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# Open-Circuit Fault Diagnosis for Three-Phase Inverter in Photovoltaic Solar Pumping System Using Neural Network and Neuro-Fuzzy Techniques

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## ABSTRACT

This paper deals with the detection of single- and double-switching faults (open-circuit type "O-C") which appear in the inverter of a photovoltaic solar pumping system. Our system as a whole contains a photovoltaic module, a DC/DC step-up converter controlled by perturbation and observation maximum power point tracking technique, a three-phase DC/AC inverter controlled by the sinusoidal pulse width modulation technique, a three-phase induction motor, and a water pump. The used techniques to detect this type of faults are based on artificial intelligence (AI) (neural networks and neuro-fuzzy networks); we use AI as an observer to the inverter in order to detect the faults using extracted features from the inverter output currents. Both of the proposed fault diagnosis techniques show a good performance and high accuracy with less than $\pm$5% of error for neuron-fuzzy and $\pm$7% for artificial neural network and a response time of less than 0.1 s, which is a satisfying speed to detect the faults before a total degradation or any undesirable effects. This paper fulfills an identified need for faults diagnosis of a three-phase inverter in photovoltaic solar pumping systems using AI. The effectiveness of the AI techniques was evaluated for O-C fault detection by simulation tests using the MATLAB/Simulink environment.

***Index Terms*—**Artificial neural network, fault diagnosis, neuro-fuzzy, photovoltaic system, solar pumping, switch fault.

## ABBREVIATIONS

| | |
|---|---|
| O-C | Open-Circuit |
| P&O | Perturbation and Observation |
| MPPT | Maximum Power Point Tracking |
| IGBT | Insulated Gate Bipolar Transistors |
| SPWM | Sinusoidal Pulse Width Modulation |
| VSI | Voltage-Source Inverters |
| ANN | Artificial Neural Network |
| L–M | Levenberg–Marquardt |
| R | Pearson correlation coefficient |
| ANFIS | (neuron-fuzzy) Adaptive Neuro-Fuzzy Inference System |
| $I_{abc}$ | Inverter output current (Three phase rotating domain) |
| $I_{\alpha,\beta}$ | Inverter output current (Two phase rotating domain) Cartesian Coordinates |
| $r, \theta$ | Polar Coordinates (distance, angle) |

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## I. INTRODUCTION

As energy demand rises, and due to the shortage of fossil fuels and negative environmental effects such as increased global warming, it is becoming more and more challenging to meet the demand for conventional energy sources. On the other hand, renewable energy sources have recently come to light as the most remarkable, unbounded, clean, and promising [1]. The use of solar energy is an important part of many countries' sustainable development strategy. Due to the wide solar availability radiation in the countryside, photovoltaic uses have been the most inherent option to operate independent pumps since the early 1990s; therefore, installing stand-alone water pumps has always been a challenge and a major resource in those regions of the world that lack AC power grids and/or allocation of water systems. Regardless of rural regions or little household applications, water pumping has primary significance in these dry areas where it is the unique alternative to transport on wheels to furnish a minimum water supply to the inhabitants even over grave desiccation [2]. Generally, a solar-powered pumping system consists of a solar panel array that powers an electric motor, which in turn powers a pump to pull water. While the produced electricity supplies the entire system, a power converter is required because the electrical motor can run on DC or AC power [3].

Therefore, the inverter is one of the most important pieces of equipment in a solar energy system that regulates the flow of AC power. Its benefits include high efficiencies that can reach 97% with a high strength factor across all charge and speed domains, reduced costs of cable connection, rapid installation, and a smaller construction size [4]. Figure 1 shows that the proposed system contains a basic three-phase inverter structure. Insulated gate bipolar transistors (IGBTs) are the main components in this basic structure model (T1 to T6) which can be "on" or "off". Sinusoidal pulse width modulation (SPWM) is a common switch control technology; by switching the switches between supply and load intermittently at high frequency, the median value of load feeding voltage is controlled [3].

The intersective method is the easiest process to make a PWM signal; it necessitates a triangle waveform and a comparator. When the value of the reference signal is less than the modulation waveform, the PWM signal is in the low state, otherwise, it is in the high state [4]. While the inverter can supply pumps to pull water, crop irrigation, or domestic uses when and where needed, it is more likely to fail than any other component of a PV system, because it is made up of so many electronic parts and performs numerous duties. Thus it requires fault diagnosis and fault-tolerant systems to guarantee service continuity in such cases to ensure its reliability and safety.

Fault occurrence is natural in electronic systems, especially switching faults. The major switch faults can be classified as short-circuit S-C faults and open-circuit (O-C) faults. Typically, the short-circuit fault requires shutting down the system immediately. On the other hand, the OC fault does not but rather reduces its efficiency and it can result in more power conversion failures; thus, diagnostic techniques can be applied in device fault-tolerant systems to avoid converter damage and reduce maintenance costs and production loss. The IGBT becomes OFF if an O-C fault occurs and maintains it in this state regardless of the value of the gate voltage. The O-C fault is caused by the lifting of the connecting wires which is the consequence of thermic cycling. It may be caused by a driver fault or IGBT rupture induced by a short circuit fault [4].

Since diagnosing O-C faults is essential to the inverter, researchers give more attention to diagnosing complex system faults in recent years. Many fault diagnostic methods have been suggested by researchers for O-C faults [5]. By using the most approved "inverter output current-based method," the O-C fault diagnosis of power switches can be carried out [6].

In [7], a new open-switch fault real-time diagnosis method in the voltage-source inverters (VSIs) based on the phase currents was presented, This diagnostic method guarantee robustness to the transient condition and shows relatively fast fault detection compared with similar techniques. In [8], they proposed a non-intrusive fault diagnosis method for O-C faults in inverter semiconductor power

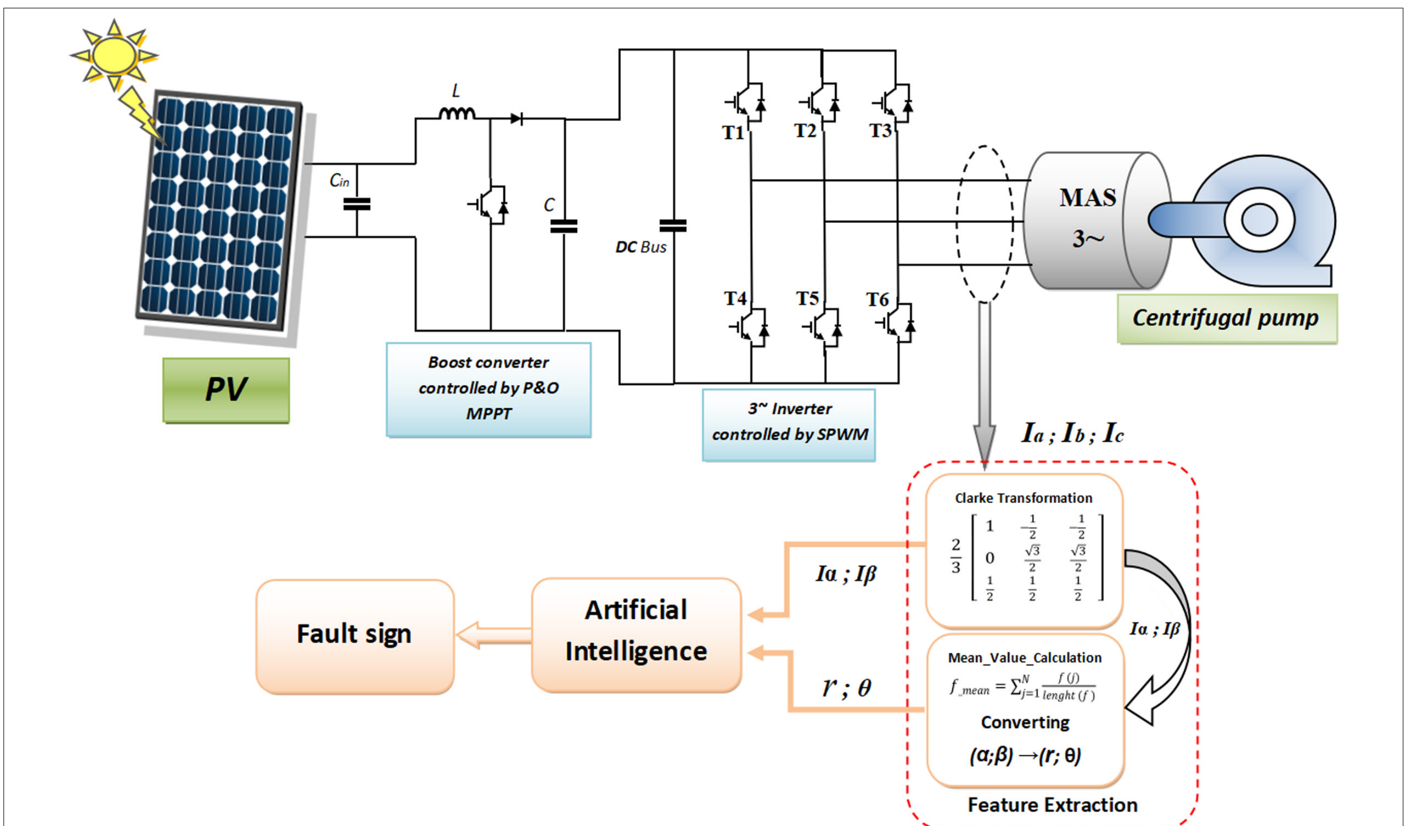


**Fig. 1.** Photovoltaic solar pumping system with proposed fault detection intelligent technique.

switches; this one needs only a current signal, and they verified its performance and precision by utilizing a "hardware-in-the-loop" experiment. In [9], three different fault detection and diagnosis systems for a three-phase inverter were presented as a comparative investigation; these techniques depend on the artificial neural network (ANN) for fault detection. In [10], feature extraction and the ANN technique were used for fault detection and diagnosis in a three-phase inverter. In [11], authors purpose two Artifical Neural Network (ANN) based approaches for detecting IGBT open-circuit faults in a two-level inverter fed induction motor with indirect vector control strategy, the study conducts a comparative analysis and provides experimental validation to detect and localize IGBT O-C faults in a two-level inverter-fed controlled induction motor is investigated. In [12], the fault diagnostics system was developed as a rule-based fuzzy logic system for fault cases of the inverter power semiconductor switches. It was capable of recognizing the type of inverter fault and localizing it. Diverse faults of the motor drive system were presented in [13]; they used intelligent fault detection and diagnosis by introducing the stator currents and the time as inputs to the fuzzy system.

In the literature, numerous fault detection techniques have been used which is showing acceptable efficacy in the clarity case at variance with the noisy case. As we note from the previously mentioned literature that inverter fault detection is directly dependent on the output current or voltage load being sensed with sensors and sampling for further operations which can be affected by noise, then feature extraction techniques are utilized to obtain the most diverse and efficient features possible. During that, it is also possible for the sensors to fall into the fault which will lead to uncertainty or noisy data and therefore fails to detect the fault. Thus, using advanced and intelligent techniques became very important to get a robust fault detection system and ensure better performance in general, especially in the case of noise.

So, this research work aims to synthesize a robust and optimal fault detection observer of a three-phase inverter in a solar pumping system against an open-switch fault using Clarke transformation-based ANN and neuro-fuzzy. Compared to other techniques, the combination of the Clarke transformation with artificial intelligence (AI) has improved robustness because Clarke transformation is robust to noisy measurements, which gives the AI a better convergence rate, which allows for more effective fault detection and diagnosis that makes it suitable for: Real-time applications, monitoring and control applications, and appropriate for noisy applications.

The remaining of this paper is organized as follows:

Section II provides an overview of the system under processing, the fault diagnosis algorithm used, and how the faults were generated to create a fault table that contains the attribute values for each fault condition by extracting features. Section III presents a brief description of the used AI techniques for fault detection. Then AI training results and its utilization for fault detection with a discussion of the obtained results are discussed in Section IV followed by a conclusion in the last section.

## II. DESIGN/METHODOLOGY/APPROACH

### A. System Under Processing

Typically, a solar pumping system consists of at least two of the following: solar panels and motor pumps. An electric motor is driven by a solar panel array directly or a converter linking to that latter, and the motor drives a pump that draws water. Depending on the system topology, an electric motor can be powered by either DC or AC power; whereas the generated electricity powers the entire system, it requires an inverter in the case of an AC motor. For that, we propose the photovoltaic solar pumping system shown in Fig. 1.

The system constists of a photovoltaic module as a power resourse connected to a boost converter (DC-DC controller) for controlling the power flow to extract the maximum power using the perturbation and observation maximum power point tracking (MPPT) technique, as well as a three-phase inverter of six IGBT gates named T1 through T6 that are taken into account for fault scenarios, controlled by the SPWM technique (to convert DC power to AC power). The inverter is connected to a three-phase induction motor that is connecting to a water pump.

### B. Fault Diagnosis Algorithm

The first step is measuring and sampling three-phase inverter currents ($I_{abc}$) in healthy and all faulty cases under consideration. In the second step, applying Clarke transformation on ($I_{ab}$c) currents and convert it from Cartesian form to polar form in order to extract features, and then calculate the mean values and use it to create a fault table coordinating to feature value under every fault. It should be noted that sensor error affects both positive and negative alternance; because of the sinusoidal waveform signals; so, by using the Clarke transformation (to convert AC waveform into DC signals to extract features), and calculating the average values of many samples leads to filtering the data in general, and detecting faults even while sensor gives unclear information.

Next, the AI block is trained using this table to be capable of identifying the faults. Finally, detecting faults using the AI block in our proposed system. The system flowchart is shown in Fig. 2.

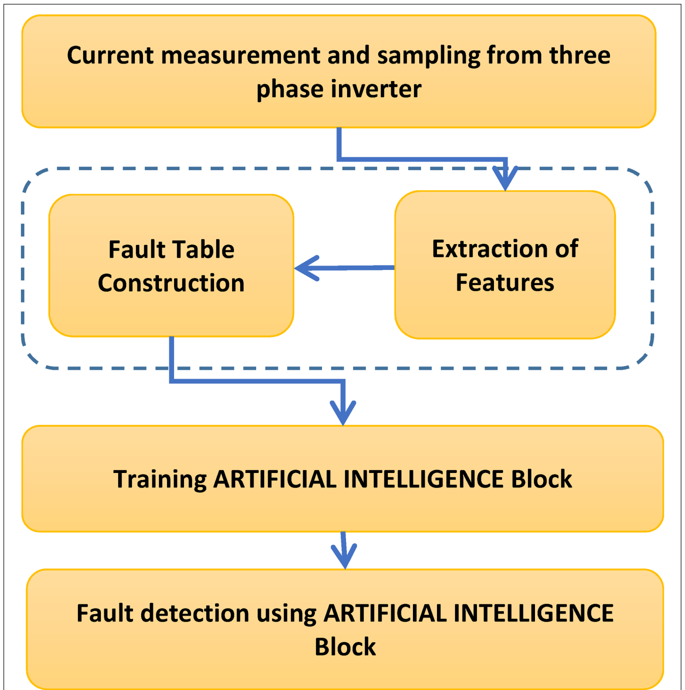


**Fig. 2.** Proposed fault diagnosis algorithm flowchart.

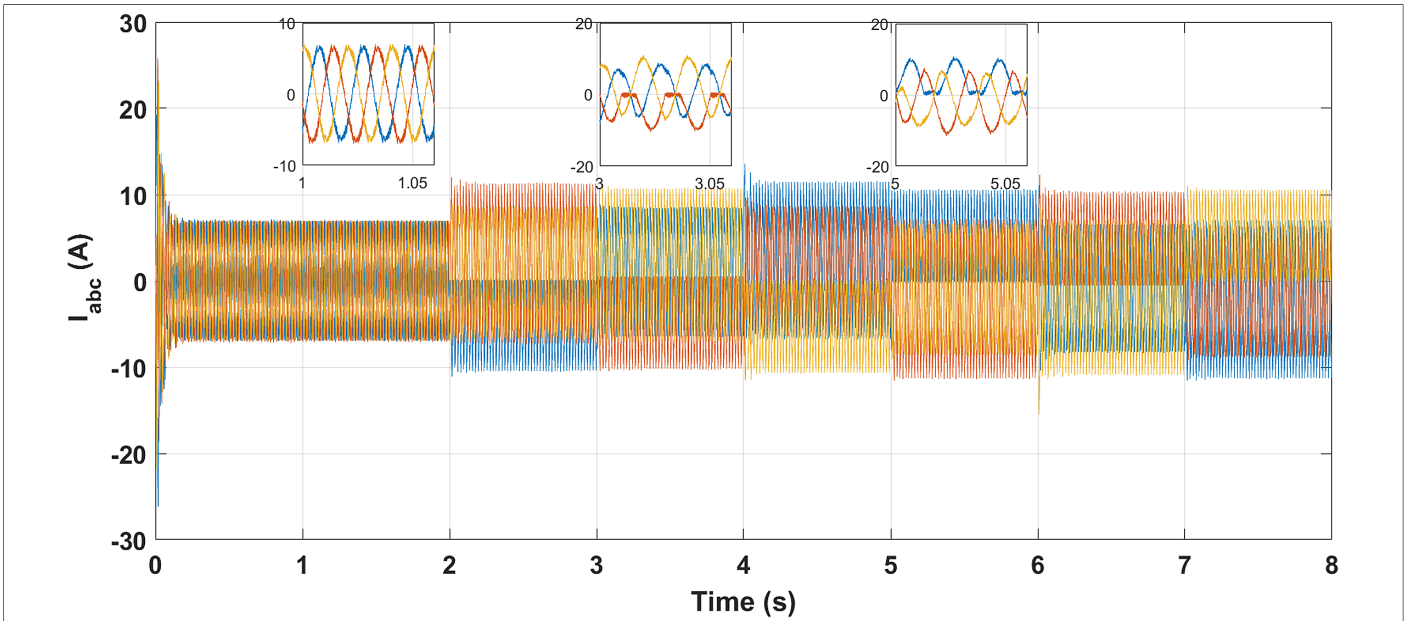


**Fig. 3.** $I_{abc}$ inverter output currents.

### C. Fault Generation

Fig. 3 represents three phase currents of the inverter output, from 0 s to 2 s in the healthy case, and then the faults were generated externally in regular periods; every fault remains for 1 s and then it will be corrected automatically (disappeared) and moved to the next fault to see all scenarios in a single time. Single and double open-switch faults are created through opening one or two IGBTs of the inverter, the opening of an IGBT can be given via disconnecting the respective control line or feeding the gate by a zero control signal; thus the IGBT becomes in the off state [9].

### D. Extraction of Features

Feature extraction is the main stage of the suggested fault detection and classification process. Better features lead to improved system performance and reliability because the accuracy of a system consists of the quality and durability of the feature extraction process. The suggested fault diagnosis system treats inverter output current signals with the following:

Clarke transformation: it is a mathematical tool that simplifies the three-phase circuit. A three-phase system's time domain components where a three-phase system in a time domain components (abc) is transformed by the Clarke transform into two components in an orthogonal stationary frame ($\alpha\beta$) [14]:

$$\left[I_{\alpha\beta 0}\right]=\left[T\right]\left[I_{abc}\right]$$

$$\left[T\right]=\frac{2}{3}\begin{bmatrix} 1 & -1/2 & -1/2 \\ 0 & \sqrt{3}/2 & \sqrt{3}/2 \\ 1/2 & 1/2 & 1/2 \end{bmatrix}$$

Then, calculate the mean values of ($I_\alpha$, $I_\beta$); the main goal of using the mean values of signal in our work is to eliminate noise and minimize the AI learning data. The mean of a function is its average value over its domain; it is defined for one variable over the interval ($a$,$b$) by:

$$\begin{cases} I_{\alpha\_mean}=\sum_{j=1}^{N}\dfrac{I_\alpha(j)}{lenght(I_\alpha)} \\ I_{\beta\_mean}=\sum_{j=1}^{N}\dfrac{I_\beta(j)}{lenght(I_\beta)} \end{cases}$$

where $N$ is the number of samples.

It is worth mentioning that the fundamental sample time of the simulation is 1e-5, which means 100 000 samples per second.

**TABLE I.** FAULT TABLE BASED ON EXTRACTED FEATURES

| Fault Location | $I\alpha_{mean}$ | $I\beta_{mean}$ | $\lvert r\rvert_{mean}$ | Angle $\theta$° | CODE (Fault Sign) |
|---|---|---|---|---|---|
| Normal | −0.03 | -0.27 | 0.30 | −100° | 0000 |
| T1 | −5.55 | 0.16 | 5.56 | 178° | 0100 |
| T2 | 2.23 | −5.23 | 5.68 | −67° | 0200 |
| T3 | 3.08 | 4.50 | 5.46 | 55.6° | 0300 |
| T4 | 5.50 | −0.68 | 5.53 | −7° | 0400 |
| T5 | −2.63 | 4.90 | 5.57 | 118° | 0500 |
| T6 | −3.25 | −4.75 | 5.76 | −124° | 0600 |
| T1 and T5 | −6.78 | 4.79 | 8.31 | 144° | 0700 |
| T1 and T6 | −7.67 | −3.46 | 8.41 | −155° | 0800 |
| T2 and T6 | −1 | −8.40 | 8.45 | −97° | 0900 |
| T2 and T4 | 6.62 | −5.07 | 8.34 | −37° | 0100 |
| T3 and T4 | 7.46 | 3.29 | 8.15 | 23° | 1100 |
| T3 and T5 | 0.68 | 8.19 | 8.22 | 85° | 1200 |

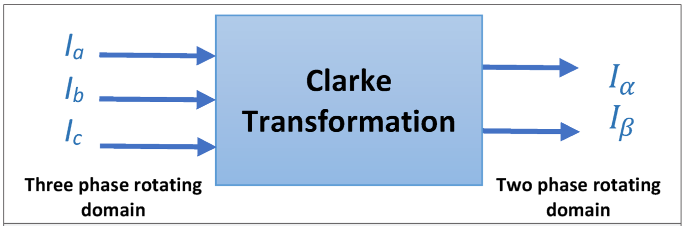


**Fig. 4.** Clarke transformation.

Then, convert from Cartesian coordinates ($I_\alpha$, $I_\beta$) to polar coordinates ($r$, $\theta$) to obtain more features using:

$$\begin{cases} r_{\_mean} = \sqrt{\left(I^2_{\alpha\_mean} + I^2_{\beta\_mean}\right)} \\ \theta_{\_mean} = \tan^{-1}\left( I_{\beta\_mean} \big/ I_{\alpha\_mean} \right) \end{cases}$$

**E. Fault Table Based on Extracted Features**

The final part is creating a fault table that contains the attribute values for each fault condition. Table I contains the approximate mean values of extracted feature signals ($I_\alpha$, $I_\beta$, $|r|$, and angle $\Theta°$) and a significant number referring to each fault as code.

The significant numbers (multiples of a hundred) are used for discrimination between each fault and another after rounding it to the hundred to eliminate the perturbation of the AI decision.

We should carefully observe these feature values in order to utilize them for training the ANN and the neuron-fuzzy in the next steps.

## III. ARTIFICIAL INTELLIGENCE

**A. Neural Network**

The ANN was inspired by the human nervous system and brain, it build by an input layer, hidden layer or layers, and an output layer; which consist of interconnected neurons allow learning occurs through an adjustment of the connection weights, or synaptic weights, that stores the information acquired by the network [15].

Before applying it to a particular system, hidden layer weights must first be trained and calculated in accordance with the inputs and desired outputs. During the training phase, hidden node weights are calculated to produce the precise output when input combinations are the same or nearly the same.

The ANN capable of self-learning and fitting any continuous non-linear function and eligible to parallel processing, distributed information storage, and global action. It has powerful advantages in online estimation possibility and non-linear problems, so it is very appropriate for fault detection [16].

The Levenberg–Marquardt method converges very quickly when the network weight is small compared with other improved algorithms [17].

The designed fault detection and diagnosis ANN architecture that we are going to use is a feed-forward back-propagation network is shown in Fig. 5. Our neural network is based on: One input layer with four neurons each neuron for one of four extracted features ($I_\alpha$, $I_\beta$, $|r|$, and angle $\Theta$), three hidden layers, the first layer with four neurons, the second layer with twelve neurons, the third with six neurons, and one output layer with one neuron indicating to the code of the desired fault. For hidden and output layers, sigmoid activation function is used because all hidden layers usually use the same activation function. However, the output layer will typically use a different activation function from the hidden layers. In general, the decision is based on the model's objective or type of prediction; where the desired output of our system is as shown in code Table I.

There are two learning algorithms in this method, which are the feed-forward algorithm and the back-propagation algorithm. In the feed-forward algorithm, the input data move in a forward direction which is from the input nodes to the output nodes through hidden nodes, while the back-propagation algorithm is used for weight training of the neural network by calculating the loss function gradient regarding all weights in the network, with the aim of minimizing the loss function [15, 18, 19].

The MATLAB/Simulink ANN toolbox is utilized to learn ANN according to the extracted features shown in Table I.

**B. Neuron-Fuzzy**

The fundamental cause for the combination of the fuzzy system with ANN is the profit of the learning and training ability of ANN to upgrade the fuzzy model behavior where its inference system corresponds to a set of fuzzy IF–THEN rules that have the learning capability to approximate nonlinear functions [20].

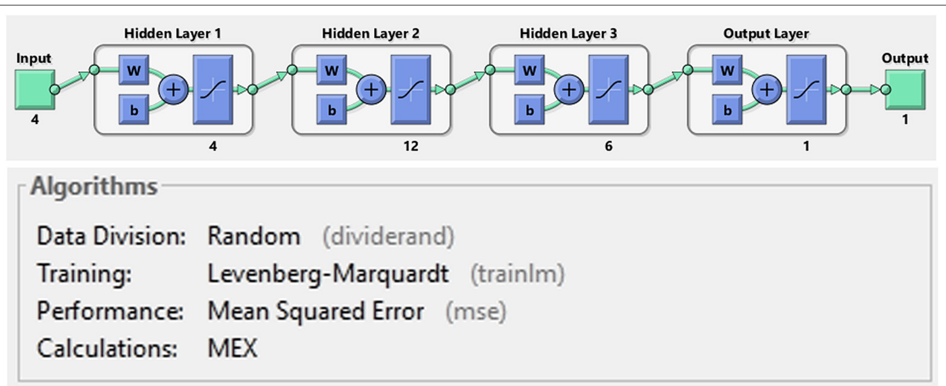


**Fig. 5.** Proposed artificial neural network architecture and algorithm.

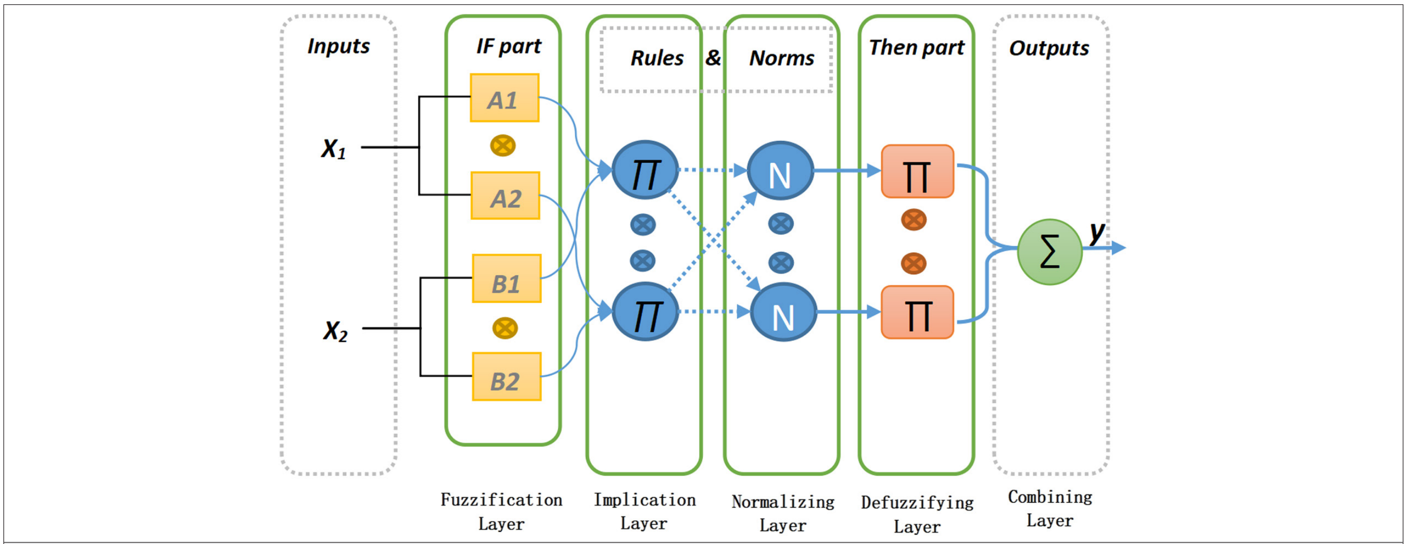


**Fig. 6.** Neuro-fuzzy (ANFIS) architecture.

The Adaptive Neuro Fuzzy Inference System (ANFIS / Neuro-Fuzzy) structure consists of five primary layers which are the fuzzification, implication, normalizing, defuzzification, and combining layers [21].

In the fuzzyfing layer, the neurons are regarded as adaptable nodes that make up the premise parameters; it translates the inputs into fuzzy inputs by utilizing membership functions.

The output node in the implication layer is created depending on receiving signals. Every neuron in the normalizing layer is a fixed neuron, and the ratio of the rule's firing determines the output. In the defuzzyfing layer, neurons are adaptable neurons that hold consequence parameters, and the fuzzy output is translated into a normal output after processing. The combining layer has a single neuron that adds up all the inputs [21, 22].

Typically, ANFIS employs learning algorithms through a certain mechanism that comprises two phases:

In the forward pass of the learning algorithm, consequent parameters are identified by the least-squares estimate.

In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm.

The parameters associated with the membership functions change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measures.

This error measure is usually defined by the sum of the squared difference between actual and desired outputs [23].

Our neuron-fuzzy model is based on:

Gauss2mf membership function for the inputs with {3 3 3 3} number of membership function in each layer (by using a combination of two Gaussian membership functions, this function computes fuzzy membership values); and constant membership function type for the outputs, and the load output data shown in Fig. 7.

In total, we have:

- Number of nodes: 193
- Number of linear parameters: 81
- Number of nonlinear parameters: 48
- Total number of parameters: 129
- Number of fuzzy rules: 81

## IV. RESULTS AND DISCUSSION

### A. Training of the Neural Network

Fig. 8, Fig. 9, and Fig. 10 show the resultants of the training: the neural network was trained with normal and faulty data. Then, this trained neural network is used for fault detection system. The minimum performance gradient and maximum iterations were defined; the training will end when any one of the conditions is fulfillment, and at the end of the training operation, the obtained model will consist of the optimal weight and the bias vector.

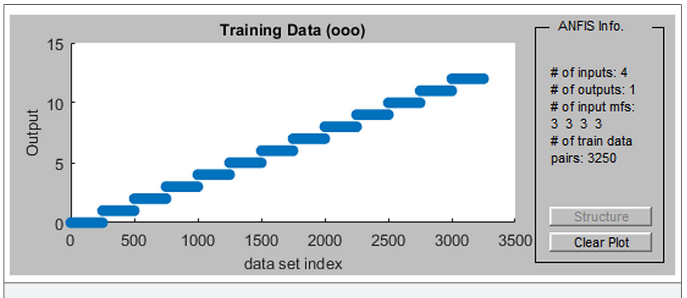


**Fig. 7.** Load output data.

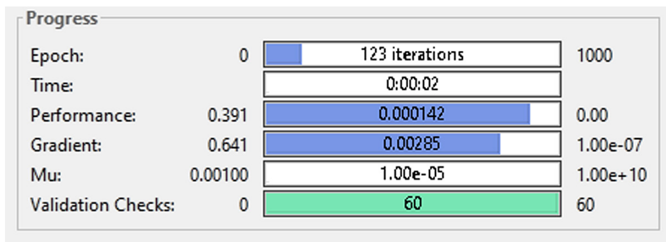


**Fig. 8.** Artificial neural network progress.

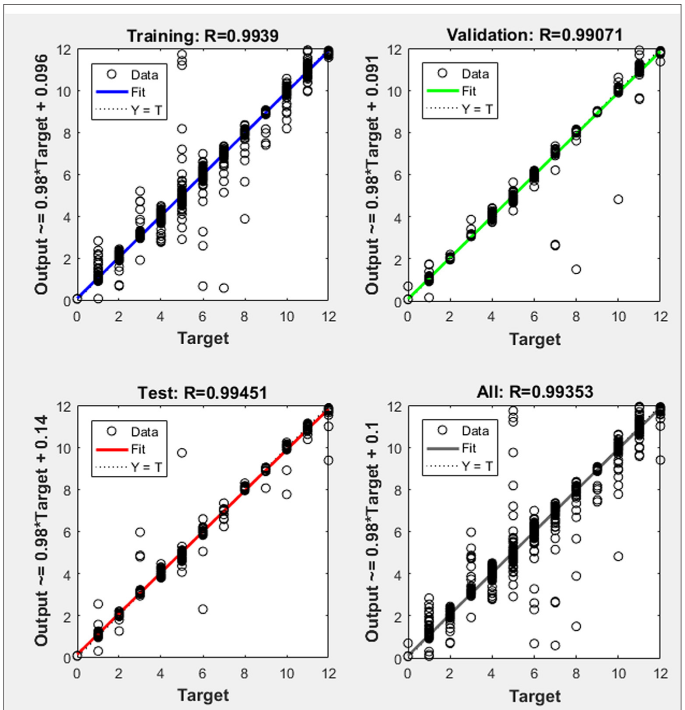


**Fig. 9.** Artificial neural network training state.

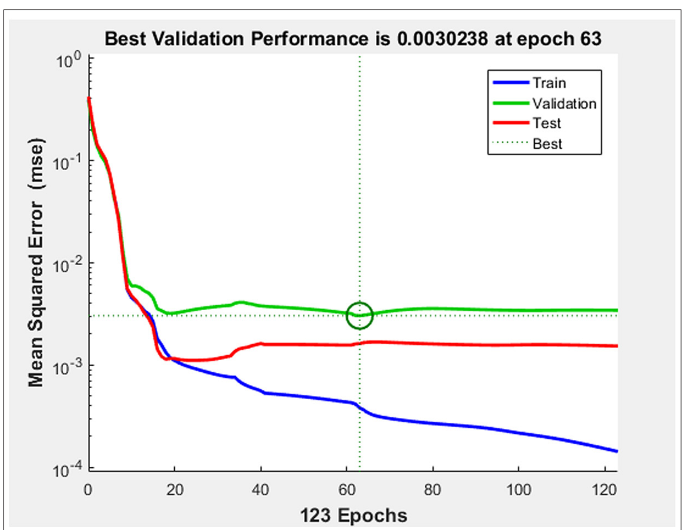


**Fig. 10.** Artificial neural network Performance.

The overall number of iterations necessary and the time required for the whole training for the fault detection network are determined by the structure and size of the ANN, the data set employed, and the complexity of the problem under examination [24].

The method used to gauge the effectiveness of the trained neural network involves plotting the linear regression that connects the targets and outputs and provides Pearson correlation coefficient $R$, as seen in Fig. 9, demonstrating that correlation coefficients for training $R=0.9939$, validating $R=0.99071$, and testing $R=0.99451$. The Pearson correlation coefficient $R$ describes the strength and direction of the linear relationship between two quantitative variables, where 0 indicates no correlation, 1 indicates an ideal positive correlation, and −1 indicates an ideal negative correlation.

In this instance, the total correlation coefficient was discovered to be 0.99353, indicating a very acceptable connection between the targets and the outputs.

The trained neural network's best mean square error is 0.0030238 at epoch 63, and Fig. 10 shows that the testing and validation curves have similar properties, which is a sign of effective training.

**B. Training of the Neuron-Fuzzy**

Fig. 11 and Fig. 12 show the resultants of the training: for ANFIS results, we say the same thing with ANN because we are using the same data and the same structure except the fuzzy rules which was standard, and the training will stop when any one of conditions is met. Error: 0; Epochs: 600.

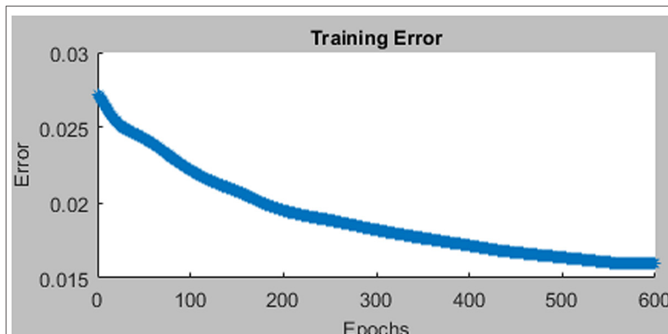


**Fig. 11.** ANFIS errors.

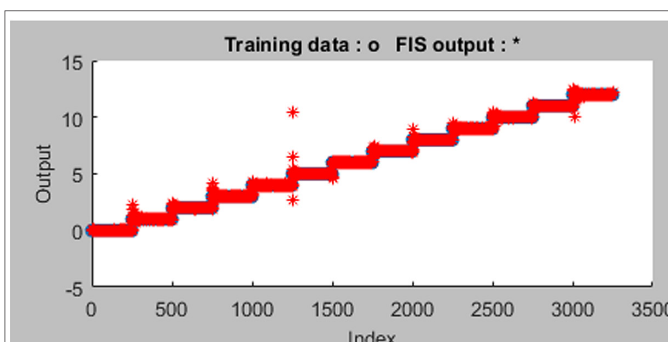


**Fig. 12.** ANFIS test.

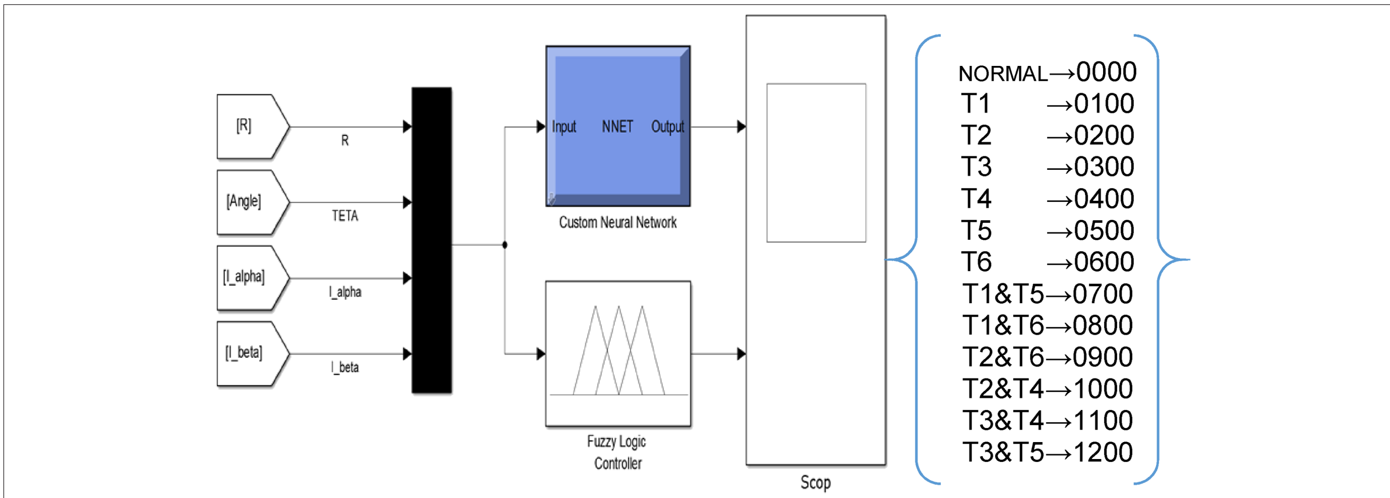


**Fig. 13.** Simulation test block.

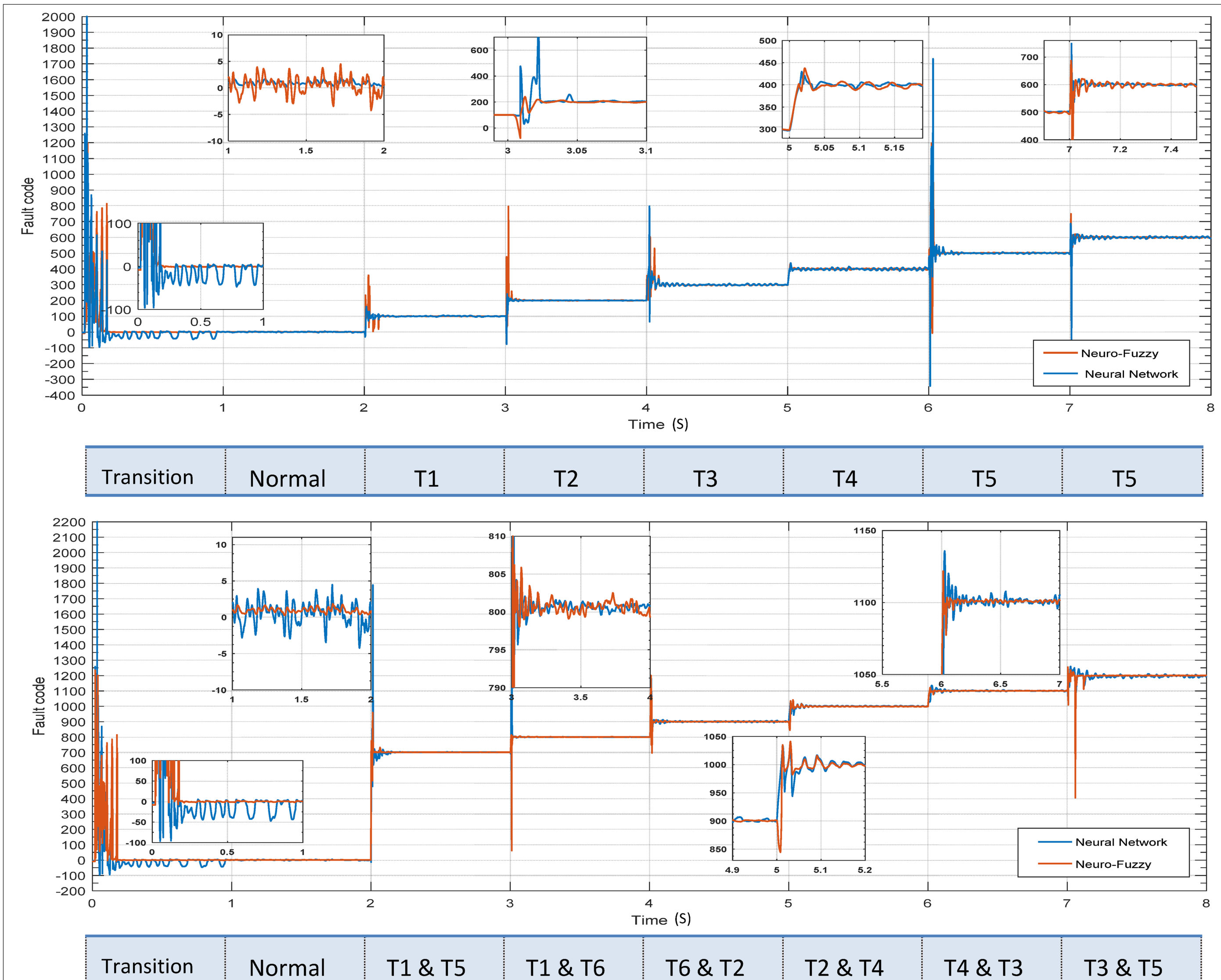


**Fig. 14.** Results of the proposed fault detection intelligent technique.

When the ANFIS training reaches epoch 600, we can see the obtained error is 0.01598, the designated epoch number has been reached, and the system has become monotonous, indicating that the ANFIS training is completed.

Figure 12 shows similarity of the output of the ANFIS and the loaded database.

### C. Obtained Results

Fig. 13 represents the simulation test block; the inputs are ($I_\alpha$, $I_\beta$, $|r|$, and angle $\Theta$) which form the photovoltaic solar pumping system and the output is the fault code, as mentioned in Table I.

It is possible to estimate the effectiveness and the performance of a developed ANN and ANFIS using the testing dataset as part of network development which is provided by the developer. Typically, the sum of difference between the outputs that are actually produced and those that are desired serves as the error measure. Fig. 14 shows the scoped output of the diagnosis system; it is notable that the results are similar enough to detect inverter faults. With less than 5% of error for neuron-fuzzy and less than 7% for ANN and response times of less than 0.1 s (dependence on fault location), both of the suggested fault diagnosis techniques demonstrate good performance and high accuracy. However, because of the fuzzy rules, the ANFIS is more resistant to noise (that it is clearfrom 0 sec to 1 sec and the transition moments of each generated fault in Fig. 14). This is a satisfactory speed to detect the faults before a complete degradation or any undesirable effects. To avoid false alarms, the alarms must remain longer than the detection time obtained by the experiments (0.1 sec) to be considered a fault.

## V. CONCLUSION

In this research work, we are presenting an application of AI (ANN and ANFIS) diagnostic techniques for a three-phase inverter faults in a solar pumping system in order to detect the problem of single and double faults in the system. The simulation results shows that the proposed fault diagnosis method is very effective for fault detection; this study simplifies the structure of the diagnosis system, and so there is no need for additional sensors and complicated calculations to design systems. Moreover, both of these techniques are utilized in same settings and situations to find out same faults to prove their effectiveness. Both techniques show a good performance.

### Perspectives

The next research work focuses on the following improvements:

1. Improving AI algorithms for better performance by using other extracted features methods.
2. Improving AI algorithms for more types of faults like short-circuit faults, phase-to-phase faults, phase-to-ground faults, and phase-to-neutral faults.
3. Generalizing those techniques and applying them to different systems in order to ensure the application are validated.
4. Additional training using a large amounth of data in a variety of environments under different circumstances (noise, coupled faults of other types of, real disturbances etc.)

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## REFERENCES

1. P. Kumari, N. Kumar, and B. K. Panigrahi, “A framework of reduced sensor rooftop SPV system using parabolic curve fitting MPPT technology for household consumers,” *IEEE Trans. Con. Electron.*, vol. 69, no. 1, 29–37. [CrossRef]
2. A. Costabeber, M. Carraro, R. Antonello, and M. Zigliotto, “A fast-MPPT low-complexity autonomous PV water pumping scheme for PMSM,” *3rd Renewable Power Gener. Conference (RPG 2014)*, 2014. [CrossRef]
3. B. Eker, “Solar powered water pumping systems,” *Trakia J. Sci.*, vol. 3, no. 7, pp. 7–11, 2005.
4. M. R. U. Ubale, R. B. Dhumale, and S. D. Lokhande, “Open switch fault diagnosis in three phase inverter using diagnostic variable method,” *Int. J. Res. Eng. Technol.*, vol. 2, no. 12, pp. 636–640, 2013. [CrossRef]
5. S. Liu, X. Qian, H. Wan, Z. Ye, S. Wu, and X. Ren, “NPC three-level inverter open-circuit fault diagnosis based on adaptive electrical period partition and random forest,” *J. Sens.*, vol. 2020, pp. 1–18, 2020. [CrossRef]
6. S. Xu, J. Wang, and M. Ma, “Open-circuit fault diagnosis method for three-level neutral point clamped inverter based on instantaneous frequency of phase current,” *Energy Convers. Econ.*, vol. 1, no. 3, pp. 264–271, 2020. [CrossRef]
7. C. Zhang-Yong, Z. Jian-jian, C. Yong, and Z. Anjian, *Open-Switch Fault Diagnosis Method in Voltage-Source Inverters Based on Phase Currents*. IEEE Publications. [CrossRef]
8. S. Cheng *et al.*, “An open-circuit fault-diagnosis method for inverters based on phase current,” *Transportation Safety and Environment*, vol. 2, no. 2, pp. 148–160, 2020. [CrossRef]
9. F. Asghar , M. Talha, and S. H. Kim, “Comparative study of three fault diagnostic methods for three phase inverter with induction motor,” *Int. J. Fuzzy Logic Intell. Syst.*, vol. 17, no. 4, pp. 245–256, 2017. [CrossRef]
10. F. Asghar, M. Talha, and S. H. Kim, “Neural network based fault detection and diagnosis system for three-phase inverter in variable speed drive with induction motor,” *J. Control Sci. Eng.*, vol. 2016, Article ID 1286318, 2016. [CrossRef]
11. B. D. E. Cherif, A. Bendiabdellah, M. Bendjebbar, and A. Tamer, “Neural network based fault diagnosis of three phase inverter fed vector control induction motor,” *Period. Polytech. Elec. Eng. Comp. Sci.*, vol. 63, no. 4, pp. 295–305, 2019. [CrossRef]
12. F. Khater, M. I. AbuEl-Sebah, and M. Osama, “Fault diagnostics in an inverter feeding an induction motor using fuzzy logic,” *J. Electr. Syst. Inf. Technol.*, vol. 4, no. 1, pp. 10–17, 2017. [CrossRef]
13. S. O. Ibrahima, N. Faris, and E. AboElzahab, “Implementation of fuzzy modeling system for diagnosis faults detection in three phase induction motor drive system. Science Direct,” *J. Electr. Syst. Inf. Technol.*, vol. 2, pp. 27–46, 2015. [CrossRef]
14. P. Krause, O. Wasynczuk, S. D. Sudhoff, and S. Pekarek, “Analysis of electric machinery and drive systems,” Piscatawy, NJ: Wiley-IEEE Press, 2013.
15. A. A. Bengharbi, S. Laribi, T. Allaoui, and A. Mimouni, “Photovoltaic system faults diagnosis using discrete wavelet transform based artificial neural networks,” *Electr. Eng. Electromech.*, vol. 6, no. 6, pp. 42–47, 2022. [CrossRef]
16. Z. Xiao, Z. Guo, and V. Balyan, “Fault diagnosis of power electronic circuits based on improved particle swarm optimization algorithm neural network,” *Electrica*, 2022. [CrossRef]
17. D. Sun, P. Chopra, J. Bhola, and R. Neware, “Computer communication network fault detection based on improved neural network algorithm,” *Electrica*, pp. 1–7, 2022. [CrossRef]
18. N. A. M. Leh, F. M. Zain, Z. Muhammad, S. A. Hamid, and A. D. Rosli, “Fault detection method using ANN for power transmission line,” *Comput.Ing. Eng. (ICCSCE) 10th IEEE International Conference on Control. System*, vol. 2020, p. 9204921, 2020. [CrossRef]
19. M. Talha, F. Asghar, and S. H. Kim, “A novel three-phase inverter fault diagnosis system using three-dimensional feature extraction and neural network,” *Arab. J. Sci. Eng.*, vol. 44, no. 3, 1809–1822, 2019. [CrossRef]

20. A. Abraham, "Adaptation of fuzzy inference system using neural learning, ", in *Fuzzy Systems Engineering: Theory and Practice, Studies in Fuzziness and Soft Computing*, vol. 181, N. Nedjah, and L. de Macedo Mourelle, Ed. Germany: Springer Verlag. CiteSeerX, pp. 53–83, 2005. [CrossRef]
21. A. Ramadan, S. Kamel, I. Hamdan, and A. M. Agwa, "A novel intelligent ANFIS for the dynamic model of photovoltaic systems," *Mathematics*, vol. 10, no. 8, p. 1286, 2022. [CrossRef]
22. D. J. Armaghani, and P. G. Asteris, "A comparative study of ANN and ANFIS models for the prediction of cement-based mortar materials compressive strength," *Neural Comput. Appl.*, vol. 33, no. 9, pp. 4501–4532, 2021. [CrossRef]
23. S. Sremac, E. K. Zavadskas, B. Matic, M. Kopica, and Z. Stevi, "Neuro-fuzzy inference systems approach to decision support system for economic order quantity," *Ekon. Istraživanja*, vol. 32, no. 1. 2019, pp. 1114–1137, 2019. [CrossRef]
24. M. Jamil, S. K. Sharma, and R. Singh, "Fault detection and classification in electrical power transmission system using artificial neural network," *SpringerPlus*, vol. 4, no. 1, p. 334, 2015. [CrossRef]

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