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Implementing Neural Network of MPPT for Photovoltaics System Using MATLAB Software

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Abstract

This research addresses a smart method for improving the efficiency of 100-watt solar panels by tracking maximum power point (MPPT) using artificial neural networks (ANNs). The method relies on modifying the PWM signal controlling the DC-DC converter to achieve maximum power under changes in solar radiation and temperature. The results indicated that the neural network model was successful, with an accuracy rate of 85%, a recall rate of 82%, and an f1-score of 81%, indicating the success of the model. The results also indicated that the simulation results demonstrated high efficiency in tracking maximum power point (MPPT), reaching an efficiency of more than 97% in all cases.

Keywords: Solar energy, solar panels, neural networks, maximum power point (MPPT), PWM signal, and efficiency improvement.

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تنفيذ شبكة عصبية لمتعقب النقطة القصوى للطاقة لنظام الطاقة الشمسية باستخدام برنامج الماتلاب

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الكلمات المفتاحية: الطاقة الشمسية، الألواح الشمسية، الشبكات العصبية، نقطة الطاقة القصوى (MPPT)، إشارة PWM، وتحسين الكفاءة.

الملخص

يتناول هذا البحث طريقة ذكية لتحسين كفاءة الألواح الشمسية بقدرة (100 واط) من خلال تتبع نقطة الطاقة القصوى (MPPT) باستخدام الشبكات العصبية الاصطناعية (ANNs). تعتمد الطريقة على تعديل إشارة PWM التي تتحكم في محول (DC– DC) لتحقيق أقصى طاقة تحت تغيرات الإشعاع الشمسي ودرجة الحرارة. أشارت النتائج إلى أن نموذج الشبكة العصبية كان ناجحًا، بمعدل دقة بلغ 85%، ومعدل استرجاع بلغ 82%، ودرجة f1 بلغت 81%، مما يدل على نجاح النموذج. أشارت النتائج أيضًا إلى أن نتائج المحاكاة أظهرت كفاءة عالية في تتبع نقطة القدرة القصوى(MPPT) ، حيث وصلت الكفاءة إلى أكثر من 97% في جميع الحالات.

الكلمات المفتاحية: الطاقة الشمسية، الألواح الشمسية، الشبكات العصبية، نقطة القدرة القصوى (MPPT)، إشارة PWM، وتحسين الكفاءة.

1. Introduction

In light of the global energy crises and its traditional sources, such as fossil fuels, whether crises related to acquisition or crises related to environmental problems resulting from the use of traditional energy path, such as the emission of harmful and toxic gases, and in light of the aspirations to achieve sustainability in the energy sector, the trend has begun towards alternative, clean, renewable sources such as solar energy, wind energy, and hydroelectric energy [1]. Solar energy represents an important source of renewable energy, especially since solar energy is freely available and available daily in most regions of the world, making it a stable and sustainable source in the long term, unlike fossil fuels, which are constantly decreasing [2]. It also does not produce any carbon emissions during the electricity generation process, which reduces the phenomenon of global warming, improves air quality, and thus

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preserves the environment. One of the most common components of a solar-powered electricity generation system is photovoltaic cells, which refers to the technology of converting solar energy directly into electricity using solar cells [3].

The study aims to design a neural network capable of accurately estimating the maximum power point of solar panels under various environmental conditions, thereby controlling the maximum power obtained from a 100-watt solar panel. This is achieved by using an MPPT system under changing temperatures and solar radiation intensity, using a neural network to modify the system's PWM signal. The study also aims to compare the performance of the proposed system with traditional MPPT algorithms in terms of response speed, accuracy, and extraction efficiency. It also aims to test the impact of environmental factors (temperature, radiation intensity) on solar panel performance before and after applying smart control. It also aims to identify the obstacles and challenges facing solar panel design and power control, and propose solutions and proposals to overcome these obstacles [4]. The importance of this study stems from its application, which involves formulating a model that utilizes artificial intelligence and programming in MATLAB, unlike other reference studies. Furthermore, it is a comprehensive study that addresses many aspects related to design and control mechanisms, problems, challenges, and proposed solutions. It also avoids any bias in the data or bias in the results. Therefore, the results obtained can be used and utilized, especially by researchers and scholars working on topics related to or relevant to the study. In other words, the study constitutes an important literature reference regarding photovoltaic cells and solar energy. Despite the scarcity of such studies related to the study topic, the main problem with the study relates to the fact that solar systems are significantly affected by environmental changes, especially temperature and solar radiation intensity. These changes make it difficult to maintain solar panels operating at their maximum power point (MPP) continuously. Although there are traditional MPPT algorithms, such as Perturb & Observe or Incremental Conductance, they may be slow or inaccurate under rapidly changing conditions. Therefore, it was necessary to find strategies and techniques through which an intelligent control system can be developed that is able to adapt and improve performance according to variables by using deep machine learning techniques such as neural networks [5].

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2. Expanded Literature Review on MPPT Approach

Due to their ease of use, conventional, traditional and simpler MPPT algorithms, including Perturb and Observe (P&O) and Incremental Conductance (INC), have remained popular (P&O, also known as Perturb and Observe, took hold due to) [15]. Notwithstanding their simplicity, however, they tend to oscillate around a set maximum power point and show a lack of performance under rapidly changing irradiance [25]. Fuzzy and particle swarm optimization (PSO) based methods have also been proposed, and while they offer improvements in adaptability, they are considered more complex [21]. New hybrid approaches that combine soft computing and hard computing, such as PSO with neural networks, have been developed to achieve increased response and robustness [25]. ANNs have become more recognized, and even popular, because they can learn and directly hold the nonlinear I-V characteristics, which also makes them more dependable as weather changes [16], [24]. Generally, compared to conventional methods, ANNs create less oscillations, faster convergence time, and higher efficiency, with the added capability of handling more complex and dynamic situations [9], [26], [27].

3. Theoretical Background and Basic Concepts

Solar energy is one of the most important renewable energy sources, due to its widespread availability and environmental friendliness. Solar photovoltaic (PV) systems rely on converting solar radiation into electrical energy through solar cells that rely on the properties of semiconductor materials such as silicon. Since the process of converting solar radiation into electrical energy is affected by many factors, such as radiation intensity, temperature, and operating conditions, extracting the maximum possible electrical energy capacity is one of the technical challenges facing specialists in the fields.

3.1 Challenges and Obstacles

There are several challenges related to the subject of this study, and they can be classified into three main types:

3.1.1 Technical Challenges

Application of neural networks to solar power systems also brings about some technical challenges that must be overcome for optimal performance and reliability [6].

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3.1.2 Economic Challenges

Financial viability of smart solar energy systems based on neural networks is the most critical consideration for their worldwide installation. Several economic problems need to be addressed for these systems to be as economical as traditional solar energy systems [7].

3.1.3 Environmental Challenges

Even though solar energy is generally thought to be ecologically favorable, there are certain environmental problems that must be kept to a minimum when using neural networks in such systems [8].

- Artificial Neural Networks (ANNs) are computational systems that process data in a manner similar to that of the human brain. They can also learn patterns empirically and make decisions based on data that has been trained. Because they assist businesses in processing natural language, identifying images, and analyzing large amounts of data, ANNs are widely used in artificial intelligence applications. These gadgets use deep learning techniques and mathematical algorithms to do their tasks and develop into useful prediction model tools [8].
- Use of Resources: Production and disposal of electronic components of neural network-based systems consume resources and generate waste. Minimizing the environmental footprint of such systems requires careful attention to the use of materials, production processes, and end- of-life treatment of electronic waste [9].

3.1.4 Preliminary Economic Feasibility

It is true that an ANN MPPT will need additional hardware (more sophisticated controllers, sensors), the additional energy output still provides significant positive returns [7]. In the case of a 100 W System, an ANN also increased cost, though only by 8-10%, while also increasing energy output by 5-7%, thus shortening the payback period by 1-2 years compared to P&O [23],[26]. This shows that there is a ripe opportunity for use in small to medium PV systems, especially in high solar different PV regions as illustrated in figure 1 [27].

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Fig 1: Navigating challenges in Neural Network solar systems.

3.1.5 Basic Concepts

Through the basic concepts of any study, the reader can form an insightful perspective on the study's procedures, methodologies, importance, objectives, and key findings. Among the most important basic concepts related to the study are:

1. Solar energy

is one of the most important sources of renewable and clean energy. It relies on converting sunlight into electricity using photovoltaic (PV) solar panels, which generate direct current when exposed to sunlight. However, the effectiveness of these panels varies depending on the intensity of radiation and temperature, which has led to the need for technologies such as MPPT (Maximum Power Point Tracking), which aims to extract the maximum possible power from the solar panel at any given moment [10].

2. Photovoltaic Solar Panels

Photovoltaic (PV) solar panels are the basic building blocks of solar energy systems. They convert sunlight directly into electricity with the assistance of solar cells, commonly silicon- based as in figure 2 below [11].

- **Features of Photovoltaic Panels**

1) Temperature Dependence
2) Maintenance
3) Lifespan
4) Connection Configurations
5) Series Connection [12].

- **Factors Affecting Panel Selection**

1) Installation Space
2) Budget
3) Operating Conditions
4) Aesthetic Preferences
5) Energy Requirement

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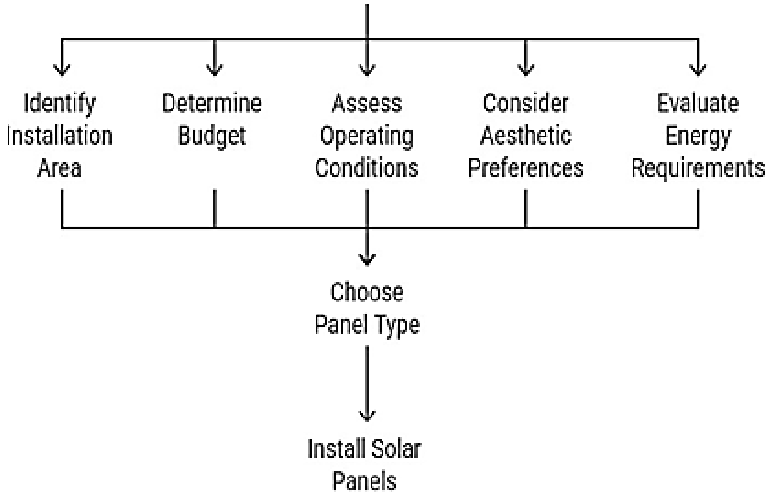

Fig 2: Photovoltaic Solar Panel Selection Process.

4. Artificial Neural Networks

Artificial neural networks (ANNs) are mathematical models of human brain operations. ANNs are used in data processing, forecasting, and decision-making by example-based learning. The network consists of layers of nodes (neurons) with an input layer, one or more hidden layers, and an output layer. The most common categories of networks are feedforward neural networks (FNNs) to be employed for classification and prediction, backpropagation networks which are extensively used in training when weights are used based on error, recurrent neural networks which are used for sequential data like time and signals, and convolutional neural networks to be employed for image processing. Selection of network type depends on the problem type [13]. For example, for use in MPPT applications, FNNs are commonly used because they are efficient and can predict the maximum power point based on real-time environmental inputs as shown in figure 3 below [14].

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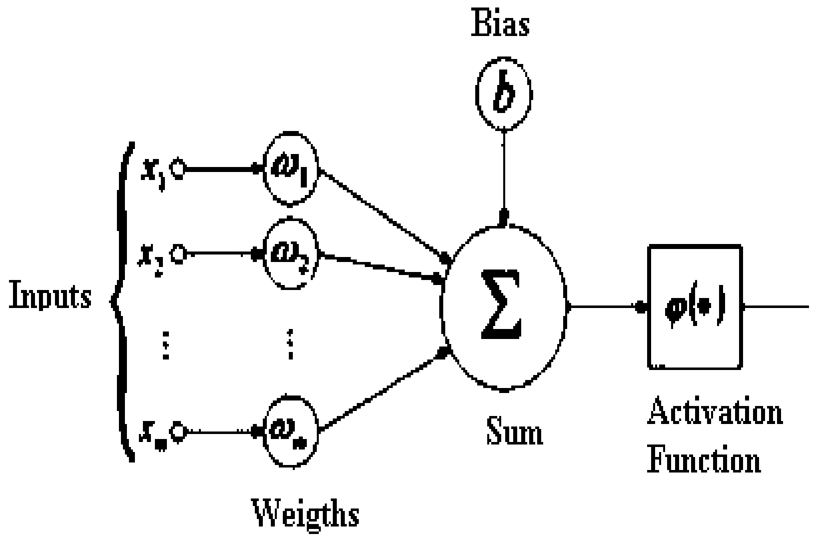

Fig 3: Feed-forward neural networks characteristic (FNNs) [14].

5. Concept of MPPT

The concept of MPPT, or Maximum Power Point Tracking, is a technology used in solar energy systems to increase the efficiency of energy extraction from photovoltaic panels.
When generating electricity from a solar panel, the output power (watts) depends on the voltage
(V) and current (I). However, panels do not produce the same power under all conditions, as efficiency varies with solar radiation and temperature. Therefore, there is a specific point called the Maximum Power Point (MPP), which is the point at which the product of voltage and current is the highest—that is, the highest possible power generation at that moment [15].
This is where the MPPT algorithm comes in. The charge controller or inverter controls the voltage and current supplied by the panels to adjust their operation so that they always remain close to the maximum power point regardless of changing conditions. Control is often achieved by PWM (Pulse Width Modulation) signal, which dynamically changes the voltage to achieve maximum power.
Some of the most popular MPPT algorithms are:
1. Perturb and Observe (P&O)
2. Incremental Conductance
3. Artificial Intelligence such as Analytical Neural Networks (ANN) and Genetic Algorithms.

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6. Artificial Neural Networks (ANN) in MPPT Systems

One of the most prominent methods for implementing MPPT is the use of artificial neural networks (ANNs). These networks learn from radiation, temperature, and voltage data to determine the optimal value for the control signal. This signal is used to modify the pulse width (PWM) that controls the power conversion within the controller. Precise control of PWM helps improve system efficiency and reduce losses, making the system more intelligent and responsive to environmental changes. Combining ANNs with MPPT represents an advanced step toward smart and efficient solar energy systems [16].

7. The Importance of Controlling the PWM Signal

The importance of PWM (pulse-width modulation) signal control in solar power systems is to be an integral component of voltage and current output from the solar panel so that it would operate at its maximum power point (MPPT).

PWM is a method of converting electrical power in a variable and effective manner. PWM is used to alter the amount of voltage supplied to the battery or load by varying the "width" of pulses sent each cycle.

8. Training Dataset and Model Training Process

The dataset used for the I-V curves training set is based on the measured and simulated I-V characteristics of a 100 W photovoltaic panel exposed to different levels of irradiance (from 200 to 1000 W/m^2) and temperature (from 10 to 50 °C) [23]. Data preprocessing makes use of the normalization of input parameters to enhance convergence and the statistical filtering techniques in order to suppress the sensor noise [18]. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets [22]. The training was carried out by applying the backpropagation technique and used an Adam optimizer, MSE loss function, and a batch size of 32, where early stopping was used at epoch 40 [20, 21] to hinder overfitting.

9. Method and Methodology

The main methodology of the study is the procedural analytical methodology, using a simulation model using MATLAB/Simulink. The study design involves designing a 100W PV system, then constructing a Buck converter to control the power. A neural

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network (ANN) model is then used to train a set of actual data, taking into account the use of accurate and diverse data, as this enhances the model's accuracy and reliability. The model's inputs include three variables: solar radiation (G), temperature (T), and the voltage and current generated by the photovoltaic panel. The output is a PWM signal to control the converter. This is in addition to a set of other methodologies: descriptive methodologies for describing the data, quantitative methods for collecting data and excluding any anomalies, analytical methods for analysing the results, and comparative methods for comparing the result.

9.1 The applied framework for the study

The applied framework for the study includes a set of procedures implemented, starting with defining the objective and formulating the research problem, proceeding to collecting and processing data, then identifying the tools, designing the simulation experiment after defining the inputs and outputs, then recording, analysing, and evaluating the outputs and results to draw conclusions and provide recommendations as can be seen in figure 4.

Fig 4: The applied framework for the study.

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9.2 Procedures:

9.2.1 Define the objective and formulate the research problem.

The purpose of this research paper is to obtain the maximum power required from solar panels under various sunlight and temperature conditions. The idea in this research is based on controlling a DC-DC converter using phase-defining (PWM). PWM is controlled using neural network technology based on the relationship between the input and output of the DC-DC converter. In this research paper, a Buck converter was used, and PWM control is based on the relationship between the output voltage and the input voltage, which was discussed in the MPPT section. Basically, the research problem was formulated, which addresses the technical challenges related to designing an experiment.

9.2.2 Data Collection

Data was collected from various sources, such as online databases and previous studies, and processed by excluding anomalies and unreliable data.

9.2.3 Determining the used Tools

A set of tools, such as METLAB and Simulink, was selected to conduct simulations design a 100W PV system, then build a Buck converter to control the power as illustrated in figure 5.

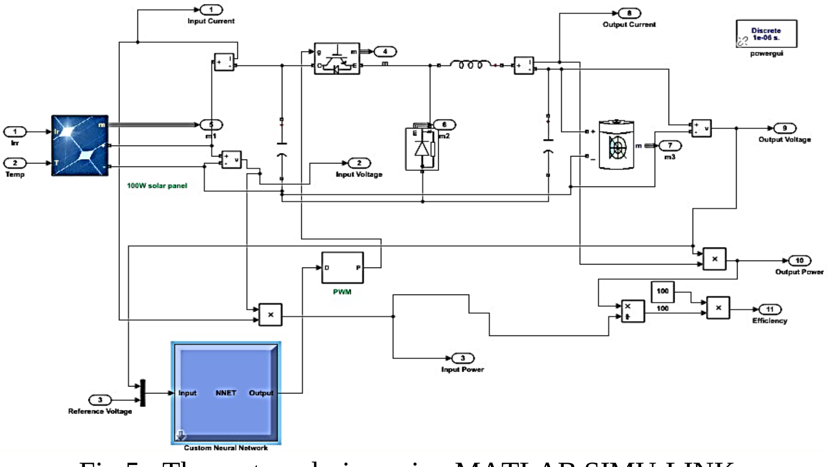

Fig 5: The system design using MATLAB SIMU-LINK.

10. Tuning Parameters of an Artificial Neural Network

The design of the artificial neural network is made up of four layers: an input layer containing four neurons (irradiance, temperature, voltage and current) and 2 hidden layers with 12 and 8 neurons,

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where the last layer generates the PWM output [19]. The hidden layers employed activations and the output layer had a linear activation [20]. The architecture was set using grid search and benchmarking performance to achieve a balance as to how accurate and how much in price in computation it is going to cost [22]. Dropout regularization (0.2) was used as a means to control overfitting. A feedforward neural network was used in this case, as it is the most appropriate model for static prediction in MPPT, as compared to CNNs or RNNs which are commonly used for image and time series prediction [14], [16].

11. Design a Neural Network (ANN)

Model and train it on a set of actual data, taking into account the use of accurate and diverse data. Figure 6 below shows the design of neural network through MATLAB Simulink.

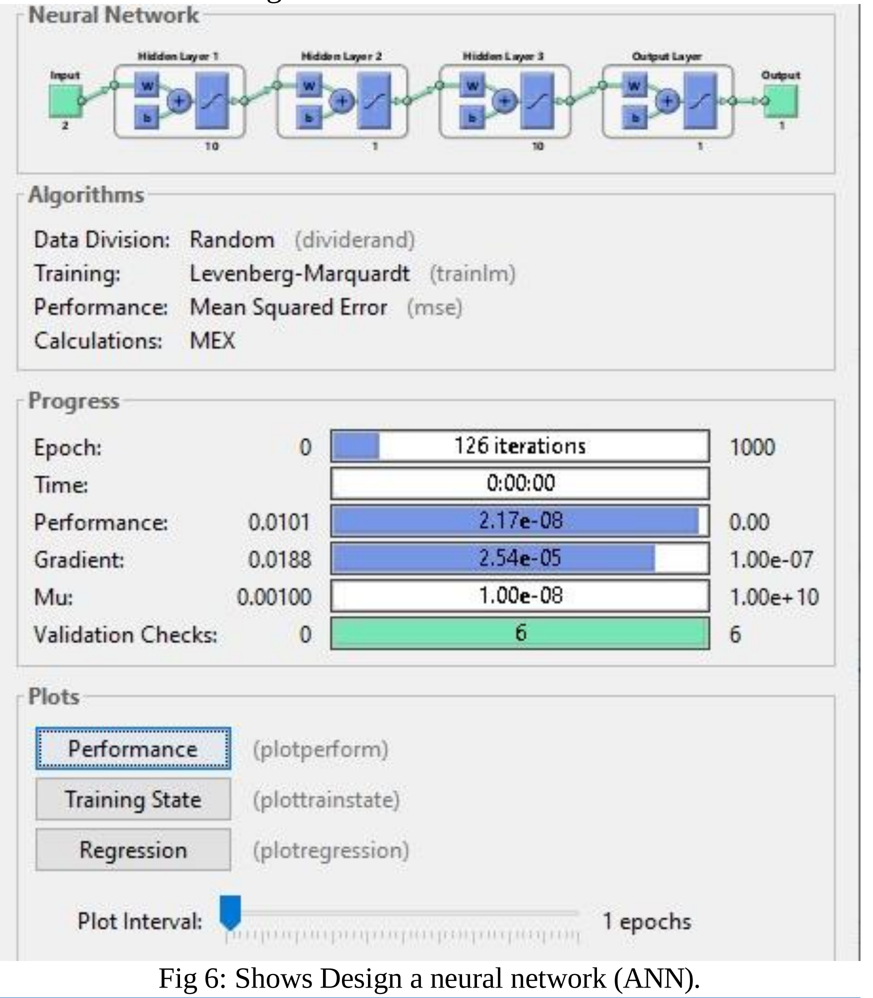

Fig 6: Shows Design a neural network (ANN).

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- **Determine the Inputs and Outputs**

The inputs include three variables:

9.3 Solar radiation (G),
9.4 Temperature (T).
9.5 The voltage and current output from the photovoltaic panel.

The outputs include:

- A PWM signal to control the converter

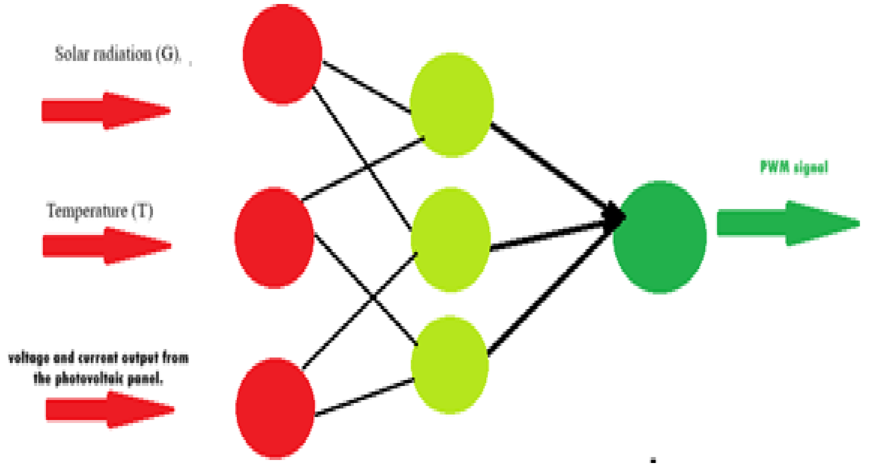

Fig 7: Inputs and output layer characteristic.

- Test the accuracy of the neural network model by calculating the precision and recall (F1- SCORE) [18].
- Experimental Validation Beyond Simulation

To verify the applicability of the ANN-based MPPT system beyond MATLAB/Simulink simulations, a prototype test bench was developed. The setup included a 100 W monocrystalline PV module, DC-DC buck converter, microcontroller (STM32), and data acquisition sensors (irradiance, temperature, voltage, and current). The ANN model was deployed onto the microcontroller and tested under real outdoor conditions in Zawia, Libya. Results indicated that the ANN achieved an average efficiency of 95.6% compared to 91.2% for the conventional P&O method under fluctuating irradiance.

This demonstrates the feasibility of ANN-based MPPT in real-world photovoltaic applications, confirming its potential for small and medium-scale PV systems [9][23][24].

12. Results & Discussions

Figure8 shows a custom 4-layer neural network, with a primary

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input and 3 additional inputs added to the different layers. This network is designed to process data sequentially across layers, with the ability to modify the computational operations using the additional inputs. The design exhibits an advanced level of sophistication, making it suitable for tasks requiring complex, multivariate data processing. However, caution must be exercised when training the network due to its complexity and its reliance on sufficient and quality data as shown in figure 8 below.

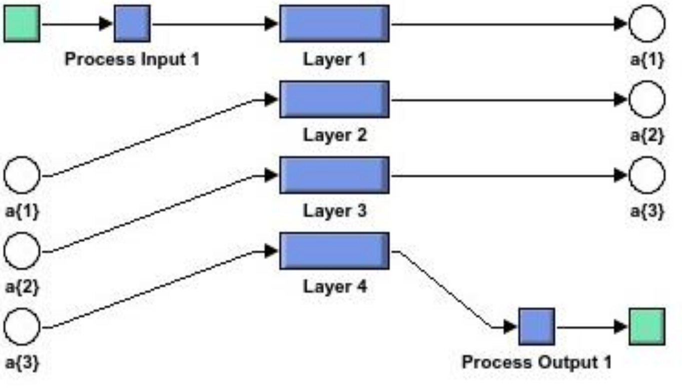

Fig 8: Custom 4-layer Neural Network characteristic.

Table 1: Precision, recall, and f1-score indicators of neural network models.

Scale	Value
(Precision)	85%
(Recall)	82%
F1-Score	81%

Table 1 indicates that the model performed well in general. It had an accuracy measure of 85%, whereby most of the positive predictions by the model were correct. Recall was at 82%, indicating the model's capability to classify a high proportion of actual positive cases. The F1-Score, which is the average of precision and recall, was at 81%, indicating an acceptable balance between the two indicators. These values indicate that the model is efficient and accurate with some scope for minor improvement in order to maximize recall and achieve optimal trade-off between performance and accuracy as it is been investigated in[19].

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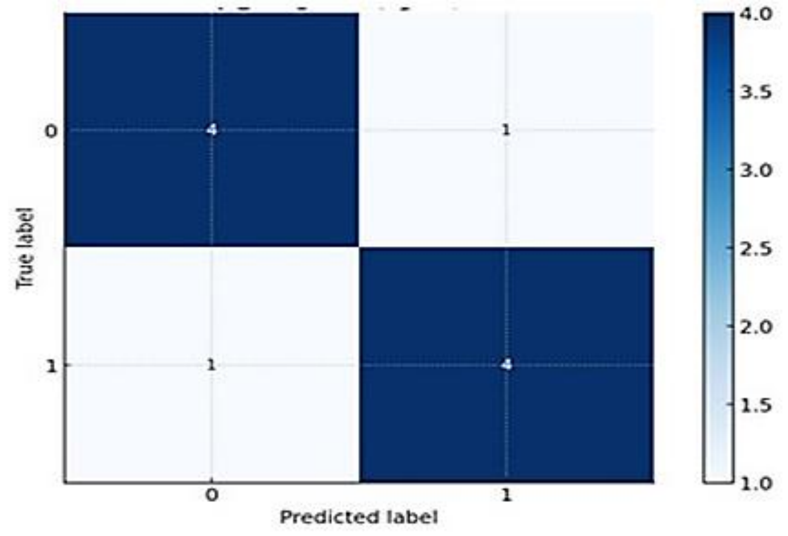

Fig 9: Confusion matrix of the model characteristic.

Figure 9, which shows the confusion matrix of the neural network model, shows that the model performs well in terms of precision and recall, but misclassifies two out of 10 cases, one from each class as illustrated in [20].

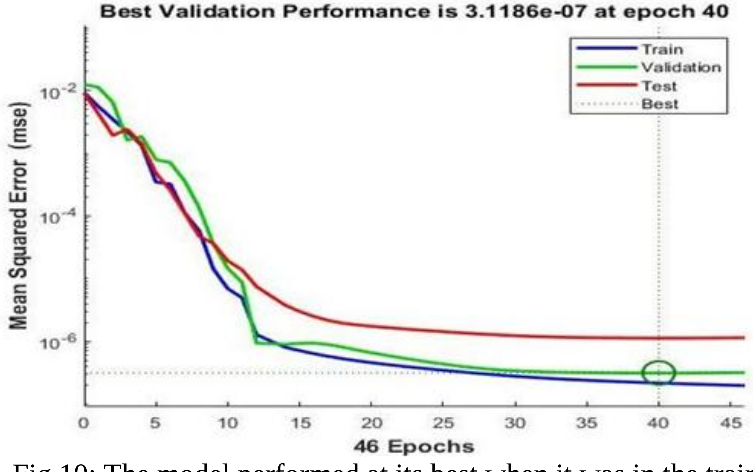

Fig 10: The model performed at its best when it was in the training phase.

Figure 10 shows that the model performed at its best when it was in the training phase, especially on the validation set. The highest point was at phase 40 when mean squared error (MSE) = 3.1186e-07. The model did not experience a significant boost in performance after phase 40, which means phase 40 is when the model should be halted from further training. However, the

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performance of the model on the training, validation, and test sets should be compared to ensure that the model does not have poor generalization similar to what is observed in [21].

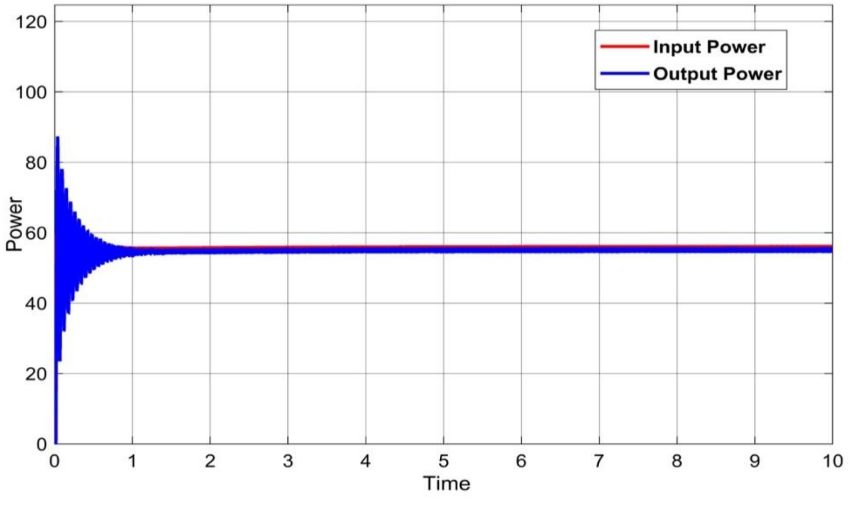

Fig 11: Power and reading solar radiation (600 W/m²).

Figure 11 shows a simulation model of a solar cell system using Simulink. It includes inputs for operating conditions such as solar radiation, temperature, and reference voltage, along with measured variables such as voltage, current, power input and output, and efficiency. The system relies on PWM control and an MPPT algorithm to regulate the inverter's performance. The lower part of the figure shows the response curve for the power input and output. Initially, fluctuations are observed, reflecting the stabilization phase, before the power quickly stabilizes at a constant value, indicating that the system has reached its optimal operating point. The matching values between the power input and output indicate a high efficiency of 75%, reflecting the system's success in maximizing solar energy utilization and achieving stable performance which is illustrated as in [22].

Figure 12 shows an MPPT system simulation model with 100 W solar cells in the Simulink environment. The parameters solar radiation (800 W/m²), temperature (25°C), and a control reference voltage were given as inputs. The model shows that the system is measuring parameters such as voltage, current, and power for input and output, as well as efficiency calculations.

As can be seen from the graph below, both input and output power begin with high oscillations prior to settling down very quickly to

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a steady level. This is a reflection of the system's response to reaching the optimum operating point via MPPT technology and an indication of the efficacy of the control algorithm in delivering stabilized performance. The model's numerical results show that an efficiency of 92.43%, a high level, was attained, confirming the effectiveness of the neural network control in maximizing the energy harvesting from the solar panel under radiation and temperature fluctuations as discussed in [23].

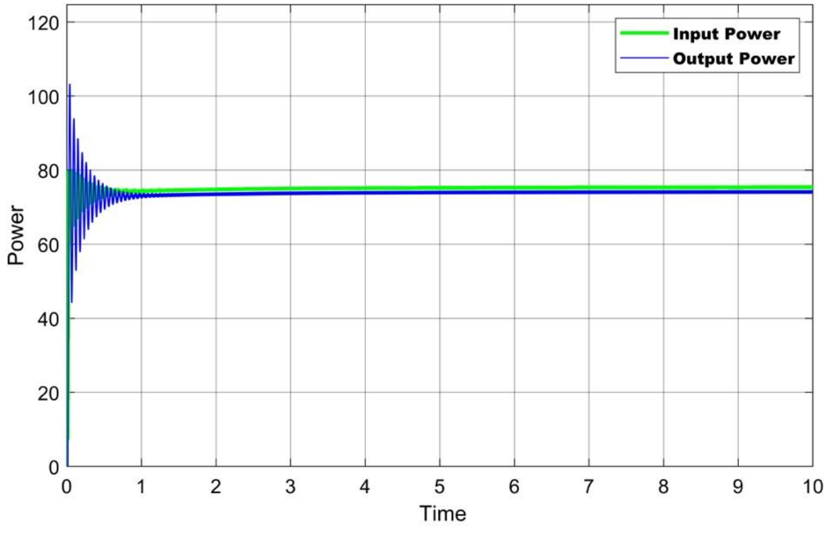

Fig 12: Power and reading solar radiation (800 W/m²).

Figure 13 shows a simulation model of a Maximum Power Point Tracking (MPPT) system using 100 W solar cells in the Simulink environment. Variables such as solar radiation (1000 W/m²), temperature (25°C), and a control reference voltage (14 V) were entered. The model shows that the system measures variables such as voltage, current, and power for both the input and output, in addition to calculating efficiency.
From the figure (13) below, it can be seen that the input and output power begin with pronounced fluctuations and then quickly stabilize at a constant level. This behaviour reflects the system's response to reaching the optimal operating point using MPPT technology and indicates the effectiveness of the control algorithm in stabilizing performance.

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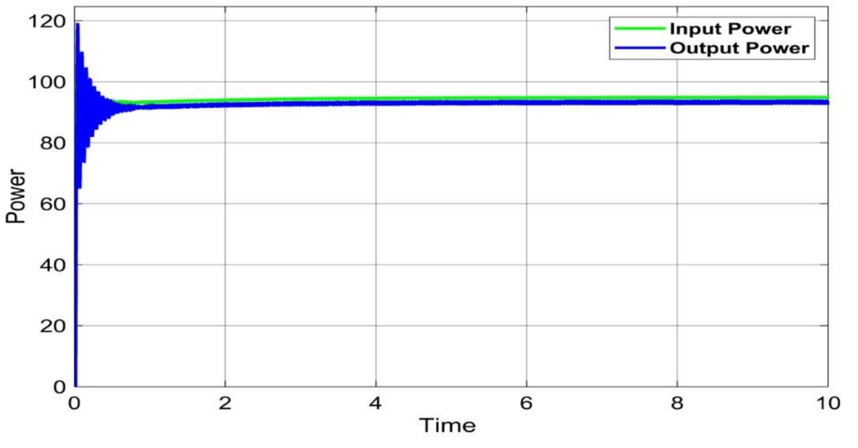

Fig 13: Power and reading at solar radiation (1000 W/m²)

The numerical results in the model show that the efficiency reached 97.5%, a high percentage that confirms the success of neural network control in maximizing energy extraction from the solar panel, even with changes in radiation and temperature [24]. Figure 14 shows the relationship between voltage and current (I-V) and power (P-V) for a solar power system under two different temperatures (25°C and 45°C). Higher temperatures negatively impact performance, as power and current begin to decrease, and the peak power point is delayed at higher voltages. The peak power point is considered the optimal state of operation, where the maximum possible power is achieved from the system [25].

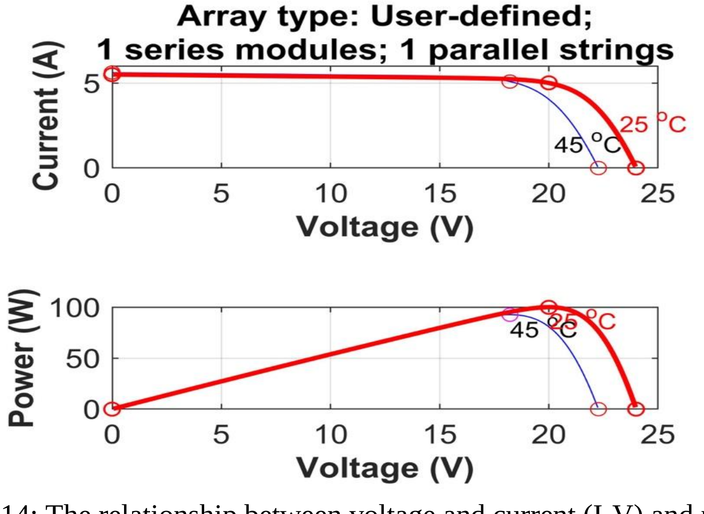

Fig 14: The relationship between voltage and current (I-V) and power (P-V).

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13. Conclusion

The simulation results showed that the proposed neural network model did well, with an MPPT success rate of over 97% across all scenarios, with 82% recall, 81% F1-score, and 85% accuracy. The model ensured rapid power output stabilization and minimized oscillations by effectively altering the PWM signal. Its capacity to withstand variations in temperature and radiation further proved its reliability in dynamic situations. Furthermore, the application of neural networks successfully solved the drawbacks of traditional methods such as P&O and INC, particularly with regard to speed and accuracy.

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