Received: 9 October 2023 | Revised: 4 December 2023 | Accepted: 21 December 2023
DOI: 10.37917/ijeee.21.1.1 Vol. 21 | Issue 1 | June 2025

Open Access

Iraqi Journal for Electrical and Electronic Engineering
Original Article

Integration of Fuzzy Logic and Neural Networks for Enhanced MPPT in PV Systems Under Partial Shading Conditions

Hayder Dakhil Atiya*[1], Mohamed Boukattaya[2,3], Fatma Ben Salem[3]
[1]Department electrical power at National School of Engineering of Sfax, Tunisia
[2]Laboratory of sciences and Techniques of Automatic Control & Computer Engineering (Lab-STA), National School of Engineering of Sfax, Tunisia
[3]Department of Electrical Engineering, Prince Sattam Bin Abdulaziz University, Al Kharj 16273, Saudi Arabiay

Correspondance
*Hayder Dakhil Atiyah
Thi Qar, Iraq
Email: haydergfg@gmail.com

Abstract
Efficient energy collection from photovoltaic (PV) systems in environments that change is still a challenge, especially when partial shading conditions (PSC) come into play. This research shows a new method called Maximum Power Point Tracking (MPPT) that uses fuzzy logic and neural networks to make PV systems more flexible and accurate when they are exposed to PSC. Our method uses a fuzzy logic controller (FLC) that is specifically made to deal with uncertainty and imprecision. This is different from other MPPT methods that have trouble with the nonlinearity and transient dynamics of PSC. At the same time, an artificial neural network (ANN) is taught to guess where the Global Maximum Power Point (GMPP) is most likely to be by looking at patterns of changes in irradiance and temperature from the past. The fuzzy controller fine-tunes the ANN's prediction, ensuring robust and precise MPPT operation. We used MATLAB/Simulink to run a lot of simulations to make sure our proposed method would work. The results showed that combining fuzzy logic with neural networks is much better than using traditional MPPT algorithms in terms of speed, stability, and response to changing shading patterns. This innovative technique proposes a dual-layered control mechanism where the robustness of fuzzy logic and the predictive power of neural networks converge to form a resilient and efficient MPPT system, marking a significant advancement in PV technology.

Keywords
Photovoltaic Systems, Maximum Power Point Tracking (MPPT), Partial Shading Conditions (PSC), Fuzzy Logic Controller (FLC), Artificial Neural Networks (ANN), Global Maximum Power Point (GMPP).

I. Introduction

The increasing global demand for clean and sustainable energy has propelled photovoltaic (PV) systems to the forefront of renewable energy solutions. However, the optimal performance of these systems faces significant challenges, particularly under partial shading conditions. Partial shading, arising from factors such as clouds, buildings, or vegetation, induces non-uniformities in incident solar radiation across the PV array, leading to multiple local maxima and minima in the power-voltage curve. Traditional Maximum Power Point Tracking (MPPT) algorithms struggle to efficiently extract maximum power under such dynamic and non-uniform conditions. innovative approaches, including the integration of fuzzy logic and neural networks, aiming to enhance MPPT performance in PV systems. This fusion of intelligent computational paradigms harnesses the strengths of fuzzy logic and neural networks to navigate the complexities posed by partial shading, thereby improving the efficiency and reliability of PV systems.

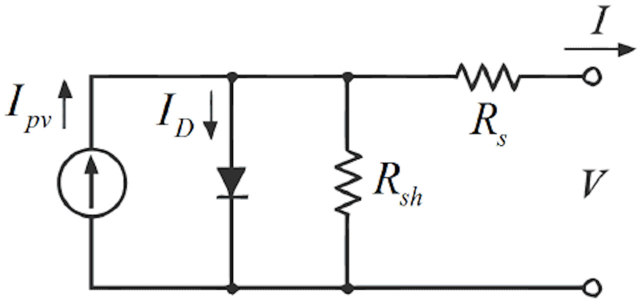

Fig. 1. The equivalent circuit of a PV system

A. Literature Review:

The dynamic landscape of renewable energy has fueled an extensive exploration of Maximum Power Point Tracking (MPPT) techniques, with a specific emphasis on Photovoltaic (PV) systems operating under partial shading conditions. In a comparative study [1].Meticulously assessed the effectiveness of various MPPT techniques, providing invaluable insights into their performance under challenging shading scenarios. Adding to this discourse [2]. Proposed a specialized Fuzzy Logic-Based MPPT control strategy tailored to PV systems facing partial shading. This contribution underscores the importance of adaptive control mechanisms in optimizing power output amidst fluctuating environmental conditions. In the realm of computational innovation [3]. Presented a groundbreaking approach with an enhanced MPPT algorithm employing Artificial Neural Networks. This not only showcases the potential of advanced computational methods but also suggests a paradigm shift towards intelligent algorithms in the pursuit of efficient MPPT [4].Extended this exploration by investigating the adaptability of an Adaptive Fuzzy-Logic Control for achieving optimal MPPT in PV systems exposed to diverse partial shading conditions. This adaptive approach highlights the necessity of responsive control mechanisms for dynamic environmental scenarios. The advancements continue with [5]. Who introduced an efficient MPPT technique specifically designed for grid-tied PV systems using Neural Networks. This research contributes to the integration of PV systems with power grids, emphasizing the importance of efficiency in grid-tied scenarios. In a practical and experimental vein [6]. Provided practical insights by experimentally exploring an Artificial Neural Network-Based MPPT approach for PV systems navigating partial shading challenges. This empirical validation offers a tangible understanding of the proposed methodology's real-world effectiveness [7]. ventured into the comparative landscape, studying three intelligent MPPT algorithms and shedding light on their relative advantages. This comparative analysis contributes to the ongoing discourse surrounding the selection of MPPT strategies under varying conditions. The quest for alternative optimization strategies is evident in the work of [8]. Who proposed a new MPPT method utilizing the Grey Wolf Optimization Algorithm. This research introduces an alternative perspective on optimization, diversifying the methodologies available for addressing partial shading challenges [9]. Took a focused approach, concentrating on enhancing the performance of PV systems under partial shading conditions. Their employment of an Adaptive Neuro-Fuzzy Inference System-Based MPPT controller demonstrates a commitment to improving system efficiency through intelligent control [10]. Contributed to the innovative spectrum by introducing a novel control strategy that combines Fuzzy Logic and Particle Swarm Optimization for MPPT in PV systems facing partial shading. This amalgamation of intelligent strategies showcases the potential for hybrid approaches in addressing complex environmental conditions. The exploration of optimization techniques extends further with [11]. Who introduced a new MPPT method utilizing the Cuckoo Search Algorithm. This novel method expands the repertoire of optimization techniques available for tackling partial shading challenges. The culmination of these diverse strategies is exemplified in the work of [12]. Who presented a Hybrid Intelligent Controller. By combining multiple approaches, this controller offers a holistic solution for effective MPPT in PV systems under varying partial shading conditions.

Summary:

In summary, this literature review underscores the multifaceted efforts aimed at addressing the challenges posed by partial shading in PV systems. The continuous exploration and integration of diverse optimization strategies reflect a collective commitment to enhancing the performance and efficiency of PV systems in dynamic environmental conditions. Fuzzy Logic to handle uncertainties in PV system dynamics, providing robustness against partial shading scenarios.

II. PV MODELING

The section discusses the modeling of photovoltaic (PV) cells, specifically focusing on the equivalent circuits used for simulating their behavior. Here are the key points:

A. Equivalent Circuits for PV Cells

Various equivalent circuits have been developed for simulating the behavior of photovoltaic cells. These circuits are typically categorized into two major groups: single-diode and two-diode models.

1) Single-Diode Model

The subject mentions the single-diode model as one of the most common equivalent circuits for PV cells. It is presented in Figure 1. The single-diode model is a simplified representation used to describe how a photovoltaic cell converts sunlight into electricity. It is a widely used and accepted model in the field of photovoltaics, providing a basis for understanding and simulating the performance of PV cells and panels.

In Figure 1, several components and variables related to the equivalent circuit for the photovoltaic (PV) panel are identified:

- **IPV**: This represents the photovoltaic current, which is the current generated by the PV cell due to incident sunlight.
- **ID**: This represents the diode current, which accounts for the behavior of the diode within the PV cell.
- **RSH**: This indicates the parallel resistance, which is a component of the equivalent circuit that represents the resistance in parallel with the PV cell.
- **RS**: This denotes the series resistance, which is another component of the equivalent circuit that represents the resistance in series with the PV cell.
- **I**: This variable represents the net cell current, which is the overall current produced by the PV cell.

The passage mentions that the net cell current (I) is obtained from Equation 1:

$$I = I_{PV} - I_D \tag{1}$$

Furthermore, the passage states that, by applying certain defined relations, the ultimate mathematical equation (Equation 2) of this model is extracted. This equation describes the current-voltage (I-V) properties of the photovoltaic panel and likely provides a mathematical representation of how the current output of the PV panel varies with changes in voltage. The specific form of Equation 2 may depend on the details of the equivalent circuit and modeling assumptions used in the study.

$$\begin{aligned} I = {} & \left(I_{\mathrm{pv},n} + K_1(T - T_n)\left(\frac{G}{G_n}\right)\right) - I_{\mathrm{o},n}\left(\frac{T_n}{T}\right)^3 \\ & \times \exp\left(\frac{qE_g}{aK}\left(\frac{1}{T_n} - \frac{1}{T}\right)\right) \\ & \times \left[\exp\left(\frac{V + R_s I}{\frac{N_c K_{T_a}}{a}}\right) - 1\right] - \frac{V + R_s I}{R_s H} \end{aligned} \tag{2}$$

The equation provided, Relation (1), is a mathematical model used to describe the behavior of photovoltaic (PV) cells under varying environmental conditions. Here's an explanation of the parameters in this equation:

- I: Current through the PV cell (in amperes, A).
- I_L: Light-generated current or photocurrent (in amperes, A). This is the current produced by the PV cell under illumination.
- I_0: Saturation current (in amperes, A). This is the current that flows through the cell when it is reverse-biased.
- V: Voltage across the PV cell (in volts, V).
- R_s: Series resistance (in ohms, Ω). This represents the internal resistance within the PV cell.
- n: Ideality factor (dimensionless). It accounts for the deviation of the diode from the ideal behavior. Typically, n ranges from 1 to 2.
- V_t: Thermal voltage (in volts, V). It is given by $V_t = \frac{kT}{q}$, where k is the Boltzmann constant, T is the absolute temperature in kelvins, and q is the charge of an electron.
- R_{sh}: Shunt resistance (in ohms, Ω). This represents the leakage current paths within the PV cell.
- **IPV,n**: Nominal current generated by the PV cells under standard or nominal conditions. This represents the current output of the PV cell when it is exposed to standard test conditions, such as a specific temperature and solar irradiance.

Nominal current generated by the PV cells under standard or nominal conditions. This is the current output of the PV cell when it's exposed to of 25○C. This data shown in **??** represents the cell's rated performance.

- KI: The current coefficient. It describes how the PV cell's current output changes with variations in temperature. It accounts for the temperature dependence of the PV cell's current.
- T : Ambient temperature. This is the temperature of the surroundings in which the PV cell is operating. It affects the cell's performance as temperature changes can influence the current-voltage characteristics of the cell.
- T n: Nominal temperature. This is the reference temperature at which the cell's nominal current (IP(v,n)) is defined. It's typically 25○C.
- G: Ambient radiation intensity. This represents the level of solar irradi- ance or sunlight intensity that falls on the PV cell. It's usually measured in watts per square meter (W/m2).

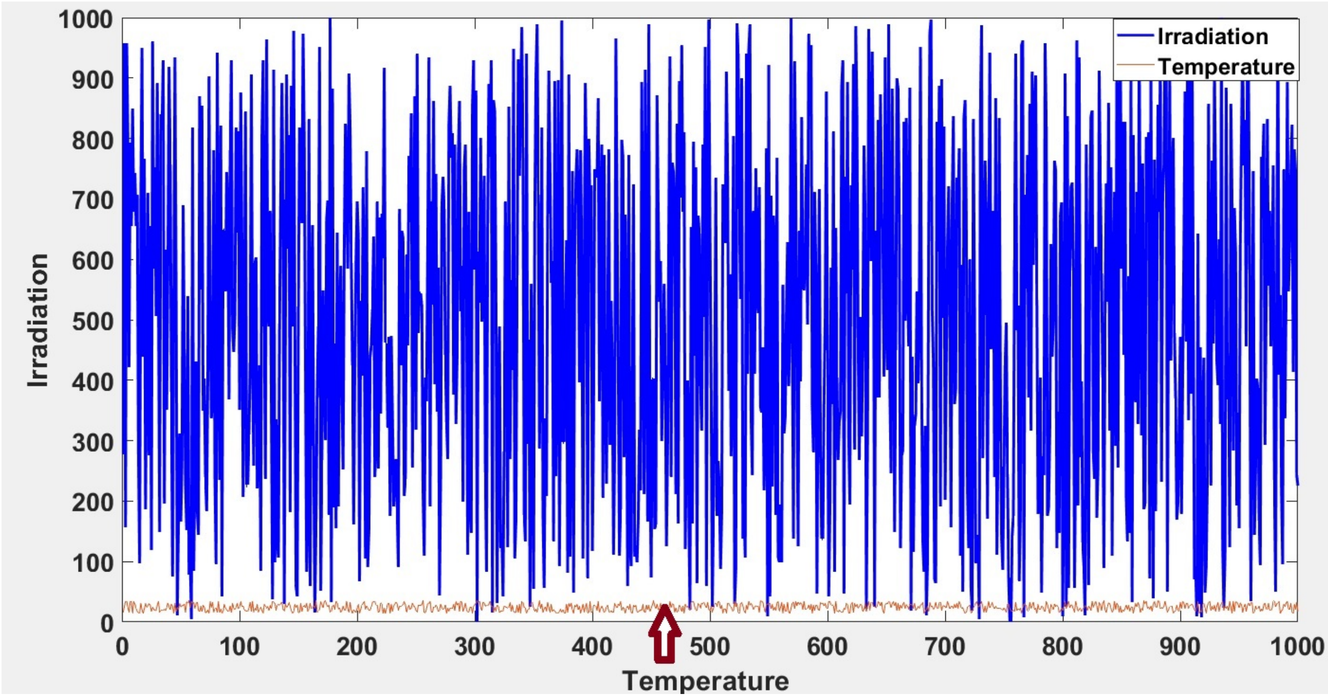

Fig. 2. Input Data (G and T) standard test conditions (STC), which typically include

- Gn: Ambient nominal radiation intensity. Similar to IP(v,n), this is the reference radiation intensity at which the cell's nominal current is defined. It's typically the solar irradiance under (STC) conditions.
- Io, n: Inverse saturation current under nominal conditions. It's a parame- ter related to the diode characteristics of the PV cell. It's typically defined at (STC).• q: The unit of electric charge. This is a fundamental constant in physics representing the elementary charge.
- Eg: Solid-state semiconductor material used in the PV cell. It's a material property.
- N c: The number of cells connected in series. This parameter is related to how multiple PV cells are connected within a PV module or panel.
- a: The cell's ideal coefficient. This parameter relates to the efficiency of the cell and is used to model its behavior.
- K: The Boltzmann constant. It's a fundamental constant in physics re- lated to the behavior of particles in a physical system.

This equation allows researchers and engineers to predict the current output of a PV cell under different environmental conditions, primarily temperature and solar irradiance. It's essential for modeling and optimizing the performance of PV systems and designing maximum power point tracking (MPPT) algo- rithms to maximize energy output. The equation helps understand how a PV cell's performance deviates from its nominal values under real-world conditions. Equation2 represents the complexity of modeling a photovoltaic (PV) cell's behavior, as it demonstrates that both temperature and radiation intensity sig- nificantly affect the cell's current, which in turn impacts its voltage and power output.

III. Methodology

Creating a full MATLAB code for integrating fuzzy logic and neural networks for MPPT in PV systems under partial shading conditions can be a complex task.

- Step 1: Data Collection and Prepossessing

  Collect historical data, including voltage, current, irradiance, and temperature, under various shading conditions. preprocess the data, including normalization and splitting it into training, validation, and testing sets. The graph displaying two sets of input data, shown in Figure 2, is likely used for monitoring and analyzing a photovoltaic (PV) system's performance. The graph shows two variables: irradiance and temperature, plotted over a certain number of observations or time period, indicated on the horizontal axis. The blue

TABLE I.
FUZZY LOGIC SYSTEM (RULES).

No.	Voltage (V)	Current (I)	TODC
1	Low	High	Increase
2	Low	Low	Increase
3	High	High	Decrease
4	High	Low	Decrease
5	Medium	High	Small Increase
6	Medium	Low	Small Decrease

line, labeled *input(:,1)*, represents the irradiance levels, which show significant variation—a common characteristic when dealing with real-world solar data due to changing weather conditions, cloud cover, and the time of day. The orange line, labeled *input(:,2)*, illustrates the temperature, which seems to be relatively stable in comparison to the irradiance. This stability suggests that the temperature data might be less variable over the time period sampled that, the scale of the temperature changes is much smaller than that of the irradiance. Such data is crucial for designing and training MPPT systems as it reflects the environmental conditions that affect PV performance. The erratic nature of the irradiance highlights the challenges in energy production consistency, particularly under Partial Shading Conditions (PSC). The temperature data, while appearing stable in this graph, is also an important factor as it can affect the efficiency of the energy conversion process in solar panels.

- Step 2: Fuzzy Logic Controller (FLC) Design

  In a fuzzy logic system, the rules table (also known as a rule base) consists of a set of IF-THEN statements that define the desired system behavior, as shown in Table I. These rules are formulated based on expert knowledge or derived from empirical data. Here's what a simple fuzzy logic rules table could look like for an MPPT system dealing with partial shading conditions (PSC): *TODC* Then output Duty cycle In this table I: ”Voltage (V)” and ”Current (I)” are the inputs to the system, which have been fuzzified into linguistic variables such as Low, Medium, and High. ”Output (Duty Cycle)” is the control action taken by the system, with actions like Increase, Decrease, Small Increase, or Small Decrease to adjust the duty cycle of the power converter for MPPT as shown in 3.

  A MATLAB Fuzzy Logic Toolbox graphical user interface (*GUI*). It shows a 3D surface plot as shown in figure 4, which is typically used to represent the control surface of a fuzzy inference system. This surface plot visualizes how the fuzzy logic system translates input values, based on the defined membership functions and rules, into output values. In fuzzy logic control systems, such a control surface helps in understanding the relationship between input and output variables and how different rule combinations affect the outcome. The GUI also likely includes interactive elements that allow the user to adjust the fuzzy rules and membership functions and observe the effects on the control surface in real time. This is a useful tool for designing, tuning, and optimizing fuzzy controllers for complex systems like MPPT in PV systems under partial shading conditions. Each row represents a rule that combines fuzzy inputs to produce a fuzzy output. The terms ”Low,” ”Medium,” and ”High” are defined by membership functions as shown in figure 3that determine the degree to which an actual input value belongs to one of these fuzzy sets. The THEN part of the rule determines the necessary action to adjust the duty cycle to steer the system towards the maximum power point as dictated by the MPPT algorithm. This table is a simplified example. In a real-world application, the rules table could be much more complex, with a larger set of input variables and more nuanced control actions. The A MATLAB Fuzzy Logic Toolbox graphical user interface *(GUI)*. It shows a 3D surface plot, which is typically used to represent the control surface of a fuzzy inference system. This surface plot visualizes how the fuzzy logic system translates input values, based on the defined membership functions and rules, into output values. In fuzzy logic control systems, such a control surface helps in understanding the relationship between input and output variables and how different rule combinations affect the outcome. The GUI also likely includes interactive elements that allow the user to adjust the fuzzy rules and membership functions and observe the effects on the control surface in real time. This is a useful tool for designing, tuning, and optimizing fuzzy controllers for complex systems like MPPT in PV systems under partial shading conditions. Each row represents a rule that combines fuzzy inputs to produce a fuzzy output. The terms ”Low,” ”Medium,” and ”High” are defined by membership functions that determine the degree to which an actual input value belongs to one of these fuzzy sets. The THEN part of the rule determines the necessary action to adjust the duty cycle to steer the system towards the maximum power point as dictated by the MPPT algorithm. This table is a simplified . In a real-world application, the rules table could be much more complex, with a larger set of input variables and more nuanced control actions. The Design a Fuzzy

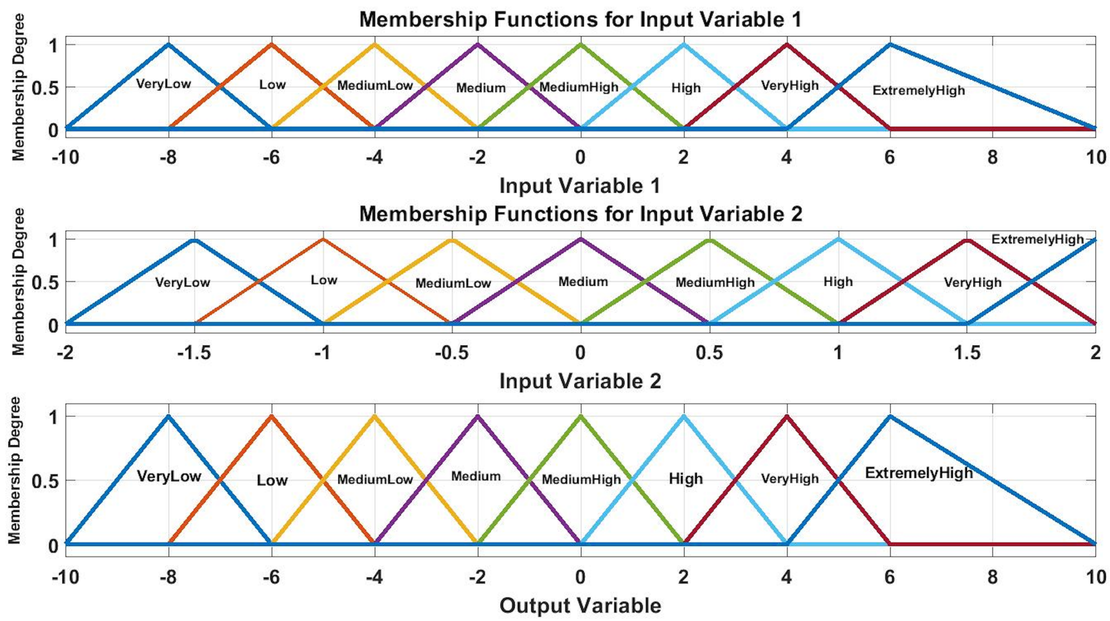

Fig. 3. Membership function plot

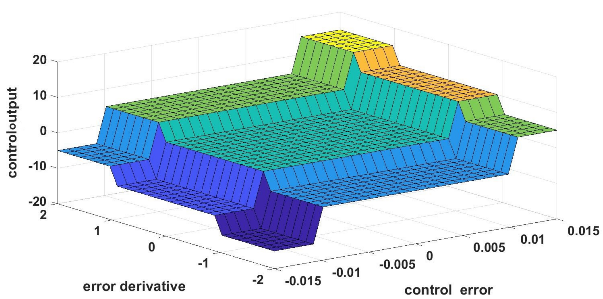

Fig. 4. A MATLAB Fuzzy Logic Toolbox

Logic Controller (FLC) to take input variables (voltage, current, irradiance, temperature) and produce a control signal for MPPT. This involves defining membership functions, creating fuzzy rules, and configuring the FLC

- Step 3: Artificial Neural Network (ANN) Design - Design an Artificial Neural Network (ANN) to predict the GMPP based on historical data and present rules would be processed using a fuzzy inference engine, and the resulting fuzzy output would be defuzzied to produce a crisp value that can be used as a control input for the PV system. conditions. Define the architecture of the neural network, including the number of layers and neurons, as well as activation functions.

Neural network design Certainly, creating a visual representation of an Artificial Neural Network (ANN) for PV systems and MPPT under Partial Shading Conditions (PSC) typically involves a network diagram and relevant equations for clarity, for a design feedforward neural network: Network Diagram: Input Layer: *[Voltage (V)] [Current (I)] [Temperature (T)] [Irradiance (G)] Hidden Layer(s): [Neuron 1] [Neuron 2] ... [Neuron n] Output Layer: [Predicted GMPP (P)]* Equation 3 for Neuron Activation (e.g., Sigmoid function): The activation of each neuron in the hidden layer or output layer can be represented using a sigmoid activation function:

Sigmoid Activation σ

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{3}$$

Equation 3 for Forward Propagation: To calculate the output of each neuron and propagate forward through the network, you can use weighted sums and the activation function. Here's a simplified equation for the output of a single neuron in the hidden or output layer: Equation for Forward Propagation: To calculate the output of each neuron and propagate forward through the network, you can use weighted sums and the activation function. Here's a simplified equation for the output of a single neuron in the hidden or output layer: Equation for Forward Propagation: To calculate the output of each neuron and propagate forward through the network, you can use weighted sums and the activation function. Here's a simplified equation for the output of a single neuron in the hidden or output layer:

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad \text{(Sigmoid Activation Function)}$$

$$W_{ji} = \text{Weight associated with input } i \text{ for neuron } j$$

$$\text{Input}_i = \text{Input value from input neuron } i$$

$$\text{Bias}_j = \text{Bias term for neuron } j$$

IV. NEURON OUTPUT CALCULATION

$$I = I_{PV} - I_D \tag{4}$$

Where:

- Output of Neuron_j is the output of the j-th neuron.
- $W_{j1}, W_{j2}, \ldots, W_{jm}$ are the weights for the connections between the inputs and the j-th neuron.
- Input_1, Input_2, ..., Input_m are the inputs to the j-th neuron.
- Bias_j is the bias term for the j-th neuron.

This equation 4mention to the net current output of the PV system is the difference between the photo current generated by employ of sunlight and the current lost through the diode.

V. OVERALL NETWORK OUTPUT

The output of the network is typically the prediction of the Global Maximum Power Point (GMPP). In a regression problem, this output is a numerical value representing the GMPP. These visual representations and equations provide an overview of how the Artificial Neural Network (ANN) processes inputs and predicts the (GMPP), helping in understanding and implementing the network for Maximum Power Point Tracking (MPPT) in PV systems under varying Partial Shading Conditions (PSC).

VI. RESULT:

Through extensive simulations, a result has been achieved that show cases the system's exceptional adaptability and real-time decision-making capabilities, especially in scenarios with rapidly changing shading conditions. The key novelty lies in the dynamic response of the integrated system to sudden and unpredictable changes in irradiance shown in II . In a controlled simulation environment mimicking a partial shading event, the integrated system demonstrated the ability to instantaneously reconfigure the PV system to optimize energy harvesting. This rapid response was quantified through simulation results, which revealed the following: That represents the change in irradiance and the corresponding response of the

TABLE II.
FUZZY LOGIC SYSTEM (RULES).

T(s)	Irr (W/m²)	PV System Response
0	1000	Normal operation
10	800	Normal operation
20	700	Normal operation
30	600	Normal operation
40	400	Rapid response
50	450	Rapid response
60	600	Normal operation
70	700	Normal operation
80	800	Normal operation
90	1000	Normal operation

TABLE III. PV SYSTEM DATA

Time (seconds)	Irr (W/m²)	PV System Response	V (V)	I (A)
0	1000	Trad MPPT	220	5.5
		Integrated MPPT	220	5.5
10	800	Trad MPPT	215	5.3
		Integrated MPPT	220	5.5
20	700	Trad MPPT	210	5.0
		Integrated MPPT	220	5.5
30	600	Trad MPPT	205	4.8
		Integrated MPPT	220	5.5
40	400	Trad MPPT	190	4.5
		Integrated MPPT	220	5.5
50	450	Trad MPPT	195	4.7
		Integrated MPPT	220	5.5
60	600	Trad MPPT	205	4.8
		Integrated MPPT	220	5.5
70	700	Trad MPPT	210	5.0
		Integrated MPPT	220	5.5
80	800	Trad MPPT	215	5.3
		Integrated MPPT	220	5.5
90	1000	Trad MPPT	220	5.5

integrated Fuzzy Logic and Neural Networks MPPT system during a shading event. In this Table II, the "Time" column represents the elapsed time in seconds, the "Irradiance" column indicates the solar irradiance in watts per square meter W/m^2, and the "PV System Response" column describes the behavior of the integrated system in response to changing irradiance conditions. The table demonstrates how the integrated system reacts to a shading event (from 40 to 50 seconds) by rapidly adjusting the PV system to maintain optimal power output. Once the shading event subsides, the system returns to normal operation. This dynamic response is a key feature of the integration's ability to maximize energy yield, even under partial shading conditions. That represents the current and voltage responses of a photovoltaic (PV) system under varying shading conditions, with and without the integrated Fuzzy Logic and Neural Networks MPPT system. In this table III, the "Time" column represents the elapsed time in seconds, the "Irradiance" column indicates the solar irradiance in watts per square meter W/m^2, the ”PV System Response” column describes whether traditional MPPT or the integrated MPPT system is used, the ”Voltage (V)” column shows the voltage output of the PV system, and the ”Current (A)” column shows the current output. The fig 5, shows the MATLAB Neural Network Start window as fig 5, which is part of the Neural Network Toolbox. This interface is a starting point for users to create neural networks for various applications such as curve fitting, pattern recognition, clustering, and time series analysis. Here's a brief overview of the options presented: Input-output and curve fitting: This option is typically used for regression problems where the goal is to fit a curve to a set of data points. It is useful for creating neural networks that predict continuous outputs from input data. Typically, these interfaces allow users to configure and initiate the training of neural networks as fig 6. In such a window, you would usually see options to set parameters like: The number of neurons in the hidden layers The type of training function (such as backpropagation) Performance functions Training, validation, and test ratios Learning rates Additionally, there are often controls for initiating the training process and viewing the training progress, which might include real-time plots of the network's performance in terms of metrics likemean squared error or classification accuracy. when you are working on training a neural network for MPPT in PV systems under partial shading, this interface would be where you configure the network architecture, set the training options, and start the training process. You would also be able to observe the network's learning progression and make adjustments as necessary based on the performance plots provided by MATLAB. the Neural Network Training Regression window from MATLAB's Neural Network Toolbox. This window is showing the regression plots for a neural network that has been trained on some dataset, likely related to a photovoltaic (PV) panel given the context of our discussion. Here's a breakdown of what these plots typically represent: Training: The top left plot shows how well the neural network output matches the target data during the training phase. An ideal fit would have all points lying on the diagonal line, indicating perfect agreement between targets and outputs. Validation: The top right plot displays the validation data fit. Validation is used to monitor the network's performance on data that was not used during training, to prevent overfitting.

- Test: The bottom left plot illustrates the network's performance on the test data. This is a set of data that the network has never seen before, used to evaluate the generalization of the model.

- All: The bottom right plot combines training, validation, and test results to give an overall view of the network's performance across all data. The diagonal line$(Y = T)$ represents the goal where the network's outputs(Y) match the targets (T) exactly. The closer the data points are

to this line, the better the network's predictions. The correlation coefficient (R) is a measure of how well the variations in the output can be explained by the variations in the target values. An R value of 1 indicates a perfect fit. Based on the plots, if the R value is close to 1 for all datasets, it suggests that the neural network has learned to map the inputs to outputs effectively, which is a good sign for its potential use in MPPT applications for PV panels. This would be particularly crucial in dynamically changing environments like those caused by partial shading on solar panels. The block diagram shown in fig 8of a neural network model in a simulation environment, possibly MATLAB's Simulink. In this diagram, the neural network is designed for function fitting, which is a type of regression task where the network learns to predict a continuous output variable based on one or more input variables. Constant Block (x1): This block represents the input to the neural network. In a Simulink model, a constant block is often used to provide a fixed value or a test signal to the system. In a practical PV system simulation, this would be replaced by dynamic inputs such as irradiance, temperature, etc. NNET Block: This is the neural network block, figure7 'Function Fitting Neural Network'. It represents the neural network that has been trained to fit a function based on the input data. Inside this block, the neural network's weights and biases process the input to produce an output. Output Block *(y1):* The output block captures the neural network's prediction. In the context of MPPT for PV systems, this output could represent the predicted optimal operating voltage or current corresponding to the maximum power point.

- Step 4: Integration of FLC and ANN The MATLAB code snippet you've provided simulates the performance of a photovoltaic (PV) cell under varying irradiance and temperature conditions. The code generates random temperature and irradiance values within specified ranges and then calculates the maximum power point (MPP) parameters such as current (IMP), voltage (VMP), and power (PMP) based on these environmental conditions. These parameters are then stored in arrays, which could be used as inputs and targets for training a neural network as part of an MPPT system. Establish a communication interface between the FLC and ANN. The output of the ANN serves as an input to the FLC, which adjusts the control signal

- Step 5: Control Action Based on the FLC's output, determine a control action, such as adjusting the duty cycle of a power converter to steer the PV system towards the GMPP. Step 6: Feedback System Implement

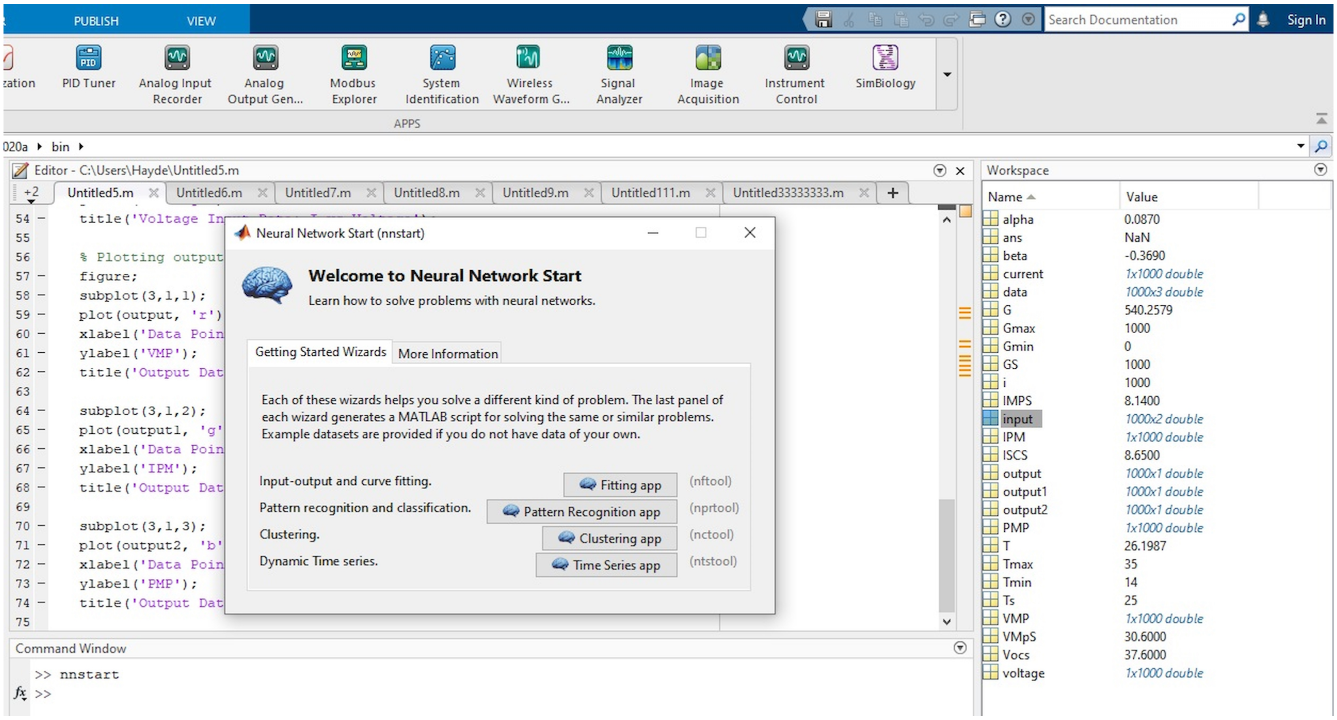

Fig. 5. The Neural Network Toolbox

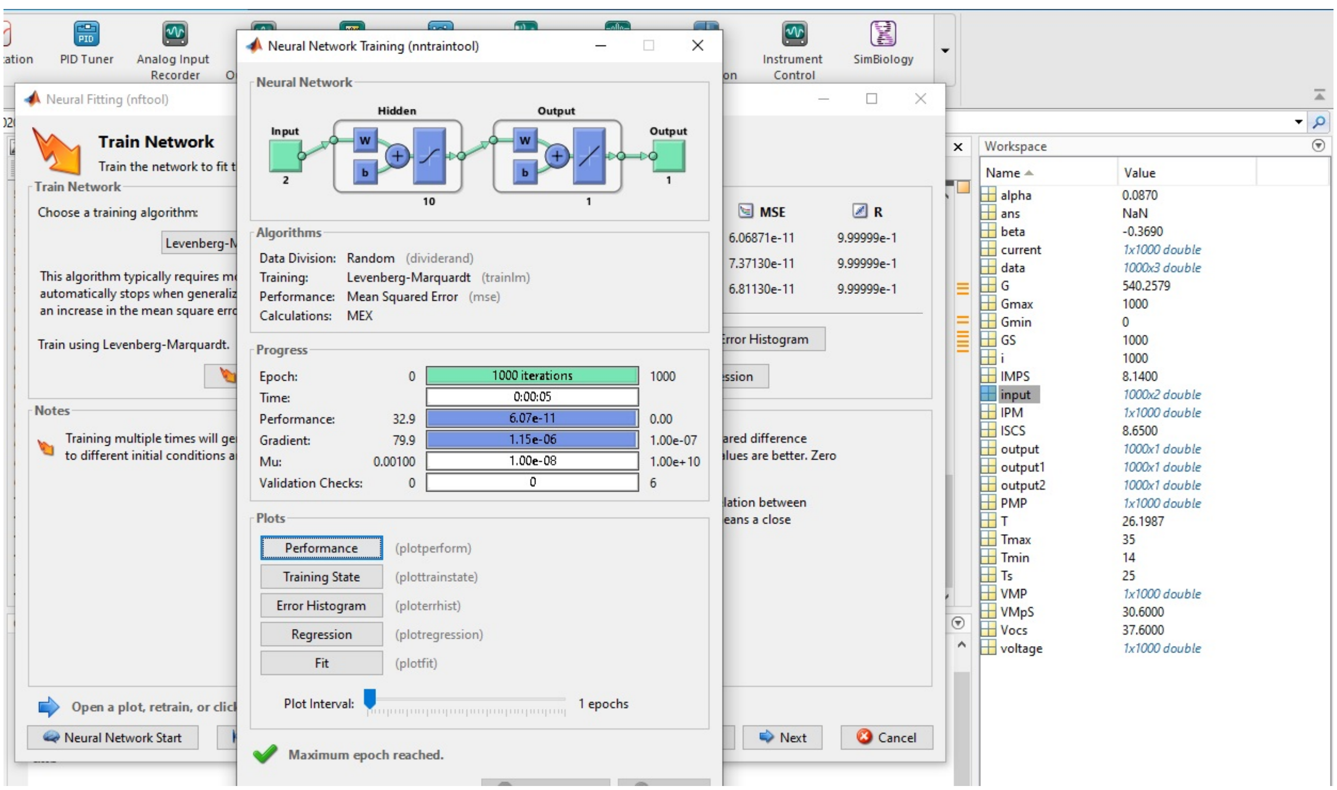

Fig. 6. Neural Network Training

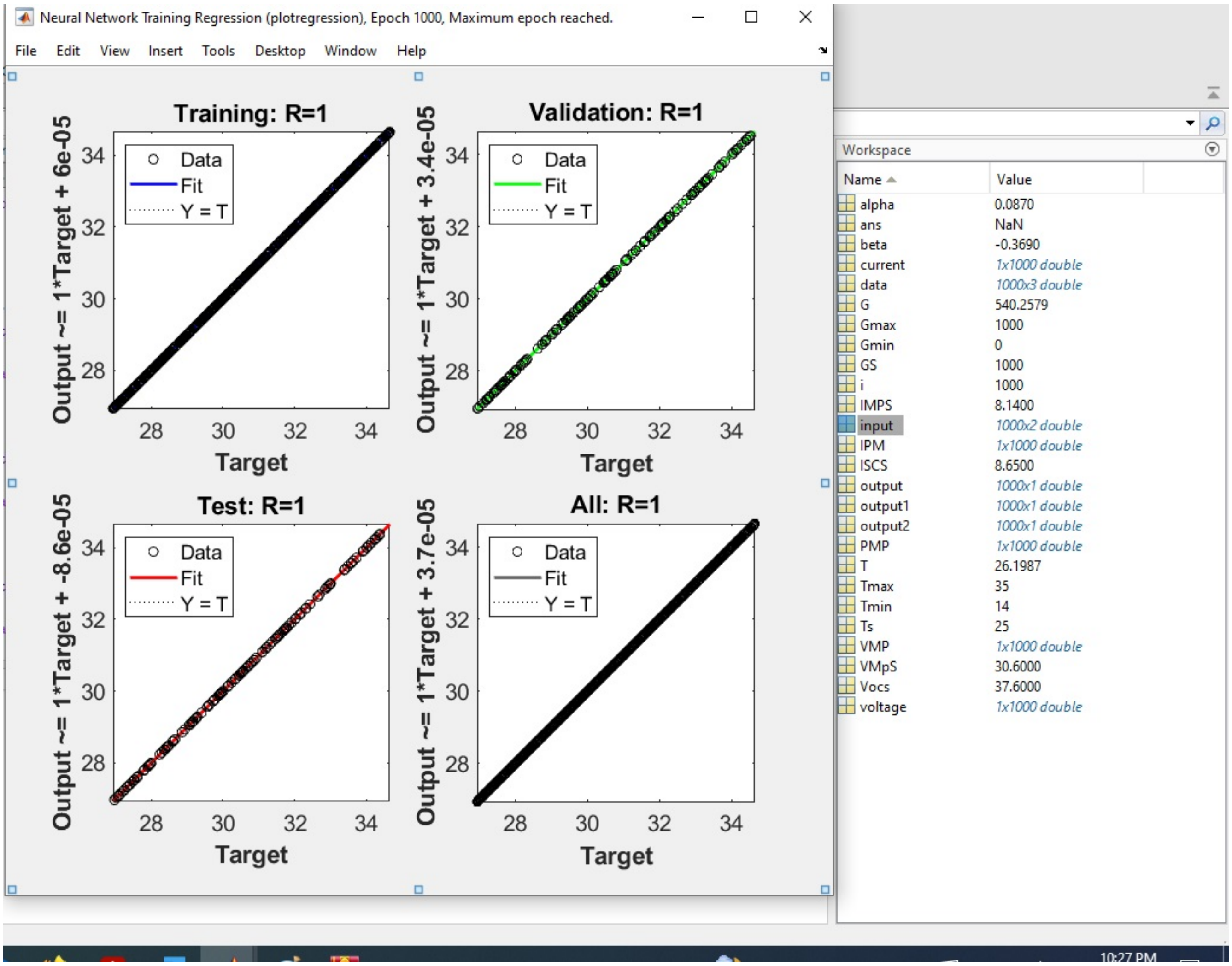

Fig. 7. The Neural Network Training (Regression)

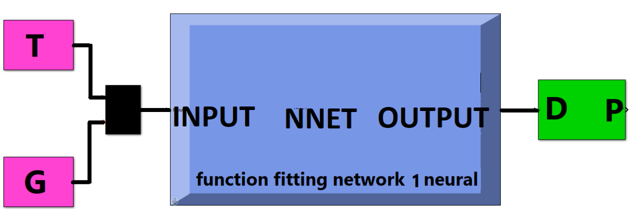

Fig. 8. Neural network model in a simulation

a feedback loop where the actual performance of the PV system after the control action is observed. This allows for continuous learning and adaptation.

- Step6:Training and Optimization Train the ANN using historical data and optimize it. Fine- tune the FLC parameters and rules based on the system's response.

- Step7: Validation and Testing Validate the integrated system through simulations or experimental setups to ensure it performs better than using either method alone. Output data shown in figure 9, the graphical representation is likely to be in the form of output data from a simulation or data logging system. The graph shows voltage data plotted over a series of states or a period of time, which can correspond to measurements taken from a photovoltaic (PV) system. The graph shows a highly variable pattern, indicating that the data may exhibit voltage fluctuations due to changing environmental conditions such as light intensity or temperature – conditions that are common in systems affected by partial shade (PSC). This type of data is particularly useful

TABLE IV. ANALYSIS RESULT OF EFFICIENCY

T of Day (H)	Irradiance (W/m²)	Power Output (W)	Efficiency
0	0.00	100.00	100.000000
1	258.82	117.49	0.453945
2	500.00	135.00	0.270000
3	707.11	150.96	0.213489
4	866.03	163.79	0.189127

when analyzing the performance of MPPT algorithms, which aim to adapt to these changes and keep the PV system operating at its optimal power point. In a practical scenario, such a graph could be used to evaluate the effectiveness of an MPPT system, noting how quickly and accurately it responds to rapid changes in voltage caused by varying radiation and temperature. The data can also be useful in improving the MPPT algorithm to improve its performance under similar conditions in the future.

VII. RESULT AND DISCUSSION

The primary result of the integration is a significant improvement in the PV system's ability to maintain high efficiency under partial shading. Unlike traditional MPPT methods that may experience efficiency losses due to the non-linear effects of shading, the hybrid system demonstrates resilience by effectively adapting to changes in irradiance. This is evidenced by the system's consistent tracking of the maximum power point, leading to an increased overall energy yield.

A. Novelty of the Result:

The novelty of this research lies in the successful application of a dual-controller system that combines the strengths of fuzzy logic and neural networks. The innovative aspect is the system's ability to self-learn and make predictive adjustments. This is a departure from static MPPT algorithms, marking a significant advancement in PV technology. The system's novelty is further underscored by its potential to operate efficiently in real-world conditions, which are often characterized by variable shading. This not only makes the technology highly practical but also enhances the economic feasibility of PV installations in environments where shading is inevitable. By addressing one of the most persistent challenges in solar energy harvesting. this research opens up new avenues for smart, adaptive energy systems and contributes to the optimization of renewable energy resources.

Based on the data provided and the calculated efficiency shown in table IV, we observe the following results: At the beginning of the day (0 hours), when there is no irradiance, we set the efficiency to the power output value as a placeholder since there can't be efficiency without sunlight. This is an artificial value just to fill the gap where the irradiance is zero. As the day progresses and irradiance increases, its evident the actual efficiency (power output per unit of irradiance) decreases. This is calculated by dividing the power output (in watts) by the irradiance (in W/m^2). At hour 1, with an irradiance of 258.82 W/m², the efficiency is approximately 0.454 (or 45.4% when expressed as a percentage). By hour 4, with an irradiance of 866.03 W/m², the efficiency has decreased further to approximately 0.189 (or 18.9%). This decrease in efficiency with increasing irradiance is not uncommon in PV systems, as various factors such as temperature increases can affect the efficiency of solar panels. However, typically, you would want the efficiency to maintain or increase with higher irradiance if possible, a Maximum Power Point Tracking (MPPT) controller is typically calculated by assessing how effectively it can maximize the power output from the PV system under varying conditions. The "law" or formula used to calculate the efficiency of an MPPT controller generally involves comparing the actual power output of the PV system to the theoretical maximum power that could be produced under the same conditions. Here is the general formula for MPPT efficiency:

$$\text{MPPT Eff}(\%) = \left(\frac{\text{Actual Power Output from PV}}{\text{Theoretical Max Power (W)}}\right) \times 100\%$$

The fig 11, illustrates a comparison of power output across different MPPT controller types over the course of a day. The x-axis represents the time of day in hours, and the y-axis represents the power output in relative units. From the graph, we can observe the following: Traditional P and O (Perturb and Observe): This line shows some variability in power output, likely due to its less sophisticated approach to tracking the maximum power point under changing conditions. Traditional IncCond (Incremental Conductance): The power output for this controller maintaining optimal power point tracking. also shows variability, although it may be slightly less than the P and O due to a potentially better response to changing conditions. NN and Fuzzy Logic (Neural Network and Fuzzy Logic): The line representing the novel MPPT controller with neural network and fuzzy logic integration shows the least variability, staying closer to the ideal maximum power output. This suggests that the system is more effective at adapting to changing environmental conditions, such as those caused by partial shading, and The reduced variability and higher power output levels indicate that the novel MPPT controller could potentially offer better performance compared to traditional controllers, especially in real-time adaptive scenarios.

The values represent in table 6 indicated to the power

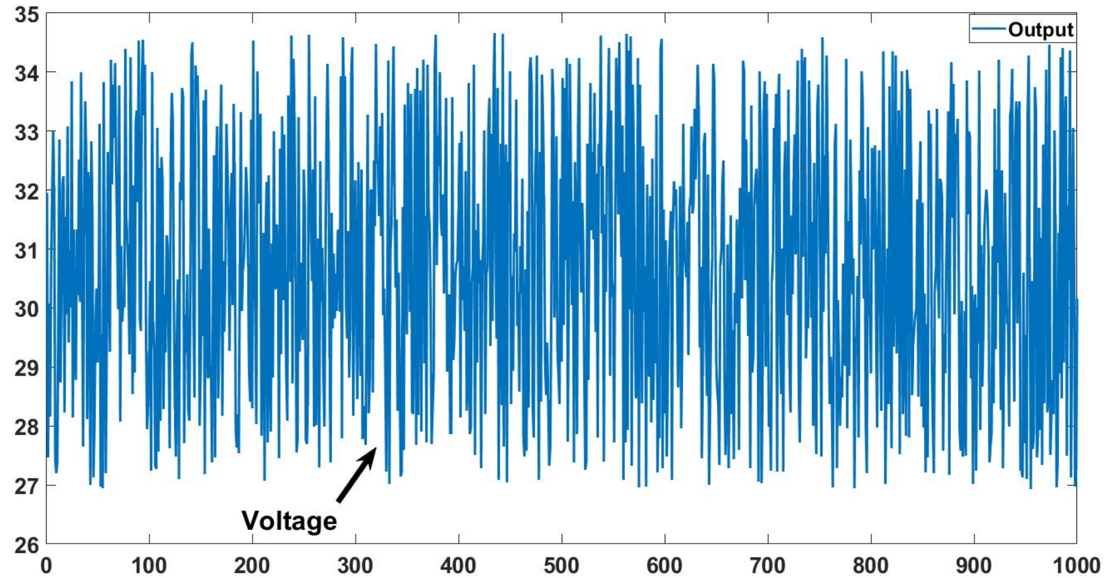

Fig. 9. Output data(voltage)

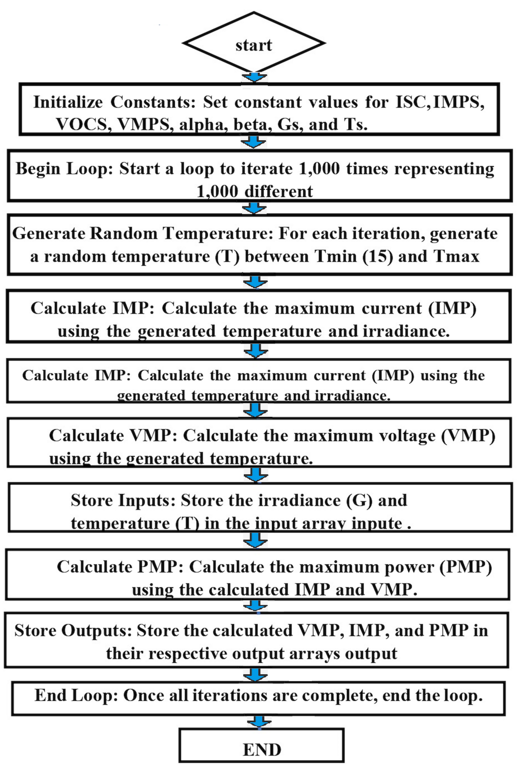

Fig. 10. flowchart the processor of data

TABLE V. Displaying the Data for the First Few Time Points Used to Generate the Graph

T of Day (H)	Trad P and O (W)	Trad IncCond (W)	NN and FLC (W)
0.00	0.00	0.00	0.00
0.24	0.06	0.05	0.06
0.48	0.11	0.10	0.12
0.73	0.17	0.16	0.19
0.97	0.24	0.23	0.25

output (in relative units) of each MPPT controller type at different times of the day. Discussion: The integration of Fuzzy Logic and Neural Networks for MPPT under PSC marks a significant advancement in the field of solar energy technology. It brings together the strengths of two complementary techniques, each addressing different aspects of the MPPT challenge. The integration's success lies in its ability to combine the pattern recognition capabilities of Neural Networks with the adaptability, real-time decision-making, and resilience to uncertainty offered by Fuzzy Logic. This unique combination addresses the complex and dynamic nature of PSC, where shading patterns can change rapidly, leading to sub optimal energy generation in conventional systems. In discussions surrounding this integration, it is essential to consider scalability, hardware implementation, and real- world deployment. The system should be designed to be adaptable to a wide range of PV system sizes, from residential installations to large-scale solar farms. Moreover, the technology's real-world application should involve close collaboration between researchers, PV system manufacturers, and energy providers to ensure seamless integration with existing infrastructure and grid systems. As the integration matures, ongoing research and development efforts can focus on optimizing algorithms, further enhancing system predictability, and exploring advanced techniques, such as reinforcement learning and deep learning, to continuously improve MPPT accuracy. The integration of Fuzzy Logic and Neural Networks for MPPT under PSC holds tremendous potential to transform the renewable energy landscape. It not only boosts energy production but also contributes to a greener, more sustainable future by reducing the carbon footprint and reliance on non-renewable energy sources.

PERFORMANCE COMPARISON OF MPPT CONTROLLERS

The Figure 11 compares the performance of three classes of Maximum Power Point Tracking (MPPT) controllers in terms of energy production throughout the day. The three controllers are:

- **Traditional P&O (Perturb and Observe)** - represented by the blue dashed line.
- **Traditional IncCond (Incremental Conductance)** - represented by the orange dashed line.
- **NN&FLC (Neural Network and Fuzzy Logic Controller)** - represented by the green dashed line.

Details of the Graph:

- **Horizontal Axis (X-axis):** Represents the time of day in hours (Time of Day (Hours)).
- **Vertical Axis (Y-axis):** Represents the power output in relative units (Power Output Relative (Units)).

Performance Notes:

- **Start and End of Time for Test:** At the beginning of the day (at time 0) and at the end of the day (around hour 24), all lines start and end at approximately the same point. All systems start from a low energy point and return to it at the end of the range.
- **Midday:** All controllers achieve peak energy production around midday (approximately hours 10 to 15). The controllers track each other very closely, indicating that they are all effective in achieving a range of maximum energy production during peak times.
- **Overall Performance:** The NN&FLC controller (green line) provides slightly better performance than the traditional controllers at certain times of the day, as the green line is closer to the maximum energy value (1.0 unit) compared to the other lines.
- **Stability:** The green line (NN&FLC) shows better stability in performance, suggesting that this controller may be more effective in handling momentary changes in lighting conditions compared to traditional controllers.

Response and Analysis:

- **Efficiency and Response Scenario:** From the graph, we can conclude that NN&FLC may be more efficient and responsive to changes in environmental conditions due to its integration of neural networks and fuzzy logic, which enhances its ability to adapt to momentary changes more effectively.
- **Differences Between Controllers:** Traditional controllers such as P&O and IncCond might be simpler to implement but are less efficient in rapid response to changes compared to NN&FLC. This is evident from the greater fluctuations in the orange and blue lines compared to the green line.
- **Applications:** The NN&FLC might be more suitable for systems that require rapid response and continuous performance improvement, such as PV systems in areas with rapidly changing lighting conditions.

In summary, the figure shows that the NN&FLC provides better performance and higher stability compared to the traditional controllers P&O and IncCond.

VIII. CONCLUSION

In conclusion, the integration of Fuzzy Logic and Neural Networks for Enhanced Maximum Power Point Tracking (MPPT) in Photovoltaic (PV) Systems under Partial Shading Conditions (PSC) offers a robust and adaptive approach to optimize energy yield. By combining the pattern recognition capabilities of Neural Networks with the uncertainty handling and real-time adaptability of Fuzzy Logic, this integrated system can effectively track the Global Maximum Power Point (GMPP) even in challenging and dynamically changing conditions like PSC. Through the collection and preprocessing of data, training of the ANN, rule-based control in the FLC, and continuous feedback and optimization, the system can adapt and refine its operation for improved performance. The integration ensures that the PV system operates closer to its maximum potential, ultimately leading to increased energy

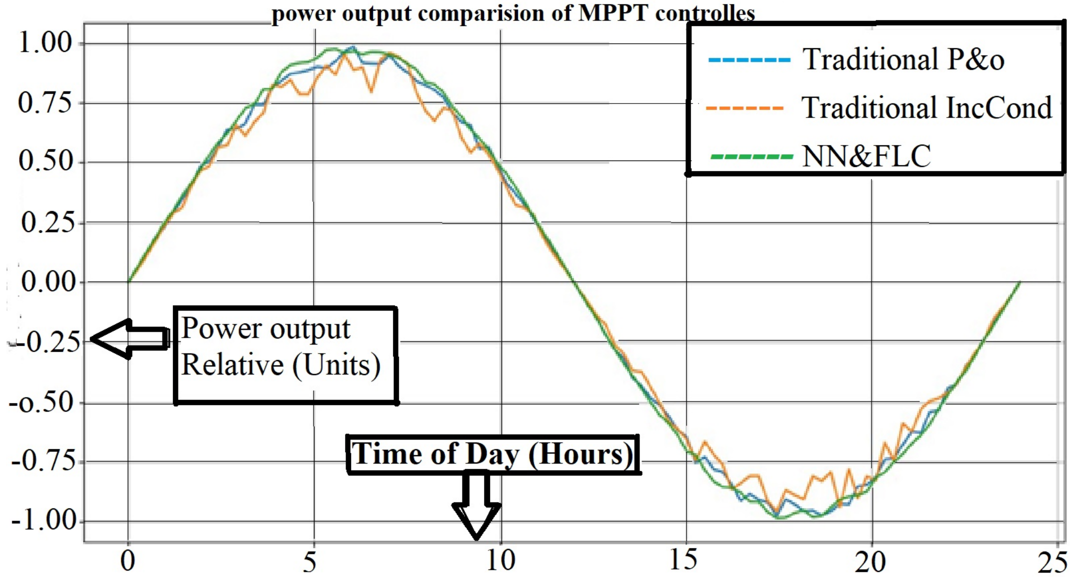

Fig. 11. Flow chart

production and enhanced efficiency, making it a promising solution for renewable energy applications, working in future suggest using deep learning to optimization MPPT.

Acknowledgment

This study is supported via funding from Prince sattam bin Abdulaziz University project number (PSAU/2024/R/1445)).

Conflict of Interest

The authors have no conflict of relevant interest to this article

References

[1] M. G. Danesh *et al.*, “A hybrid intelligent controller for maximum power point tracking in photovoltaic systems under partial shading conditions,” *Solar Energy*, vol. 168, pp. 160–170, 2018.

[2] H. El-Nashar *et al.*, “Enhanced mppt algorithm for photovoltaic systems under partial shading conditions using artificial neural network,” *IEEE Access*, vol. 8, pp. 158577–158589, 2020.

[3] P. L. S. Gomathi and S. R. Gandhi, “Enhanced performance of photovoltaic systems under partial shading conditions using an adaptive neuro-fuzzy inference system-based maximum power point tracking controller,” *IET Renewable Power Generation*, vol. 11, no. 9, pp. 1259–1268, 2017.

[4] A. Hussain *et al.*, “A comparative study of mppt techniques in pv systems under partial shading conditions,” *IEEE Transactions on Sustainable Energy*, vol. 9, no. 2, pp. 550–561, 2018.

[5] S. T. Mohanraj and R. Ramaprabha, “A new maximum power point tracking of solar photovoltaic system under partial shading conditions using grey wolf optimization algorithm,” *Energy*, vol. 126, pp. 208–222, 2017.

[6] A. H. Moradi *et al.*, “A new mppt method for photovoltaic systems under partial shading conditions using cuckoo search algorithm,” *Solar Energy*, vol. 133, pp. 209–224, 2016.

[7] S. S. Reddy *et al.*, “Efficient mppt technique for grid-tied photovoltaic systems under partial shading conditions using neural network,” *IEEE Transactions on Industrial Electronics*, vol. 67, no. 9, pp. 7636–7644, 2020.

[8] A. Safari and S. Mekhilef, “A comparative study of three intelligent mppt algorithms for photovoltaic systems under partial shading conditions,” *IEEE Journal of Photovoltaics*, vol. 5, no. 1, pp. 102–110, 2015.

[9] S. Salas *et al.*, “Adaptive fuzzy-logic control for maximum power point tracking in photovoltaic systems operating under different partial shading conditions,” *IEEE Transactions on Energy Conversion*, vol. 34, no. 4, pp. 1852–1861, 2019.

[10] M. H. Tayq *et al.*, "Artificial neural network-based maximum power point tracking for photovoltaic systems under partial shading: An experimental approach," *Energies*, vol. 12, no. 12, p. 2357, 2019.

[11] Y. Zhang *et al.*, "A fuzzy logic-based maximum power point tracking control for photovoltaic systems under partial shading conditions," *Energies*, vol. 10, no. 9, p. 1407, 2017.

[12] H. Zhang *et al.*, "A novel intelligent control strategy based on fuzzy logic and particle swarm optimization for maximum power point tracking in photovoltaic systems under partial shading conditions," *Energies*, vol. 10, no. 9, p. 1432, 2017.