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Fault Detection System of Photovoltaic Based on Artificial Neural Network

Ali Salman Zamzeer [1], Mansour S. Farhan [1], Haider TH. Salim ALRikabi [1]

Affiliations

Affiliations
[1]Department of Electrical Engineering, Wasit University, Wasit, Iraq

Correspondence
Ali Salman Zamzeer
Department of Electrical Engineering, Wasit University, Wasit, Iraq
Email: alis302@uowasit.edu.iq

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Abstract

Using PV systems, solar energy may be used to create electricity. Every year, the proportion of solar energy in the electric system increases significantly. On the other hand, photovoltaic cells are susceptible to malfunctions that diminish their efficiency and profitability. Due to the severity of the defects, fault detection and diagnosis (FDD) in the PV system have become difficult. Thus, the primary objective of the proposed study is to detect and diagnose particular types of PV system problems using an artificial neural network (ANN). This early operation is more effective for avoiding errors during PV installation and minimizing PV system power losses. A new solar cell model is created in the MATLAB/SIMULINK environment and is used to identify the fault dataset. The solar cell consists of three parallel strings and three series modules, with each module containing 20 series-connected photovoltaic cells. This model determines four parameters (V-load in Volts, I-load in Amps, Irradiance in W/m2, and Temperature in Celsius) under varying situations (five temperature values, three irradiance values, and three-time events), which are repeated for all faults evaluated. In the training and testing phases of the proposed ANN, these four parameters are utilized as effective features. Additionally, this network possesses eight outputs, one for each defect. Using implementations with three different numbers of hidden layers and an identical fault dataset, the performance of the proposed network is tested. The findings of the simulation indicate a considerable proportion of fault detection and diagnosis accuracy, ranging between 95% and 98%. The computed RMSE reveals that the training period yields 0.193% improvement, whereas the testing phase yields 0.365%.

Keywords: fault detection and diagnosis (FDD); AI Algorithms; photovoltaic (PV) systems; Artificial Neural Network (ANN).

الخلاصة: باستخدام الأنظمة الكهروضوئية، يمكن استخدام الطاقة الشمسية لتوليد الكهرباء. كل عام، تزداد نسبة الطاقة الشمسية في النظام الكهربائي بشكل كبير. من ناحية أخرى، فإن الخلايا الكهروضوئية عرضة لأعطال تقلل من كفاءتها وربحيتها. نظرًا لخطورة العيوب، أصبح اكتشاف الأخطاء وتشخيصها في نظام الكهروضوئية أمرًا صعبًا. وبالتالي، فإن الهدف الأساسي للدراسة المقترحة هو اكتشاف وتشخيص أنواع معينة من مشاكل النظام الكهروضوئية باستخدام شبكة عصبية اصطناعية. هذه العملية المبكرة أكثر فاعلية في تجنب الأخطاء أثناء التثبيت الكهروضوئي وتقليل فقد طاقة النظام ويستخدم لتحديد مجموعة بيانات الأعطال. تتكون الخلية الشمسية من ثلاث محاكاه/ الكهروضوئي. يتم إنشاء نموذج خلية شمسية جديد في بيئة ماتلاب سلاسل مربوطة على التوازي وثلاث وحدات مربوطة على التوالي، تحتوي كل وحدة على 20 خلية كهروضوئية متصلة بالتوالي. يحدد هذا النموذج أربع معلمات (الفولتية والتيار وشدة الاشعاع ودرجة الحرارة بالدرجة المئوية) في حالات مختلفة (خمس قيم لدرجة الحرارة، وثلاث قيم للإشعاع، وأحداث ثلاث مرات)، وهي مكرر لجميع العيوب المقيمة. في مرحلتي التدريب والاختبار للشبكة العصبية الاصطناعية المقترحة، يتم استخدام هذه المعلمات الأربعة كميزات فعالة. بالإضافة إلى ذلك، تمتلك هذه الشبكة ثماني مخرجات، واحد لكل عيب. باستخدام تطبيقات بثلاثة أعداد مختلفة من الطبقات المخفية ومجموعة بيانات خطأ متطابقة، يتم اختبار أداء الشبكة المقترحة. تشير نتائج المحاكاة إلى نسبة كبيرة من اكتشاف الأخطاء ودقة التشخيص، تتراوح بين 95٪ و98٪. يكشف متوسط الجذر التربيعي للخطأ المحسوب أن فترة التدريب تؤدي إلى تحسن بنسبة 0.193٪، بينما تنتج مرحلة الاختبار 0.365٪.

1. INTRODUCTION

Photovoltaic systems have grown in popularity over the last decade because they are a worldwide source of power that is noiseless, pollution-free, simple to set up, and can be converted and incorporated into structures [1], [2]. As a result, optimizing the performance of PV systems is required to optimize solar energy [3]. Consequently, the incorporation of defect detection technologies is required [4], [5]. Numerous methods exist for PV array failure detection, and substantial research has been conducted to identify potential solutions [6]–[8]. The approaches may be categorized into two groups: the first does not require climatic data, while the second relies heavily on studying the PV array's current and voltage. Other researchers include intelligent-based systems [9]–[12]; nevertheless, most published approaches cannot identify more than one defect in the PV array, and others provide just the potential fault [13]–[16]. FDD are vital to the efficiency of any power system, especially solar systems. Unanticipated errors may disrupt the system, causing sensor, actuator, and system component disturbances. The primary objective of fault detection in a system is to identify when and where an error has occurred in a grid-connected solar plant [17]–[20]. Artificial intelligence (AI) methods have demonstrated their capabilities for modeling, prediction, and forecasting in PV systems throughout the previous decade [21]–[23]. Conventional methods cannot estimate the parameters of PV modules with high accuracy [10], [20], [24]. This challenge led many scientists to search for AI techniques as alternate approaches to conventional methods for PV modeling [25]–[27]. This study aims to create a comprehensive technique, neural network-based, for detecting, diagnosing, and accurately categorizing solar panel problems to prevent a reduction in photovoltaic system production and performance. The main contribution of the proposed work has been addressed as follows: creation of an effective and intelligent method that can precisely detect and diagnose the PV system faults based on the ANN technique with less complexity and high accuracy of 98.3%. The proposed method increased the reliability and safety of the DC network protection due to the fast and accurate detection of the system faults. The detection method can precisely discriminate between the fault, the other defect in the PV system, and the expected behavior's noise.

2. Related works

PV system fault has been detected and diagnosed using supervised machine learning such as SVM [28], Cascaded SVMs [28], [29], ANN [12], [20]–[22], [30]–[35], NB [36]–[39], PCA [14], [19], [40], KNN [4], [30], [41], RF [11], [15], [42], ET [9], DT [43], ANFIS [44] and MLP [42]. The work [45] presented a sophisticated method based on the Multilayer Perceptron (MLP) ANN network for diagnosing, detecting, and precisely classifying the fault in the solar panels to avoid a fall in the production and performance of the PV system. Researchers in [9] used the RF method in order to detect PV module faults. They employed an RF model to solve over-fitting and poor generalization issues that occur in ML algorithms. Jones et al. [46] offered an intelligent FDD approach based on Laterally Primed Adaptive Resonance Theory (LAPART). The approach automatically identified a single module failure in a PVS. The study [47] employed SVM with a greater accuracy of classification utilizing a climate corrected performance ratio, among other factors. However, the study does not specify which problem was investigated, or if it was a failure or a regular operation. In [38], a method for detecting line-to-line and line-to-ground faults was created, primarily based on using a multi-resolution signal decomposition (MSD) methodology on a fuzzy inference system.

The study [48] proposed an intelligent fault diagnostic approach to detect and categorize probable problems in PV strings based on an examination of the symptoms detected in the I-V characteristic. Two algorithms make up the technique: The first allows for the classification of faults that do not evolve in the same way, but the second requires the development of two ANNs to classify faults that are not distinguishable by the first method. The developed approach accurately identifies and classifies the defects under investigation. Authors of [17] devised a fuzzy logic approach for detecting faults in a PVA. With a high degree of accuracy (90–98%), the developed algorithm can distinguish between the most common PVM module failures, such as increasing series losses, BPD, and BKD. Using principal component analysis (PCA), [49] achieves an average detection accuracy of 97% for shading faults PV systems. An intelligent PV fault detection system using ANFIS methodology was presented by the authors in the study [44]. Utilizing some research data, train the ANFIS model for an effective PV fault detection and classification system using procedures of grid partition and subtractive clustering. The statistical analysis showing that the ANFIS SC model with radius 0.6 can suitably identify PV system problems. The study [35] proposed a new fault diagnosis approach in a stand-alone photovoltaic system based on three layers feed-forward ANN, where several common faults are established, such as PV module short circuits, PV module open circuits, and battery short circuits. It did not require any preservation information to locate the defect, instead relying solely on electrical measures like as voltage and current from the SAPV system to train the ANN and then anticipate failures. This study used a MNN with a scaled algorithm to classify different types of PV faults in SP and TCT interconnections made of polycrystalline and thin-film PV arrays [41]. The SCG training approach properly recognized all created defects in thin-film and polycrystalline PV materials with a high accuracy of 99.6% and a quick computation time of 0.08 seconds. The paper [50] uses a convolutional NN-based technique to extract features from scalograms and classify errors with 73.5% accuracy without considering different PV materials. In [45], PV errors were identified with 99% accuracy regardless of PV material and array arrangement.

3. METHODOLOGY

The FDD machine learning approaches consist of many methodologies, each with its own principles and frameworks. According to the percentage of papers on PV FDD published by renowned publishers, ANN is the most prevalent machine learning technique utilized for FDD. Our proposed methodology consists of three stages: designing the PV system faults based on MATLAB/Simulink environment, using Neural Networks for fault detection and diagnosis, and then evaluating the proposed module's performance as illustrated in the Fig. 1.

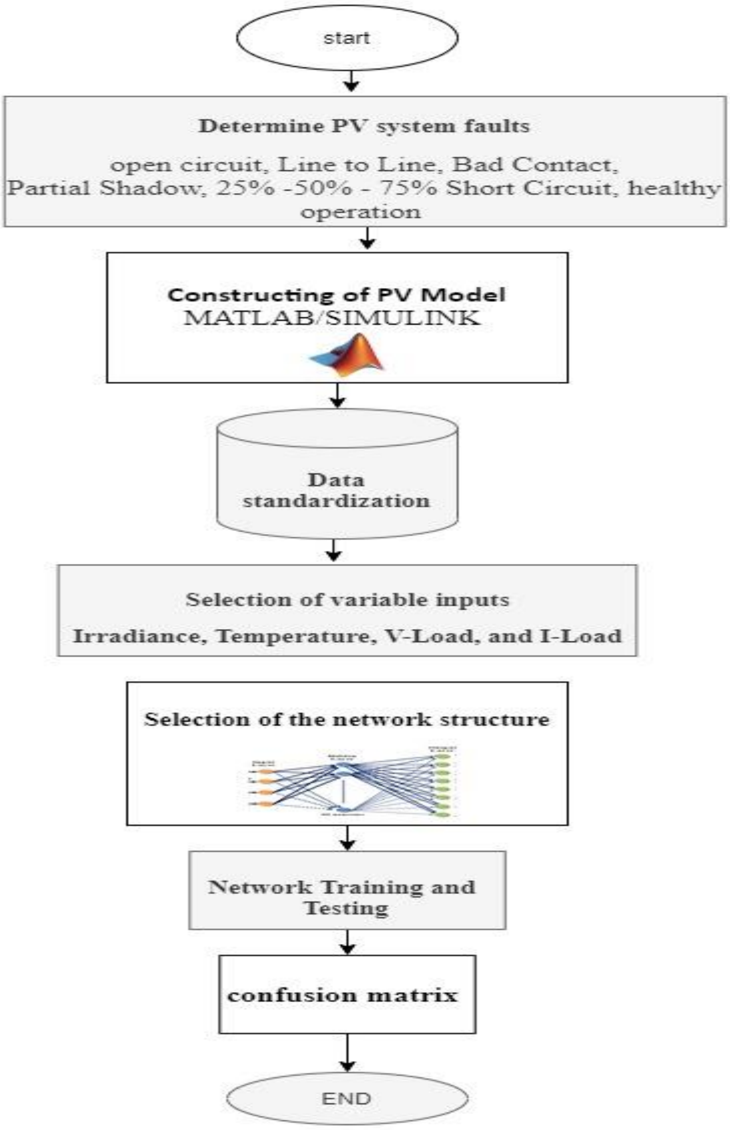


Figure 1. Proposed Work Flowchart

3.1.Design PV System Faults using MATLAB/SIMULINK

The system is designed using a MATLAB/SIMULINK environment based on seven kinds of PV faults (open circuit, Line to Line, Bad Contact, Partial Shadow, 25% -50% - 75% Short Circuit) and healthy operation [25], [44]. In addition, to the eight types of PV faults, another band of variations is applied to the four input features to the proposed PV FDD (Irradiance, Temperature, V-Load, and I-Load) [8]. Five different values of temperature and three different values of irradiance and the obtained V-Load and I-Load are considered the effective dataset for each type of PV fault. At each time of implementation, three different values of irradiance (500, 750, and 1000) and five different values of temperature (15, 20, 25, 30, and 35) are considered. The V-load and I-load values are reordered in three different time events within the SIMULINK running. Thus, the total number of samples done each time is 45. Thus, the overall samples of all implementations include 360 samples. The values of VIIT effective features are different from each implementation to another because the type of fault which is affected the PV model is different. The proposed PV, FDD power system, consists of 3 parallel strings; each string has four series modules.

Each module consists of 20 cells connected in series. The proposed PV model's graphical block diagram (MATLAB/ Simulink view) is mentioned in Fig. 2.

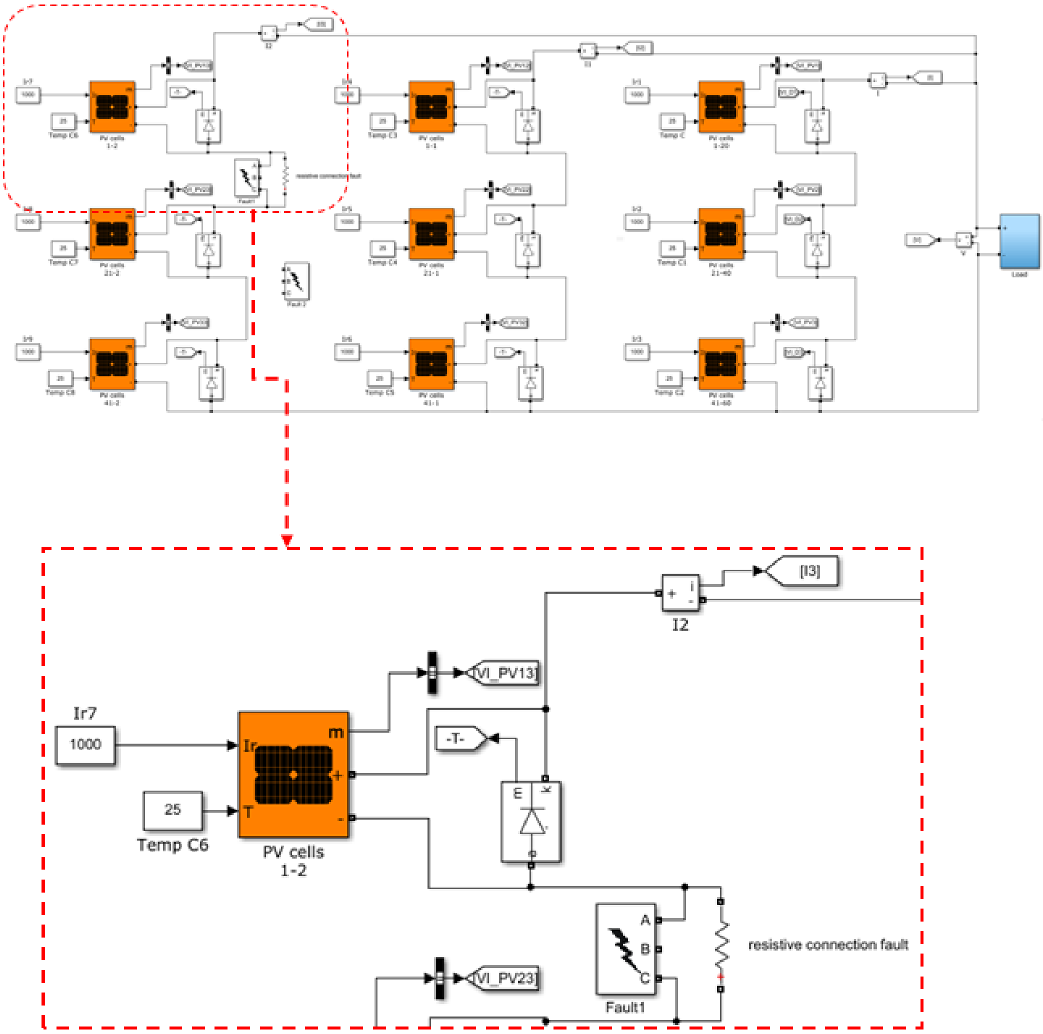


Figure 2. MATLAB/Simulink PV model

The main characteristics of the proposed PV system can be summarized as: the open-circuit voltage is 37.92 volt, the short circuit current is 3x8.62 Amp, and the maximum power is 3x83.284 Watt.

3.2. Neural Networks for Fault Detection

To detect PV system faults, ANN is utilized in this paper. The three layers of ANN in the proposed PV FDD system are an input layer which is composed of four valuable features input PV parameters VIIT [51]. The output layer comprises eight neurons, each representing one kind of PV fault from seven types and the healthy PV module [52]. Thus, the proposed ANN is implemented three times with three different numbers of hidden layers (25, 30, and 40) in each implementation, as demonstrated in Fig. 3.

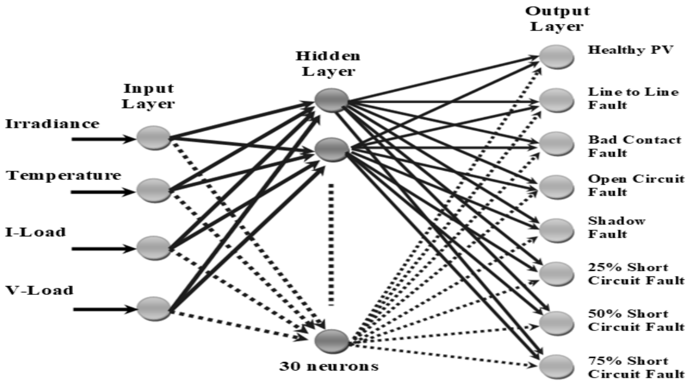


Figure 3. Three-layer feed-forward ANN structure

These samples are divided into two groups. The first group includes 70% of samples which are used in the training phase of ANN, while the second group includes 30% which are used in the testing phase of ANN. The distributing scenario of samples is performed in fact that the three records in each implementation with the same conditions of irradiance and temperature are divided into two groups; two records in the first group, and the other record in the second group. Thus, the first group includes 240 samples with 30 samples for each type of PV fault and the second group includes 120 samples with 15 samples for each type of the PV fault. The proposed algorithm type is a feed-forward neural network using the training algorithm Levenberg-Marquardt backpropagation with a maximum number of epochs to train equal to 1000000 and a minimum performance gradient equal to 1e-20.

3.3. Evaluation Analysis

In this part, the simulation results obtained from the suggested ANN implementations are confirmed by comparing them to the equivalent simulation results from several well-known current studies employing ANN to identify various PV defects [42], [44], [53], [54-60]. As shown in Eq. (1), Root Mean Square Error (RMSE) was utilized as the key statistic to evaluate the performance of constructed models.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2} \quad (1)$$

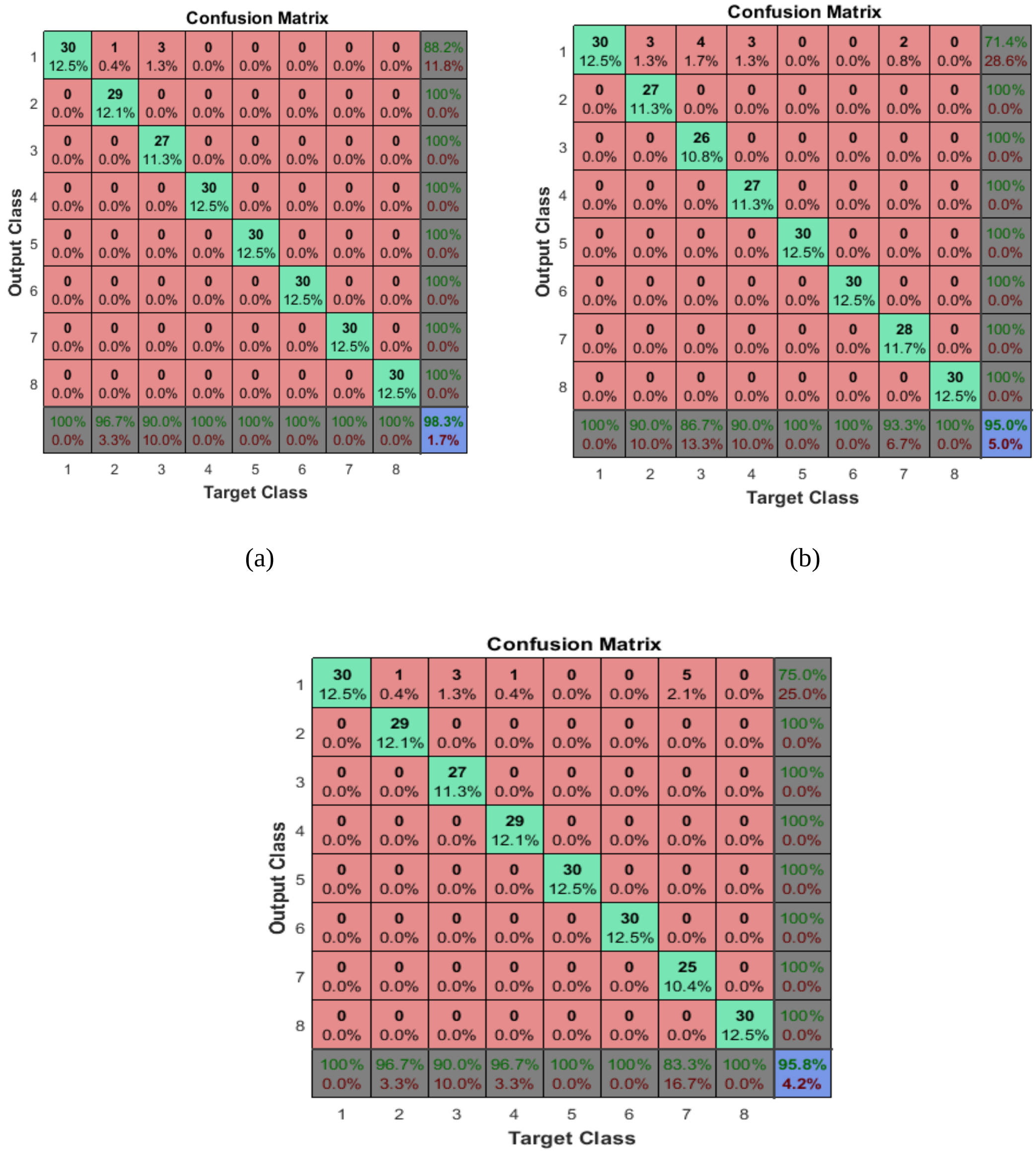
Where: n: number of samples, f: forecasts, and o: observed values. In this work, RMSE is used as a primary metric. In this work, RMSE is used as a primary metric.

4. RESULTS AND DISCUSSION

The system consisted of two major components: the first component was the fault generation model used to gather the training data for the suggested schema. The second component is the proposed ANN schema that is trained to properly categorize and detect problems.

4.1.Results and Discussion.

The simulation results collected from impl44ementing the proposed ANN in the training and testing phases are in more detail in this section. The resulting 360 samples that obtained from using a MATLAB/SIMULINK model are trained and tested according to the Levenberg-Marquardt backpropagation algorithm. The structure of the proposed ANN for diagnosing faults in the PV module is mentioned in Fig. 2. When the training process of the ANN is finished, the trained network must be evaluated to validate the network's performance; we use a confusion matrix for this purpose. The results of the algorithm are shown in the form of a confusion matrix in Fig. 4 a, b, and c, respectively. The confusion matrix diagram acquires exceptional importance compared to the other evaluation diagram based on the fact that all the standard evaluation parameters true positive (TP), true negative (TN), false positive (FP), and false negative (FN), are obtained in this diagram. The diagonal part in this matrix, marked with green, contains the true positive elements with the correct fault classification value. Also, the diagonal cell in the right lower corner, marked with blue, includes the overall accuracy for all classification categories.



(a) (b)

(c)

Figure 4. **T**he Resulted Confusion Matrix Diagram of Three Implementation of the Proposed ANN in the training phase with; (a) 25, (b) 30, and (c) 40 Hidden Layers

Also, Tables 1 and 2 show the simulation results of the training and testing phases, respectively, with the accuracy calculated from the confusion matrix of each predicated fault by the proposed ANN.

Table 1. The simulation results of the training phase

Fault Name	No. of Training Samples	Predicated Faults by Proposed ANN			Accuracy %
		Correct fault	Wrong faults	Details of wrong faults	
Healthy PV (FF1)	30	30	0		100%
Bad Contact (FF2)		29	1	1 Fault FF3	96.6%
L-L fault (FF3)		30	0		100%
25% short (FF4)		30	0		100%
50%short (FF5)		30	0		100%
75%short (FF6)		28	2	1 Fault FF3 1 Fault FF2	93%
Shadow (FF7)		30	0		100%
Open circuit (FF8)		30	0		100%
Average Accuracy					98.73%

Table 2. The simulation results of the testing phase

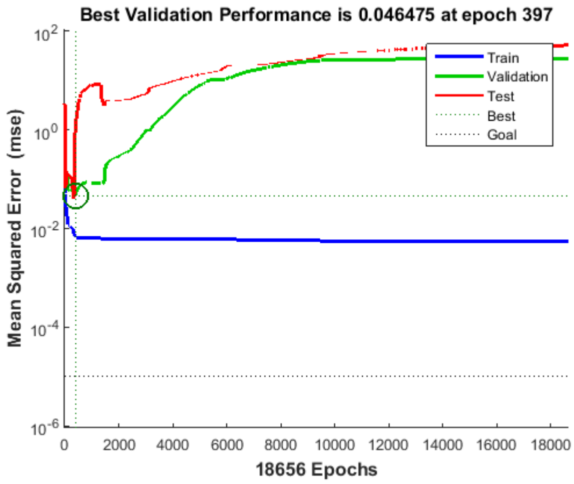
Fault Name	No. of Testing Samples	Predicated Faults by Proposed ANN			Accuracy %
		Correct fault	Wrong faults	Details of wrong faults	
Healthy PV (FF1)	15	15	0		100%
Bad Contact (FF2)		14	1	1 Fault FF6	93.3%
L-L fault (FF3)		14	1		100%
25% short (FF4)		14	1		93.3%
50%short (FF5)		15	0		100%
75%short (FF6)		14	1	1 Fault FF3	93.3%
Shadow (FF7)		15	0		100%
Open circuit (FF8)		15	0		100%
Average Accuracy					97.48%

The simulation results in three confusion matrix diagrams view that the best overall accuracy is recorded in the first implementation of the proposed ANN with 25 hidden layers. The maximum overall accuracy is (98.3%), while in the second implementation with 30 hidden layers is (97.5%) and (95.8%) for the third implantation of 40 hidden layers. The estimated RMSE show that the training phase gains 0.193 and the testing phase has 0.365.

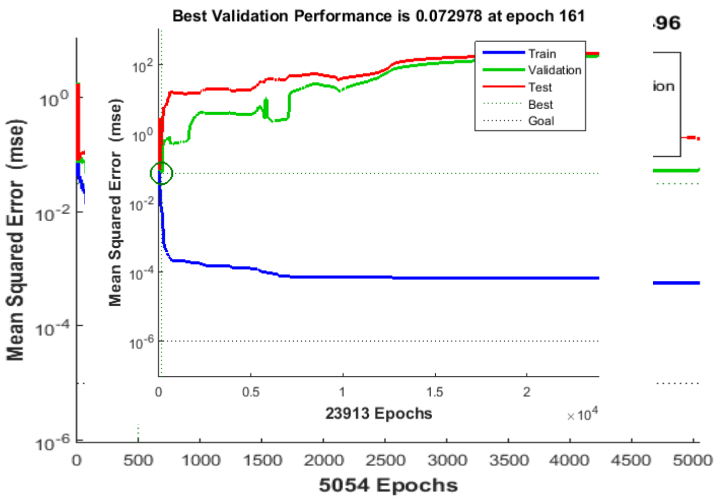
4.2.Performance diagrams

As mentioned previously, the maximum number of epochs considered in the training phase is 100000. The performance diagrams for the three implementations which are mentioned in the previous section are shown in Fig 5.a, b, c, respectively. In each diagram, the green line represents the validated fault, while the red line represents the test fault. The behavior of red and green curves is different. In Fig 5.a, the two curves go in a parallel way and there is no convergence between them even at the minimum error point marked with a black circle and a dashed line vertical. While, the same two curves in Fig 5.b and 5.c go nearest each other when the epochs counting of training is increased. On the other hand, the blue line in these diagrams represents the flow of the training process. The behavior of this line in Fig 5.b and 5.c goes to the steady-state value for a long time. While there are many fluctuations in the blue line before reaching the state of stability as presented in Fig 5.a. The previous discussion about the three performance diagrams proves the quality of the second and third implementation according to the matching between the validated and tested lines in addition to the long period of steady-state value for the training process.

(a)



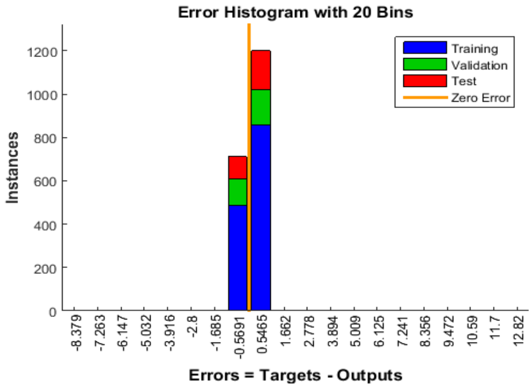
(b)



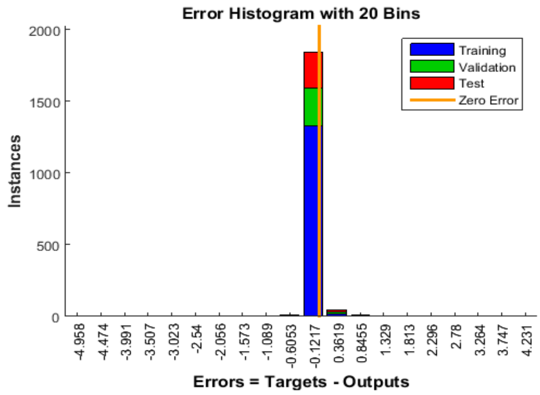
(c)

Figure 5. Performance Plotting Diagram of Training the Proposed ANN with; (a) 25, (b) 30, and (c) 40 Hidden Layers

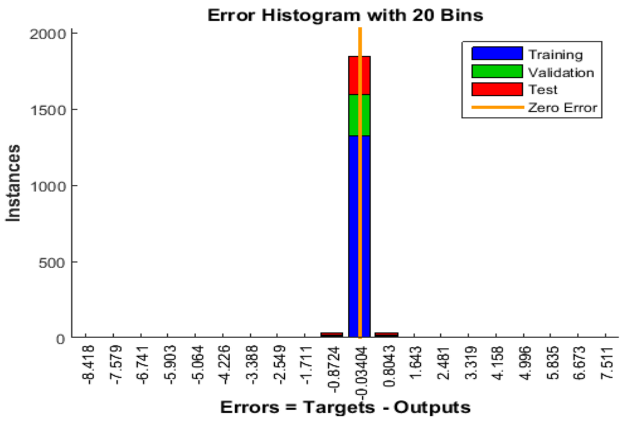
Another evaluating diagram called the error histogram diagram is presented. This diagram takes the greatest importance in the evaluation process based on the fact that this diagram views the determined error between the resulted and predicated outputs. The histogram error diagram for the three implementations of the proposed ANN is mentioned in Fig. 6.a, b, and c, respectively. The simulation results in these figures view that the determined errors of tested, validated, and trained data in the three diagrams go nearest the zero-error vertical line marked with orange color.



(a)



(b)



(c)

Figure 6. The Error Histogram Diagram of Three Implementation of the Proposed ANN in the training phase with; (a) 25, (b) 30, and (c) 40 Hidden Layers.

5. CONCLUSION

A new fault detection technique in a PV system based on three layers of feed-forward ANN is proposed, and its feasibility is validated through experiments and simulations in which some typical faults, including a short circuit of PV module, an open circuit of PV module, and short circuit of the battery, are established. Experiment and simulation data demonstrate this method's high accuracy in distinguishing between fault types and normal functioning. On the other hand, the first approach with concealed equals 20 yields the most accurate total simulation results. This situation has occurred repeatedly. Future research might utilize this technology for real-time monitoring of PV systems, extend it to large ones, and examine more defects.

6. References

[1] N. Kahoul Laboratoire D'electrotechnique, D', A. Badji, and M. Mekki Laboratoire D'electrotechnique D', "Adaptive P&O MPPT Technique for Photovoltaic Buck-Boost Converter System," *Int. J. Comput. Appl.*, vol. 112, no. 12, pp. 975–8887, 2015.

[2] N. Ismail, F. Hani Nordin, and Z. A. M. Sharrif, "Short-Circuit Incipient Faults Detection from Single Phase PWM Inverter using Artificial Neural Network," *Indian J. Sci. Technol.*, vol. 10, no. 25, pp. 1–10, 2017, doi: 10.17485/ijst/2017/v10i25/116506.

[3] H. Tuama, H. Abbas, N. S. Alseelawi, and H. T. H. S. AlRikabi, "Bordering a set of energy criteria for the contributing in the transition level to sustainable energy in electrical Iraqi projects," *Period. Eng. Nat. Sci.*, vol. 8, no. 1, pp. 516–525, 2020.

[4] S. R. Madeti and S. N. Singh, "Modeling of PV system based on experimental data for fault detection using kNN method," *Sol. Energy*, vol. 173, pp. 139–151, 2018, doi: https://doi.org/10.1016/j.solener.2018.07.038.

[5] S. Fadhel *et al.*, "PV shading fault detection and classification based on I-V curve using principal component analysis: Application to isolated PV system," *Sol. Energy*, vol. 179, no. December 2018, pp. 1–10, 2019, doi: 10.1016/j.solener.2018.12.048.

[6] H. A. Abd el-Ghany, A. E. ELGebaly, and I. B. M. Taha, "A new monitoring technique for fault detection and classification in PV systems based on rate of change of voltage-current trajectory," *Int. J. Electr. Power Energy Syst.*, vol. 133, p. 107248, 2021, doi: https://doi.org/10.1016/j.ijepes.2021.107248.

[7] A. Eskandari, J. Milimonfared, M. Aghaei, and A. H. M. E. Reinders, "Autonomous Monitoring of Line-to-Line Faults in Photovoltaic Systems by Feature Selection and Parameter Optimization of Support Vector Machine Using Genetic Algorithms," *Applied Sciences* , vol. 10, no. 16. 2020, doi: 10.3390/app10165527.

[8] J. Pan, W. He, Y. Shi, R. Hou, and H. Zhu, "Uncertainty analysis based on non-parametric statistical modelling method for photovoltaic array output and its application in fault diagnosis," *Sol. Energy*, vol. 225, pp. 831–841, 2021, doi: https://doi.org/10.1016/j.solener.2021.07.064.

[9] F. Han *et al.*, "An intelligent fault diagnosis method for PV arrays based on an improved rotation forest algorithm," *Energy Procedia*, vol. 158, no. 2018, pp. 6132–6138, 2019, doi: 10.1016/j.egypro.2019.01.498.

[10] B. Basnet, H. Chun, and J. Bang, "An Intelligent Fault Detection Model for Fault Detection in Photovoltaic Systems," *J. Sensors*, vol. 2020, p. 6960328, 2020, doi: 10.1155/2020/6960328.

[11] A. H. Omran, D. M. Said, S. M. Hussin, N. Ahmad, and H. Samet, "A novel intelligent detection schema of series arc fault in photovoltaic (PV) system based convolutional neural network," *Period. Eng. Nat. Sci.*, vol. 8, no. 3, pp. 1641–1653, 2020, doi: 10.21533/pen.v8i3.1566.

[12] S. Samara and E. Natsheh, "Intelligent Real-Time Photovoltaic Panel Monitoring System Using Artificial Neural Networks," *IEEE Access*, vol. 7, pp. 50287–50299, 2019, doi: 10.1109/ACCESS.2019.2911250.

[13] A. Khoshnami and I. Sadeghkhani, "Two-stage power–based fault detection scheme for photovoltaic systems," *Sol. Energy*, vol. 176, pp. 10–21, 2018, doi: https://doi.org/10.1016/j.solener.2018.10.014.

[14] Y. Onal and U. C. Turhal, "Discriminative common vector in sufficient data Case: A fault detection and classification application on photovoltaic arrays," *Eng. Sci. Technol. an Int. J.*, vol. 24, no. 5, pp. 1168–1179, 2021, doi: https://doi.org/10.1016/j.jestch.2021.02.017.

[15] D. Adhya, S. Chatterjee, and A. K. Chakraborty, "Performance assessment of selective machine learning techniques for improved PV array fault diagnosis," *Sustain. Energy, Grids Networks*, vol. 29, p. 100582, 2022, doi: https://doi.org/10.1016/j.segan.2021.100582.

[16] N. Sabri, "Battery Internal Fault Monitoring Based on Anomaly Detection Algorithm," A. Tlemçani, Ed. Rijeka: IntechOpen, 2020, p. Ch. 10.

[17] A. Belaout, F. Krim, and A. Mellit, "Neuro-fuzzy classifier for fault detection and classification in photovoltaic module," in *2016 8th International Conference on Modelling, Identification and Control (ICMIC)*, 2016, pp. 144–149, doi: 10.1109/ICMIC.2016.7804289.

[18] D. S. Pillai and N. Rajasekar, "A comprehensive review on protection challenges and fault diagnosis in PV systems," *Renew. Sustain. Energy Rev.*, vol. 91, pp. 18–40, 2018, doi: https://doi.org/10.1016/j.rser.2018.03.082.

[19] L. Rouani, M. F. Harkat, A. Kouadri, and S. Mekhilef, "Shading fault detection in a grid-connected PV system using vertices principal component analysis," *Renew. Energy*, vol. 164, pp. 1527–1539, 2021, doi: https://doi.org/10.1016/j.renene.2020.10.059.

[20] A. E. Lazzaretti *et al.*, "A Monitoring System for Online Fault Detection and Classification in Photovoltaic Plants," *Sensors* , vol. 20, no. 17. 2020, doi: 10.3390/s20174688.

(c)

[21] M. Dhimish, V. Holmes, B. Mehrdadi, and M. Dales, "Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection," *Renew. Energy*, vol. 117, pp. 257–274, 2018, doi: 10.1016/j.renene.2017.10.066.

[22] W. Chine and A. Mellit, "ANN-based fault diagnosis technique for photovoltaic stings," *2017 5th Int. Conf. Electr. Eng. - Boumerdes, ICEE-B 2017*, vol. 2017-Janua, pp. 1–4, 2017, doi: 10.1109/ICEE-B.2017.8192078.

[23] C. K. Khelil, K. Kara, and A. Chouder, "Fault detection of the photovoltaic system by artificial neural networks," *4th Int. Conf. Green Energy Environ. Eng.*, vol. 4, pp. 60–65, 2017.

[24] D. Kudelas, M. Taušová, P. Tauš, Ľ. Gabániová, and J. Koščo, "Investigation of Operating Parameters and Degradation of Photovoltaic Panels in a Photovoltaic Power Plant," *Energies* , vol. 12, no. 19. 2019, doi: 10.3390/en12193631.

[25] A. S. Edun *et al.*, "Finding Faults in PV Systems: Supervised and Unsupervised Dictionary Learning With SSTDR," *IEEE Sens. J.*, vol. 21, no. 4, pp. 4855–4865, 2021, doi: 10.1109/JSEN.2020.3029707.

[26] R. Fazai, M. Mansouri, K. Abodayeh, M. Trabelsi, H. Nounou, and M. Nounou, "Machine Learning-Based Statistical Hypothesis Testing for Fault Detection," in *2019 4th Conference on Control and Fault Tolerant Systems (SysTol)*, 2019, pp. 38–43, doi: 10.1109/SYSTOL.2019.8864776.

[27] S. Ahmad, N. Hasan, V. S. B. Kurukuru, M. A. Khan, and A. Haque, "Fault Classification for Single Phase Photovoltaic Systems using Machine Learning Techniques," in *2018 8th IEEE India International Conference on Power Electronics (IICPE)*, 2018, pp. 1–6, doi: 10.1109/IICPE.2018.8709463.

[28] R. Mandal and P. Kale, "Assessment of Different Multiclass SVM Strategies for Fault Classification in a PV System," 2021, pp. 747–756.

[29] R. K. Mandal, N. Anand, N. Sahu, and P. Kale, "PV System Fault Classification using SVM Accelerated by Dimension Reduction using PCA," in *2020 IEEE 9th Power India International Conference (PIICON)*, 2020, pp. 1–6, doi: 10.1109/PIICON49524.2020.9112896.

[30] IRENA *et al.*, "Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection," *Renew. Energy*, vol. 173, no. 3, pp. 257–274, 2018, doi: https://doi.org/10.1016/j.solener.2018.07.038.

[31] B. Amrouche and X. Le Pivert, "Artificial neural network based daily local forecasting for global solar radiation," *Appl. Energy*, vol. 130, pp. 333–341, 2014, doi: https://doi.org/10.1016/j.apenergy.2014.05.055.

[32] A. H.Mohamed and A. M. N. A.M.Nassar, "New Algorithm for Fault Diagnosis of Photovoltaic Energy Systems," *Int. J. Comput. Appl.*, vol. 114, no. 9, pp. 26–31, 2015, doi: 10.5120/20008-1959.

[33] R. Ghosh, S. Das, and C. K. Panizrahi, "Classification of Different Types of Faults in a Photovoltaic System," *7th IEEE Int. Conf. Comput. Power, Energy, Inf. Commun. ICCPEIC 2018*, pp. 121–127, 2018, doi: 10.1109/ICCPEIC.2018.8525170.

[34] S. Laamami, M. Benhamed, and L. Sbita, "Artificial neural network-based fault detection and classification for photovoltaic system," *Int. Conf. Green Energy Convers. Syst. GECS 2017*, no. 1, 2017, doi: 10.1109/GECS.2017.8066211.

[35] N. Sabri, A. Tlemcani, and A. Chouder, "Faults diagnosis in stand-alone photovoltaic system using artificial neural network," *2018 6th Int. Conf. Control Eng. Inf. Technol. CEIT 2018*, no. October, pp. 25–27, 2018, doi: 10.1109/CEIT.2018.8751924.

[36] C. Feng, Y. Liu, and J. Zhang, "A taxonomical review on recent artificial intelligence applications to PV integration into power grids," *Int. J. Electr. Power Energy Syst.*, vol. 132, p. 107176, 2021, doi: https://doi.org/10.1016/j.ijepes.2021.107176.

[37] A. Mellit and S. Kalogirou, "Assessment of machine learning and ensemble methods for fault diagnosis of photovoltaic systems," *Renew. Energy*, vol. 184, pp. 1074–1090, 2022, doi: https://doi.org/10.1016/j.renene.2021.11.125.

[38] Z. Yi and A. Etemadi, "Fault Detection for Photovoltaic Systems Based on Multi-Resolution Signal Decomposition and Fuzzy Inference Systems," *IEEE Trans. Smart Grid*, vol. 8, p. 1, Jan. 2016, doi: 10.1109/TSG.2016.2587244.

[39] C. H. da Costa *et al.*, "A Comparison of Machine Learning-Based Methods for Fault Classification in Photovoltaic Systems," in *2019 IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America)*, 2019, pp. 1–6, doi: 10.1109/ISGT-LA.2019.8895279.

[40] S. Fadhel *et al.*, "PV shading fault detection and classification based on I-V curve using principal component analysis: Application to isolated PV system," *Sol. Energy*, vol. 179, pp. 1–10, 2019, doi: https://doi.org/10.1016/j.solener.2018.12.048.

[41] A. Ul-Haq, H. F. Sindi, S. Gul, and M. Jalal, "Modeling and Fault Categorization in Thin-Film and Crystalline PV Arrays through Multilayer Neural Network Algorithm," *IEEE Access*, vol. 8, pp. 102235–102255, 2020, doi: 10.1109/ACCESS.2020.2996969.

[42] M. W. Ahmad, M. Mourshed, and Y. Rezgui, "Tree-based ensemble methods for predicting PV power generation and their comparison with support vector regression," *Energy*, vol. 164, pp. 465–474, 2018, doi: https://doi.org/10.1016/j.energy.2018.08.207.

[43] R. Benkercha and S. Moulahoum, “Fault detection and diagnosis based on C4.5 decision tree algorithm for grid connected PV system,” *Sol. Energy*, vol. 173, pp. 610–634, 2018, doi: https://doi.org/10.1016/j.solener.2018.07.089.

[44] M. Abbas and D. Zhang, “A smart fault detection approach for PV modules using Adaptive Neuro-Fuzzy Inference framework,” *Energy Reports*, vol. 7, pp. 2962–2975, 2021, doi: https://doi.org/10.1016/j.egyr.2021.04.059.

[45] A. Djalab, M. M. Rezaoui, L. Mazouz, A. Teta, and N. Sabri, “Robust method for diagnosis and detection of faults in photovoltaic systems using artificial neural networks,” *Period. Polytech. Electr. Eng. Comput. Sci.*, vol. 64, no. 3, pp. 291–302, 2020, doi: 10.3311/PPee.14828.

[46] C. B. Jones, J. S. Stein, S. Gonzalez, and B. H. King, “Photovoltaic system fault detection and diagnostics using Laterally Primed Adaptive Resonance Theory neural network,” in *2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC)*, 2015, pp. 1–6, doi: 10.1109/PVSC.2015.7355834.

[47] J. H. Shin and J. O. Kim, “On line diagnosis and fault state classification method of photovoltaic plant,” *Energies*, vol. 13, no. 17, 2020, doi: 10.3390/en13174584.

[48] W. Chine and A. Mellit, “ANN-based fault diagnosis technique for photovoltaic stings,” in *2017 5th International Conference on Electrical Engineering - Boumerdes (ICEE-B)*, 2017, pp. 1–4, doi: 10.1109/ICEE-B.2017.8192078.

[49] L. Rouani, M. F. Harkat, A. Kouadri, and S. Mekhilef, “Shading fault detection in a grid-connected PV system using vertices principal component analysis,” *Renew. Energy*, vol. 164, pp. 1527–1539, 2021, doi: 10.1016/j.renene.2020.10.059.

[50] F. Aziz, A. U. Haq, S. Ahmad, Y. Mahmoud, M. Jalal, and U. Ali, “A Novel Convolutional Neural Network-Based Approach for Fault Classification in Photovoltaic Arrays,” *IEEE Access*, vol. 8, pp. 41889–41904, 2020, doi: 10.1109/ACCESS.2020.2977116.

[51] C. Kapucu and M. Cubukcu, “A supervised ensemble learning method for fault diagnosis in photovoltaic strings,” *Energy*, vol. 227, p. 120463, 2021, doi: https://doi.org/10.1016/j.energy.2021.120463.

[52] M. U. Ali, H. F. Khan, M. Masud, K. D. Kallu, and A. Zafar, “A machine learning framework to identify the hotspot in photovoltaic module using infrared thermography,” *Sol. Energy*, vol. 208, pp. 643–651, 2020, doi: https://doi.org/10.1016/j.solener.2020.08.027.

[53] A. Botchkarev, “Evaluating Performance of Regression Machine Learning Models Using Multiple Error Metrics in Azure Machine Learning Studio,” *SSRN Electron. J.*, no. March, 2018, doi: 10.2139/ssrn.3177507.

[54] M. K. Abdul-Hussein "Li-Fi Future Technology, Architecture, and their Constraints," Texas Journal of Engineering and Technology, vol. 9, pp. 167-174, 2022.

[55] A. Z. Abass, Faisal T. Abed, and J. Gaidukov, "Economic Feasibility Study of a Hybrid Power Station Between Solar Panels and Wind Turbine with The National Grid in Al- Hayy City in the Central of Iraq," IOP Conf. Series: Materials Science and Engineering, vol. 1184, no. 012001, 2021.

[56] F. T. Abed, and I. A. Ibrahim, "Efficient Energy of Smart Grid Education Models for Modern Electric Power System Engineering in Iraq," in IOP Conference Series: Materials Science and Engineering, 2020, vol. 870, no. 1: IOP Publishing, p. 012049.

[57] M. Farhan, and T. N. Sultan, "Investigation The Factors Affecting on The Performance of PV System," in AIP conference proceedings, 2021, vol. 2394, no. SICPS2021: AIP Publishing LLC.

[58] F. T. Abed, H. T. Salim Alrikabi, and I. A. Ibrahim, "Efficient energy of smart grid education models for modern electric power system engineering in Iraq," in IOP Conference Series: Materials Science and Engineering, 2020, vol. 870, 1 ed., doi: 10.1088/1757-899X/870/1/012049. [Online]. Available:

[59] H. F. Khazaal, F. T. Abed, and S. I. Kadhm, "Water desalination and purification using desalination units powered by solar panels," Periodicals of Engineering and Natural Sciences, vol. 7, no. 3, pp. 1373-1382, 2019.

[60] A. Hernandez-Matamoros, H. Fujita, T. Hayashi, and H. Perez-Meana, “Forecasting of COVID19 per regions using ARIMA models and polynomial functions,” *Appl. Soft Comput.*, vol. 96, p. 106610, Nov. 2020, doi: 10.1016/j.asoc.2020.106610.