range [-2w, 2w]. 'w' decreases from 2 to 0 during iterations. Discovering the agent's location depends on the prey and current position.
- Discovering phase: Search for prey based on alpha, beta, and delta canis positions. Canisdiverges from the group for hunting. While hunting, go close to the group. The behavior of divergence is affected by coefficient vectors. If either L<1 or L<-1, then divergence happens.
- Enhancing phase. By using Felidae's position-renovating concepts for improved performance, the canis exploration phase is improved. Using the equation, the leader canis alpha's position update is stopped.

$$`J^{T+1} = J^{T+1}_{Felidae} + J^{T+1}_{Canis} \quad (6)$$

- By applying equation (8), the leader canis alpha's position update is completed.

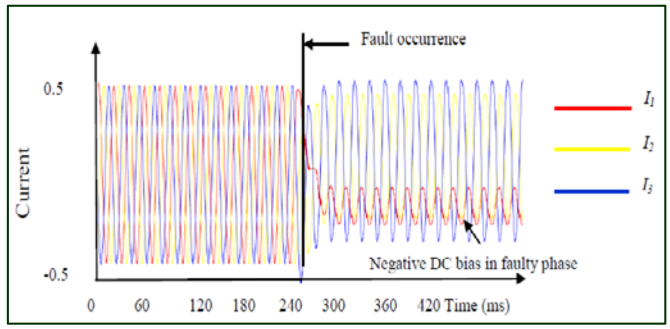
$$\alpha^{T+1} = 0.5\left[J_p^T + U_p^T + C_1 d_1\left(J^{best} - J_p^T\right)\right] + 0.5\left[\frac{J_1+J_2+J_3}{3} + U_p^{T+1}\right] \quad (7)$$

Results and Discussion

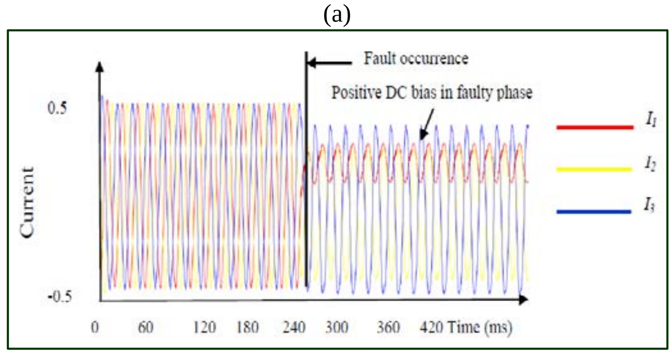
The outcomes of the techniques used to diagnose faults in three-phase VSIs are detailed in this section.

Results of OC Fault Diagnosis in VSI Using DWT and ML Approach

MATLAB-Simulink software is used to model the three-phase Pulse Width Modulation-VSI. An OCF can result from an IGBT collector terminal that is left unconnected in a VSI. This simulation archives data collected from normal and faulty conditions for future analysis.Figure 8 shows that the three-phase current will differ if OCF happens in VSI. If the IGBT malfunctions beyond Phase-1, the additional negative DC voltage applied to the Phase-1 current (I1) can be observed in Figure 8 (a). Furthermore, Figure 8 displays the positive DC voltage applied to the Phase-1 current (I1). (b) In the event of a failure in the Insulated Gate Bipolar Transistor (IGBT) associated with Phase-1.



(a)



(b)

Figure 8. GBT-T1 faulty condition (a) IGBT-T1 faulty condition. (b) (B) IGBT-T4 faulty condition

The collected current waveform is analyzed. The abovementioned characteristics are extracted using DB-1 to DB-5 mother wavelets for further analysis. DB-5 has better kurtosis and skewness than other mother wavelets but fails to distinguish good from terrible conditions. DB-1 benefits considerably from the remaining traits. After training Machine Learning algorithms with Max (Mx), Min (Mn), Median (Md), and Root Mean Square (RMS), the best classifier is identified.

Table 3 illustrates the results of testing multiple Machine Learning classifiers for defect diagnosis. These methods are implemented using 5-fold cross-validation. KNN, DT, LR, SVM, and ANN techniques are extensively tested and validated. Table 3 compares algorithms.

Table 3: Comparison of Different Classifiers

Classifier	Model Type	No. of splits	Accuracy
DT	Fine Tree	Splits=100	97.80
	Medium Tree	Splits=20	97.80
	Coarse Tree	Splits=4	97.80
LR	-	-	91.20
SVM	Linear	-	97.8
	Quadratic	-	97.8
	Cubic	-	97.8
	Fine Gaussian	-	97.8
	Medium Gaussian	-	97.8
	Coarse Gaussian	-	89.8
KNN	Fine	N=10	95.6
	Meduim	N=10	56.9
	Coarse	N=10	97.8
	Cosine	N=10	97.8
	Cubic	N=10	97.8
	Weighted	N=10	97.1
ANN	**18-10-1**	**-**	**99.6**

Wavelet transformers are effective for finding VSI switching device OC issues. The DB1 mother wavelet performs well with Max (Mx), Min (Mn), Median (Md), and Root Mean Square (RMS) characteristics. This proves that ANN is a great machine-learning algorithm. Choosing the Wavelet Transform analysis level may improve results and lead to new methods. Altering the ANN's structure, as described, can enhance accuracy.

Results of Open Switch Fault diagnosis in 3Φ Voltage Source Inverter using ANN and Fuzzy Inference System

Table 4 shows load scenario results. Both systems have high FDS accuracy under 1 mA load current since they are designed for it. Fuzzy membership functions must be modified for FL-FD load circumstances. NN-FD ANN architecture training requires data from varied load conditions. FL-FD and NN-FD accuracy evaluations are in Tables 4 and 5.

Table 4: Accuracy of FL-FD System

IGBT Device	1.2 mA	1 mA	0.75 mA
T1	70.73	64.63	66.6
T2	42.22	64.45	56.33
T3	37.50	57.67	49.69
T4	36.64	59.73	43.75
T5	46.60	57.69	55.96
T6	36.64	54.45	65.75
T1-T6	65.26	65.37	73.96
T1-T4	5.03	6.4	5.03
T1-T2	66.63	65.43	74.93
T3-T2	66.69	67.66	73.49
T3-T4	76.67	65.65	76.49
T3-T6	6.69	6.66	3.49
T5-T6	53.96	73.75	65.76
T5-T2	3.69	3.66	3.49
IGBT T5-T4	56.96	74.64	65.96
Total	**51.00**	**62.45**	**59.112**

Table 5: Accuracy ofNN-FD System

Fault	1.2 mA	1 mA	0.75 mA
T1	79.50	87.57	66.6
T2	53.33	74.35	66.33
T3	75.99	79.43	77.47
T4	76.43	77.77	73.75
T5	75.00	75.75	77.6
T6	75.75	76.36	65.75
T1-T6	79.09	77.30	76.40
T1-T4	91.59	99.5	92.94
T1-T2	73.46	86.74	74.76
T3-T2	76.00	77.57	74.3
T3-T4	34.5	67.34	49.69
T3-T6	66.55	76.04	76.5
T5-T6	65.55	78.04	56.5
T5-T2	75.49	86.70	77.04
T5-T4	71.84	80.33	71.26
Average	**71.84**	**80.33**	**71.26**

The following outcomes are observed from this method.

- Implementing Neural network fault Diagnosis requires sampling data from healthy and defective settings, considering hidden layer selection and learning rate. Reported accuracy is 80.33 percent.
- The results suggest that both Neural Network-Fault Diagnosis and Fuzzy Logic-Fault Diagnosis systems may perform effectively with the correct data or changes, but good data is hard to collect, especially when load or speed is unexpected.
- Normalizing non-stationary fault diagnostic characteristics can help models work under different settings. Artificial neural networks are harder to train than Fuzzy Logic.
- Despite their increased implementation complexity, both Fault Diagnosis systems have an advantage over other approaches in resistivity at small currents.

Results of Current Signature Analysis of OC Fault Diagnosis in 3Φ VSI under Variable Load Conditions

Understand crucial sensor data concerning non-stationary signals. This is achievable using DWT multilevel analysis. DWT is often used to gather time and frequency data. Table 6 compares extracted characteristics for each sample. In problematic situations, CSs reflect changes in $D\mathbf{O}\text{-}pf$ values. ESE ratios compare all MWs at various times during the breakdown process. Level one offers the highest amount of data for selecting wavelets and features. The DWT includes the following types of wavelets: Daubechies (DB), Coiflet, Symlet, HARR, DMEY, Biorthogonal, and Reverse Biorthogonal. Finding the maximum ESE ratio determines the optimum MW amount. This ratio is best for all wavelets at level 1.

The average ESE for each fault class and MW is graphically contrasted in Figure 9. The 18 statistical features that were previously collected are used to analyze the data that was gained from the output signal. The RelifF approach is used to obtain the best results using the FeaSelon rank base. To highlight the key elements of the investigation, we focus on the sample CSs for the faulty condition at 1200 revolutions per minute. Every mother wavelet exhibits an excellent ESE ratio at level 1. This means that in the early stages of signal breakdown, knowledge matters more than entropy. We shall be comparing it to level 1 as a result.

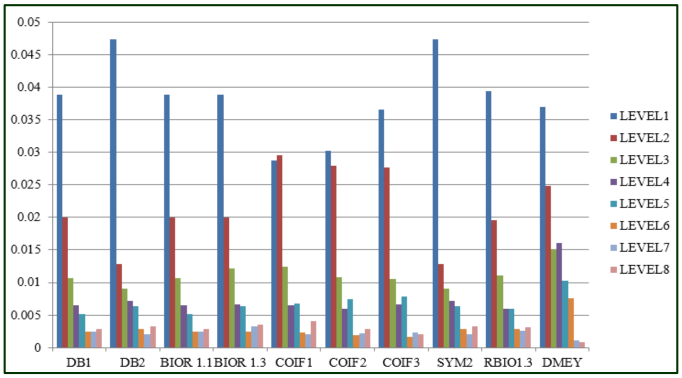


Figure 9. MW comparison at several levels

The rank basis feature is enhanced using the ReliefF approach. It is Kurtosispf that stands out as the top feature. When used independently, the Kurtosispf feature achieves an efficiency of 18.9%. Before being utilized as an input to train artificial neural networks (ANNs), the Kurtosispf feature is normalized using Eq. 10.

$$Norm_{Kurtosis\_PF} = \frac{max(Kurtosis_{pf})}{max(Kurtosispf_{pf})} \quad (10)$$

All ANN architecture variations are included in Table 5. We learned by applying the tan sigmoid activation function in conjunction with the Levenberg-Marquardt technique. Among the factors taken into account for figuring out the optimal design are the amount of training data, the number of neurons in each layer (input, hidden, and output), and the initial weight of the input signal.

Table 5. Evaluation of ANN structure

Network Architecture			Learning rate	Accuracy
Input	Hidden	Output		
3	5	6	0.02	86.79
3	10	6		90.05
3	15	6		92.99
3	20	6		94.98
3	25	6		92.01
3	5	6	0.01	86.29
3	10	6		89.00
3	15	6		90.56
3	20	6		91.99
3	25	6		93.00

Establishing as few criteria as possible helps create a method that works in most scenarios. The quality of neural network training impacts its performance. Mean square error and hidden nodes determine neural network training time. Hidden nodes increase with neural network training time. No mathematical word exists for concealed node selection. Consider the trained neural network if the output somewhat departs from the target.

How hard it is to detect the detection parameter, how intricate the mathematical operations are, and how much decision-making is involved affect how much work is needed to execute an algorithm. Implementing CSAOCFD requires much labor.

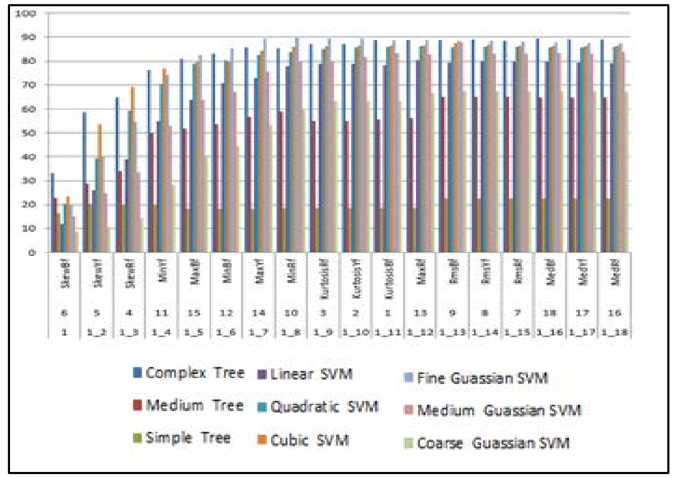


Figure 10. Ranking-based feature selection using the ReliefF algorithm

Results of Track and Hunt metaheuristic-based DNN-based fault diagnosis model for the VSI under varying load conditions

This study aims to examine the performance of the Track and Hunt optimization-based DNN classifier in diagnosing faults in three-phase VSI by comparing it to other well-known approaches.Figure 11 compares the DNN classifier based on the Track and Hunt optimization technique with other classifiers. In this context, the algorithms being questioned are KNN, AdaBoost, RF, DNN, GWO-based DNN, and CSO-based DNN. The K-fold method is considered, with values ranging from 1 to 10.Figure 11(a) illustrates the degree of precision gained from the recommended and present performance estimations. The Track and Hunt optimization-based DNN classifier achieves a performance that is 5.973% superior to that of the KNN classifier when measuring performance at K-fold 2. The accuracy of the present tactics and the suggested strategies is illustrated in Figure 11(b). At the fourth iteration of K-fold cross-validation, the Adaboost classifier surpasses the Track and Hunt optimization-based DNN classifier. The Adaboost classifier achieves a 30.196% improvement in performance. Taking into consideration recollection, Figure 11(c) illustrates a comparison between the technique that is recommended and the one that is now in use. Regarding recall rate, the DNN classifier tuned for Track and Hunt performed 8.996% better than the RF classifier when K-fold 5 was measured. The F1 Measure in Figure 11(d) illustrates the performance of both the suggested and current strategies. According to the Track and Hunt optimization, the DNN classifier outperforms the standard RF classifier by 0.194% in the F1 Measure rate at K-fold 6. The mean squared error (MSE) of existing and suggested approaches is shown in Figure 11(e). The recommended DNN classifier based on Track and Hunt optimization reduces the error rate to 4.271 percent, improving performance. Compared to the RF, DNN, GWO-based DNN, and CSO-based DNN, the recommended technique beats the existing KNN classifier by 77.85%, 79.79%, 77.18%, 59.89%, and 69.71%. The recommended method reduces errors and improves performance by 83.53% over the Adaboost classifier.

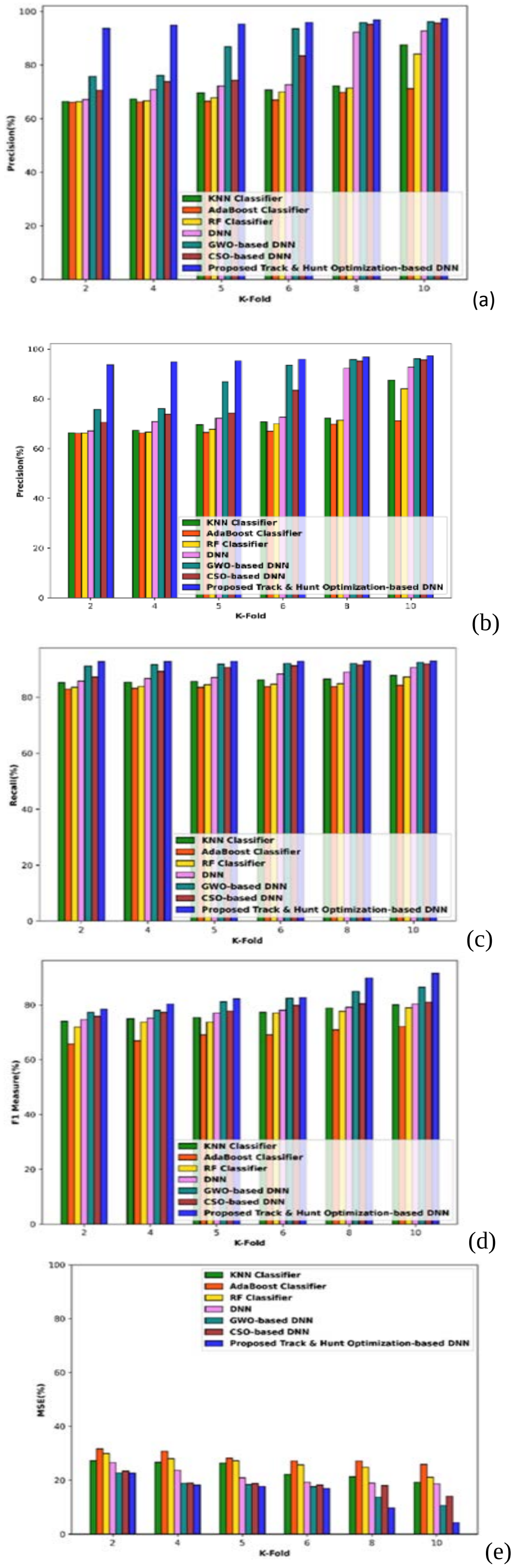


Figure 11. Comparative analysis based on a) Precision accuracy, b) Precision, c) Recall, d) F1 Measure, and e) MSE

Comparative analysis of the above four methods is tabulated in Table 6.

Table 6: Comparative analysis of Different Methods of Fault Diagnosis of Three-phase Voltage Source Inverter

Method	Accuracy
FLFD	57.52 %
NNFD	74.47 %
CSAOCFD	94.98%
Proposed Track and Hunt optimization-based DNN	**95.72%**

Table 6 compares four three-phase VSI fault diagnostic methods by accuracy.FLFD scores 57.52%, showing fault scenario constraintsNNFD uses pattern recognition to boost accuracy to 74.47%. The proposed Track and Hunt optimization-based DNN beats all approaches with 95.72% accuracy, integrating the metaheuristic with DNNs for robust fault identification in three-phase VSIs under changing load circumstances, promising industrial applications.

Conclusion

The new protection algorithm enhances 3Φ-VSIs. The new system improves performance, reliability, safety, and efficiency. Preventing conventional or catastrophic malfunctions improves power inverters' dependability, efficiency, and performance. The approach's adaptability to aging systems, strict reliability requirements, and cost competitiveness make it ideal. According to the research, online monitoring, system fault diagnosis, condition-based maintenance, and preventative maintenance are becoming more important. The strategy's effectiveness is shown by a neural network identifying 3Φ-VSI faults using the Daubechies wavelet transform of phase currents and fault categorization. Averaging 95% diagnostic accuracy is encouraging. Model-based and machine learning identify 3 phase-VSI issues.

Model-based fault diagnosis and machine learning methods enable optimization and refinement, establishing the 3-VSI fault detection research platform. Advanced machine learning can enhance defect detection in future studies. Adapting the protection algorithm to different industrial and operational environments is a promising unexplored topic. Future research can validate and deploy to assess the system's performance and adaptability. The suggested approach retains hunting effectiveness, unlike standard optimizers. This is what makes this research important. This research adjusts the simulated system load to generate the fault dictionary. Track-and-hunt uses language metaheuristic-based DNNs to anticipate defects. The study's DNN classifier uses Track and Hunt optimization to detect the transistor's three-phase voltage source inverter OC switch fault. The training method prevents convergence to local optima and optimizes classifier hyperparameters to increase prediction performance. With 95.729% prediction accuracy, the proposed classifier exceeds previous approaches. Researchers may also create user-friendly interfaces and effortlessly integrate the suggested technology into industrial installations. Working with industry stakeholders and practitioners can help refine and customize the system to fit operational needs. The fault diagnostic approach is promising for three-phase VSI innovation and progress.

Conflict of Interest Statement

The author of this paper declared that there is no conflict of Interest.

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