

Article

Not peer-reviewed version

Reinforcement Neural Network-Based Grid Integrated PV System with the Battery Management System

[Salah Mahdi Thajeel](#) * and [Doğru Çağdaş ATILLA](#)

Posted Date: 2 December 2024

doi: 10.20944/preprints202412.0113.v1

Keywords: Maximum Power Point Tracking (MPPT); Photovoltaic (PV) Systems; Fuzzy Logic Controllers (FLCs)



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Article

Reinforcement Neural Network-Based Grid Integrated PV System with the Battery Management System

Salah Mahdi Thajeel * and Cagdas Atilla

Department of Electrical and computer Engineering, Altınbaş University, Istanbul, Turkey

* Correspondence: 203720022@ogr.altinbas.edu.tr

Abstract: A Reinforcement Neural Network-Based Grid Integrated PV System with a Battery Management System (BMS) aims to enhance the efficiency and reliability of renewable energy systems. In such a setup, the photovoltaic (PV) system generates electricity, which can be used immediately, stored in batteries, or fed into the grid. The challenge lies in dynamically optimizing the power flow between these components to minimize energy costs, maximize the use of renewable energy, and maintain grid stability. Reinforcement learning (RL), combined with neural networks, offers a powerful solution by enabling the system to learn and adapt its energy management strategy in real time. The RL agent interacts with the environment (i.e., the grid, PV system, and battery), continuously improving its decisions on when to store energy, draw from the battery, and supply power to the grid. This intelligent control approach ensures optimal performance, contributing to a more sustainable and resilient energy system.

Keywords: maximum power point tracking (MPPT); photovoltaic (PV) systems; fuzzy logic controllers (FLCs)

1. Introduction

Investments of usual remnant fuel are exhaust at rapid paces. The increasing electricity demands could be encounter by using renewable energy sources that shows possible opportunity for generation of electricity. Amongst several maintainable energy bases, solar energy demonstrates practical added for power generations, since it is the sufficient, unlimited, and non-pollute sources of energies. Solar energy generation is successful at debauched rates. This evolution is because of the current progressions in accurateness, conjunction quickness for gathering extreme energy [1–5]. Wind and sun energy are projecting to stay a feature of third renewables improvement and the contributions of renewables power source in electricity's generation determination developed in practice by 40% in 2022, demonstrating the high portion of renewables energies source meanwhile the industrial evolutions is projected in this field [6–14]. Hence, solar PV electricity generation is probable to rise by 150 TW or in practice by 20% in 2022. The DC power generated from solar cell when the solar ray incident on this cell [11–15]. Hence, numerous solar cells are connecting to forms power voltage modules. Then, the group of solar module results in the realizing of the solar arrays. The modules of PV have quite low transformation competence because of the solar cell nonlinear characteristic [16–20]. Hence, it becomes required to achieve the maximum obtainable energy from the PV module. Furthermore, the maximum energy provided by the photovoltaic modules are not statics as the atmospheric parameter like irradiance levels, temperatures, dust, and the specific connecting condition like the topographical condition of an areas, effect the performances of a PV systems [15–22]. Therefore, there is require examining study relate to predicting weather condition exactly as solar power is obtainable freely of cost in nature. Thus, PV system can be either a grid connecting generation units or a standalone-generation units and the country area deprived grid power quality regions get electricity from this unit [23–28]. The P/V characteristic of the solar cells display an optimal point varies under atmospheric condition. The cells generate maximum energy at

this point. Accordingly, the MPPT method is engaged to guarantee that the PV modules activities optimal capacities at all-time [25,29–32]. The MPPTs techniques are use in PVs system to boosts the solar panels power outputs. It serves the purposes of ensure that the solar panels are produce high amounts of electric powers in case of it is function at its maximum power points (MPPs), which is positioned on currents–voltages (I–V) curve employ in PVs system to boost complete deficiency and energy productions. Temperatures, shades, and amount of sun received are fewer instance of variable influence the MPPs. The algorithm of MPPTs continuous monitors the MPPs by adjust the operation voltages and currents of solar panels to extracts a maximum quantity of probable electricity. PVs system employed MPPTs to boost total deficiency and energy outputs. High energy outputs might be realized by run the solar panels at its MPPs, which allow for better power collecting from the sunshine. This is mainly significant when the solar panels are connects to batteries or grids since it makes the greatest usage of the solar energy that is presently obtainable and improved systems performances [32–35]. The microgrid controlling hierarchy is showed in Figure 1. Generally, an intelligent microgrids EMSs must manage and coordinated a mix of DGs, energy storages system (ESS), and load to generate higher-quality, dependable, maintainable, and environmentally friendly energy at a sensible cost [36–38]. The comparison of drawbacks and advantage between NN and Fuzzy logic controls strategy are explained in Table 1 [39–41].

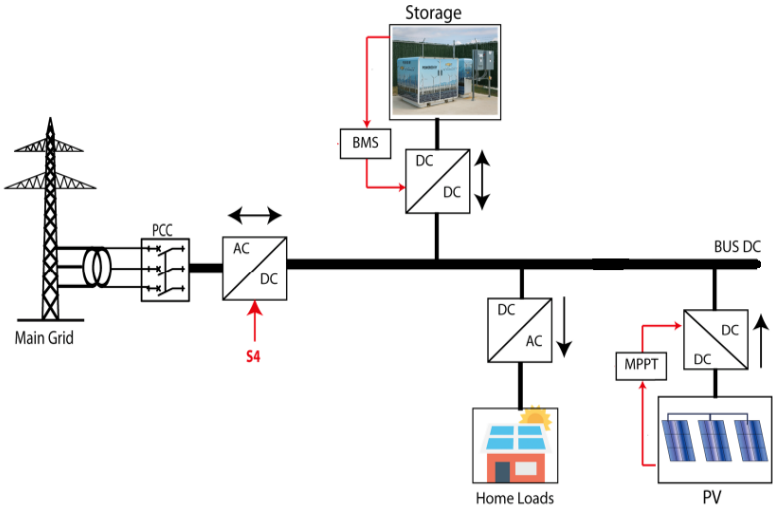


Figure1. Microgrids with MPPT structures.

Table 1. comparison between NN and fuzzy logic controller’s approach.

Technique	Advantage	Disadvantage
Neural networks Controller (NN)	<ul style="list-style-type: none">- In online or offline application, the technique can control, optimized, and identifying the system parameter- Use nonlinear data technique to solve challenge in large-scale system in MG- Self-learning and prediction are used to solve the system’s stability and fault tolerance.	<ul style="list-style-type: none">- The model structure is complicated- Difficult to determine the best networks structures when adding or raising units from the MG topology (black boxes)- Difficult to determine the best network structure when adding or raising units from the MG topology- Only possible if the system structure is stable.
Fuzzy logic Controller (FLC)	<ul style="list-style-type: none">- Better voltage and frequency management, as well as power sharing between many MGs.	<ul style="list-style-type: none">- A high-quality processing unit is required- Error methods are used for the participation function- The procedure is time-consuming.

The short circuits currents attitude for the currents flows in the short circuit’s conditions of planetary cells. The open circuits’ voltages signify the extreme voltages obtainable as of solar cells

through the open circuits' conditions. Nevertheless, open and short circuits condition is not donated to energy generations. However, definite combinations of voltages and currents controlled to extreme maximize energy production. The coordination of the combined indicates the maximums power points. The curve of the solar cell that represents an I-V and P-V are showed in Figure2 [42,43].

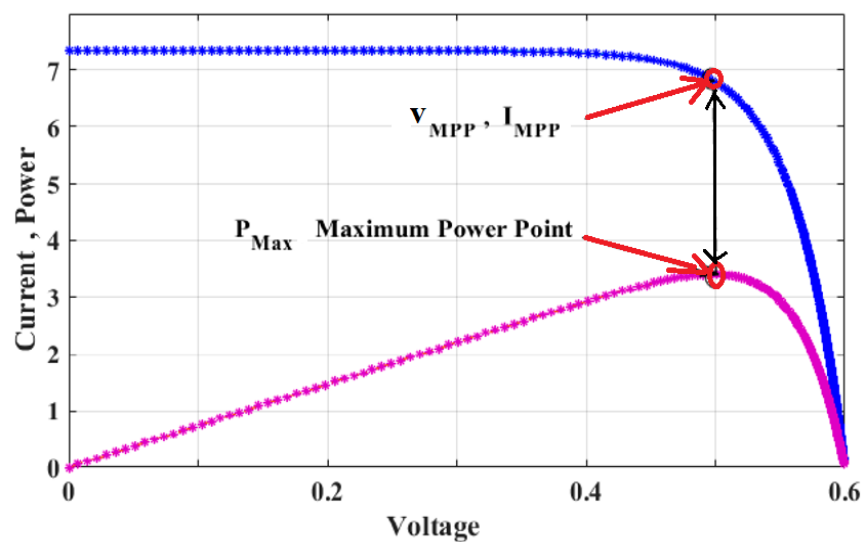


Figure2. curve of P/V and I/V solar cell characteristics.

The important impact of temperature on the presentation of the modules is illustrated in Figures 3 and Figure 4 correspondingly. Then, one could be concluded from these figures that an open circuits voltages of PV model drops with temperatures increasing and the outputs energy harvest of power voltage module resolve a drop.

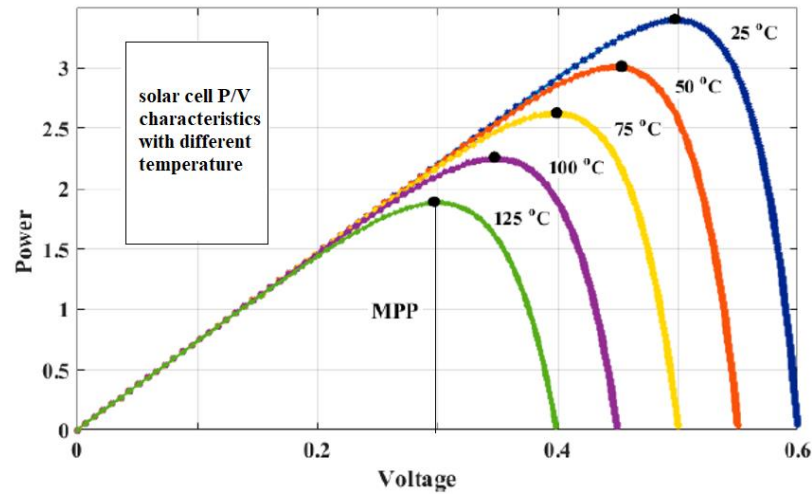


Figure 3. solar cell P/V characteristic under different temperature effecting.

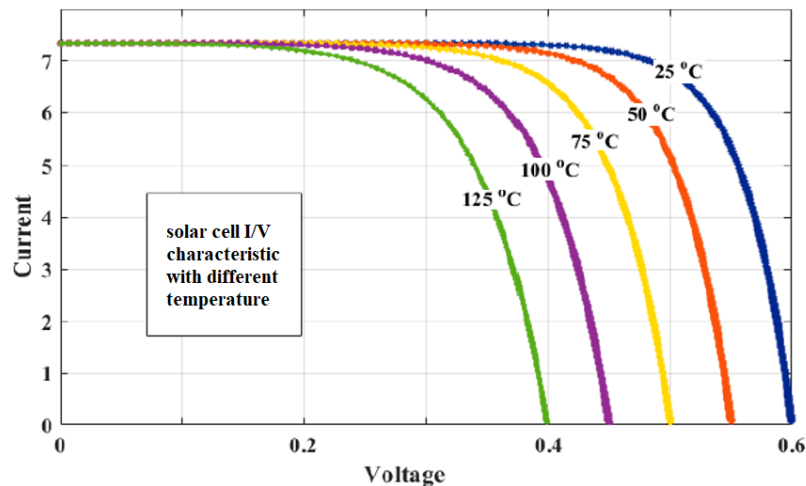


Figure 4. solar cell I/V characteristic under different temperature effecting.

2. Related Works

The state-of-the-art literatures reviews are conducted to analyze the research gaps and introduced a novel of the suggested techniques. This paper presented new MPPTs technique utilize Neural Network (NN) to efficiently track the maximum power produced by the PVs panels. The suggested NN-based MPPTs algorithms demonstrate fast and correct adaptations to varying weather conditions, counting variation in temperatures and solar radiations. Widespread research includes the design and modeling of PVs systems structures in conjunction with the NN-MPPTs controllers. The foremost goals of these approaches are to develop higher-performance NN-based MPPT controllers for solar application. In [44], the author presented the Fuzzy Logics (FLs) MPPTs algorithms, new fuzzy logic-based techniques for checking the maximal power points of PVs array. Different standards FL-MPPTs method that employing the alteration in gradient of P-V characteristic, the suggested method uses newest parameters called "Ea" that is produced from I-V characteristic. These added parameters improve the track performances in a variation of environment condition (ECs) and increased the precisions with which duty ratio change might be calculated. By use of the "Ea" parameters, the method effectively distinguishes among the operation point location in the Voltages Sources Regions (VSRs) or Currents Sources Regions (CSRs) and its proximity to the MPPs regions. Other studies highlight the importance of MPPs controller to optimize the performances of solar (PVs) module [45]. The author presents comparisons of Adaptive Neuron-Fuzzy Inference Systems (ANFISs)-based MPPTs controllers' architectures, an FL power controller, PV modules, an ANFIS reference models, and a DC-DC boost converters. During simulations in the MATLAB/Simulink environment, the suggested ANFIS-based MPPT controllers successfully harvest the maximum power from the PV modules under a variety of weather circumstances, contributing significantly to the advancements of MPPTs method for solar energy system.

The studies conducted by [46,47] close this gap by put forth methodical and logical approaches to determine the optimal PSO algorithms setting, accounting for factors like solar panel arrangements, DC-DC converters topologies, and even associated battery parameters. Moreover, these works present novel methods for determining the optimal samples periods to maximize the performances of digital MPPTs controller. The improved PSO algorithms, along with its customized parameter, best satisfy the requirement of Mppt control for PV system, representing significant steps toward increasing the overall efficiency of such system.

The choice of specific methods is still incomprehensible [48,49]. Furthermore, recent research work does not comprise all new developing of MPPT algorithm. There is excessive requirement to analyzing and reviewing the suggested approaches to offer an understanding into the choice of definite method as per the framework. This paper introduces new MPPT technique and compared on the foundation of numerous factors like track speed, implementation cost, and difficulties. This MPPT technique can be classified into two important collections, explicitly and predictable strategy.

Conventional technique contains trouble and detects, increment conductance, fractions open circuits voltages, and fractional short circuits current. All these strategies reconsidered including swarms-intelligences with bio-inspire that consist of the element swarm optimizing and colony optimizing which comprise fly squirrel search optimizing, owl search algorithms and firefly algorithms. While artificial intelligence technique includes fuzzy logic controls, neural network, and its sub-categorizations. This work structure as follows: in section two, material and methods are presents. The result is discus in section three. Section four introduces a conclusion of this work founding.

3. Discussion and Methods

The solar neural network system and the fuzzy controller system are two different approaches to processing and analyzing data and making decisions in two different contexts. I will give you a detailed evaluation of both systems:

3.1. Solar Neural Network System:

- ⦿It uses neural network models to analyze data related to the solar energy system.
- ⦿It uses data from solar panels and other environmental variables to predict solar system performance and improve its efficiency.
- ⦿It relies on the learning ability of neural networks to analyze data and gain knowledge about the optimal conditions for solar energy generation.
- ⦿Neural network models can be developed to improve system performance and make the most of solar energy.

3.2. Fuzzy Controller System

- ⦿It relies on the principles of fuzzy logic and fuzzy inference rules to make decisions.
- ⦿It uses conceptual variables and considers imprecise values of variables such as "few" or "many" rather than strict numeric values.
- ⦿It uses fuzzy inference rules to analyze data and make decisions based on fuzzy logic.
- ⦿It allows the representation of ambiguity and uncertainty in data and can deal with nonlinear and heteroscedastic variables.

It should be noted that no single system is best in all cases. The choice between a neural network system and a fuzzy controller system may depend on factors such as the specific requirements of your application, the level of complexity of the specific problem, and the availability of data and resources required.

In short, a neural network system relies on the learning ability of neural networks and uses digital data, while a fuzzy controller system relies on fuzzy logic and uses imprecise values.

Table 3. Cost, speed of performance and reliability.

Aspect	Neural Network System for Solar Energy	Fuzzy Control System
Cost	Relatively high	Relatively low
Performance Speed	Fast processing	Moderate processing
Reliability	High reliability	High reliability

Performance speed, and reliability can vary depending on the specific implementation, scale, and application of the systems. The Table 1. provides a general overview, but it's important to conduct a detailed analysis and consider other factors specific to your requirements before making a decision.

It is shown that the solar neural network system has strong learning and adaptation ability and the ability to accurately analyze and predict system performance. While the fuzzy controller system is characterized by the ability to deal with inaccurate values and deal with huge amounts of data. As Table 2.

Table 4. Learning Capability, Analysis and Prediction.

Features	Neural Network System for Solar Energy	Fuzzy Control System
Learning Capability	Strong learning and adaptation ability	Limited learning
Analysis and Prediction	Accurate system analysis and prediction	General system prediction
Efficiency and Performance	Potential for high performance and efficiency improvement	Achieves reasonable performance
Data Handling	Handles numerical data effectively	Handles imprecise values effectively
Data Processing Capacity	Can process large amounts of data	Can process large amounts of data
Scalability and Development	Can be developed and improved based on specific needs	Can be modified and improved based on specific needs

The mysterious control unit is a type of control system that works on the basis of mysterious logic rather than the traditional (real/wrong) logic. Luby logic allows to deal with uncertainty and inaccuracy in the use of linguistic variables and approximate thinking.

Here are some major points on mysterious control units:

1.Overwhelming logical principles: The mysterious logic allows a more like human being in making decisions by looking at concepts such as ' very hot 'and' cold 'cold' or 'very bright' instead of accurate numerical values.

2.The mysterious reasoning: The essence of a mysterious control unit lies in its ability to make decisions based on mysterious reasoning. These rules are defined based on experts' knowledge and used to set input variables for output procedures.

3.Dealing with inaccuracy: The mysterious control units excel in the processing of systems that may be difficult to obtain accurate or noisy numerical data. Using linguistic variables and mysterious groups, the unit can absorb inaccurate inputs and provide meaningful outputs.

4.Non -linear systems: Mental controllers are especially useful for dealing with non -linear systems as traditional control methods may be struggled. The elasticity of the mysterious logic allows effective control in systems with complex behaviors.

5.Data processing: Mental units can process large amounts of data and complex decision -making operations effectively. It is ideal for systems that require actual time amendments based on varying input conditions.

6.Performance: While mysterious control units may not always provide the best performance in terms of speed compared to some other control methods, they provide a good balance between accuracy and mathematical efficiency of many applications.

In short, a mysterious console system provides a unique approach to control and decision -making by taking advantage of the principles of mysterious logic to deal with inaccurate data and effectively uncertainty. It provides a strong and adaptive solution suitable for a variety of applications as traditional control methods may shorten. It is similar to the presence of a flexible and intuitive control unit that can move through mysterious or unclear situations easily. The ability to expand and the ability to adapt: Mental control units can be easily modified and adjusted to adapt to the changes of the variable system or environmental conditions. This flexibility makes it suitable for a wide range of applications.

3.3. Neural Network

The nerve network, also known as the artificial nerve network (AnN) or just a neural mesh, is an arithmetic model inspired by the method of biological networks in the function of the human brain. Nervous networks are commonly used in machine learning and artificial intelligence applications such as identification of patterns, classification, slope, and more.

Below is a detailed explanation of nerve networks:

1.Neurological cells: In the neuron, neurons are essential blocks and are designed similar to biological neurons. Each neuron receives input signals, treats them (for example, through stimulation functions), and produces an output.

2.Classes: Nerve cells are organized in a nerve mesh in layers. The three main types of layers are:

-Entering layer: The first layer where the input data is fed in the network.

-Hidden layers: intermediate layers between the input and output layers where complex patterns are learned in the data.

-The output layer: the final layer that produces the network output based on the used patterns.

3.Communications: Neurons are connected to the adjacent layers by communications, also known as the edges, which have associated weights. These weights determine the strength of the relationship between two neurons.

4.Activation function: The activation function is applied to take out each nerve cell to enter intolerance in the network. Common activation functions include X -ia, comfort (corrected linear unit), and Tanh.

5.Feedforward: In the nutrition process, the data is passed through the network layer according to the layer from the input to the output. Each neuron receives in a layer of inputs of neurons in the previous layer and produces an output as an entrance to the next layer.

6.Training: Neurological networks are trained using algorithms such as gradient and rear translation. During training, the network adjusts the communications weights to reduce the difference between expected output and actual output.

7.Types of nerve networks:

-Feedforward Neural Networks (FNN): The simplest type as data flows in one direction without cycles.

-Repeated nervous networks (RNN): networks with communications that make up cycles, allowing them to keep memory and process serial data.

-CNN: Specialized to process network -like data such as images.

8.Applications: Nervous networks are used in various fields, including images recognition, natural language processing, speech recognition, independent compounds, financial prediction, and more.

9.Challenges: Neurological networks may face challenges such as involvement, reduction in gradients, and arithmetic complexity, which researchers constantly seek to address through techniques such as planning and improvement algorithms.

In essence, neural networks are strong accounting models capable of learning complex patterns in data and making predictions or decisions based on this learning. The multiplicity of its uses and its effectiveness makes them an essential tool in artificial intelligence applications and modern machine learning

4. Results

We want to design an MPPT system according to several two components in order to compare the results. We design the first model, which is MPPT Fuzzy. Then we want to design MPPT Ann and a hybrid MPPT system in order to compare the results to reach the best model and clarify the possibility of integrating the first and second systems via the MATLAB program, where a list appears first for choosing. Type of model used.

4.1. MPPT Fuzzy when 1 Is Pressed

The code I provided aims to implement the MPPT (Maximum Power Point Tracking) algorithm using fuzzy logic. The MPPT algorithm is used in renewable energy generation systems such as solar panels, and aims to achieve maximum efficiency in extracting energy from the source. The algorithm is based on determining the maximum power point (MPP) of the source, which is the point at which the maximum amount of power is extracted. The voltage and current are represented using membership functions with a triangular shape (trimf), in order to determine the membership degree for each value. of voltage and current within a specified range.

The code also creates a knowledge base (rules), a matrix that defines the rules that must be followed to achieve the MPPT. Here, the base is assigned a value of one if there is a match between the voltage and current values at the given point.

The output is then calculated using the defined rules and levels. The bases are multiplied by the product of their corresponding voltage and current, then these values are added and divided by the sum of the bases to get the final result.

Finally, the output is displayed on the output screen and fuzzy logic is used in MPPT systems to deal with uncertainty in the data and changes in operating conditions. Affiliation levels and knowledge bases can be modified and changed based on the specific requirements and conditions of the system.as Figure 1.

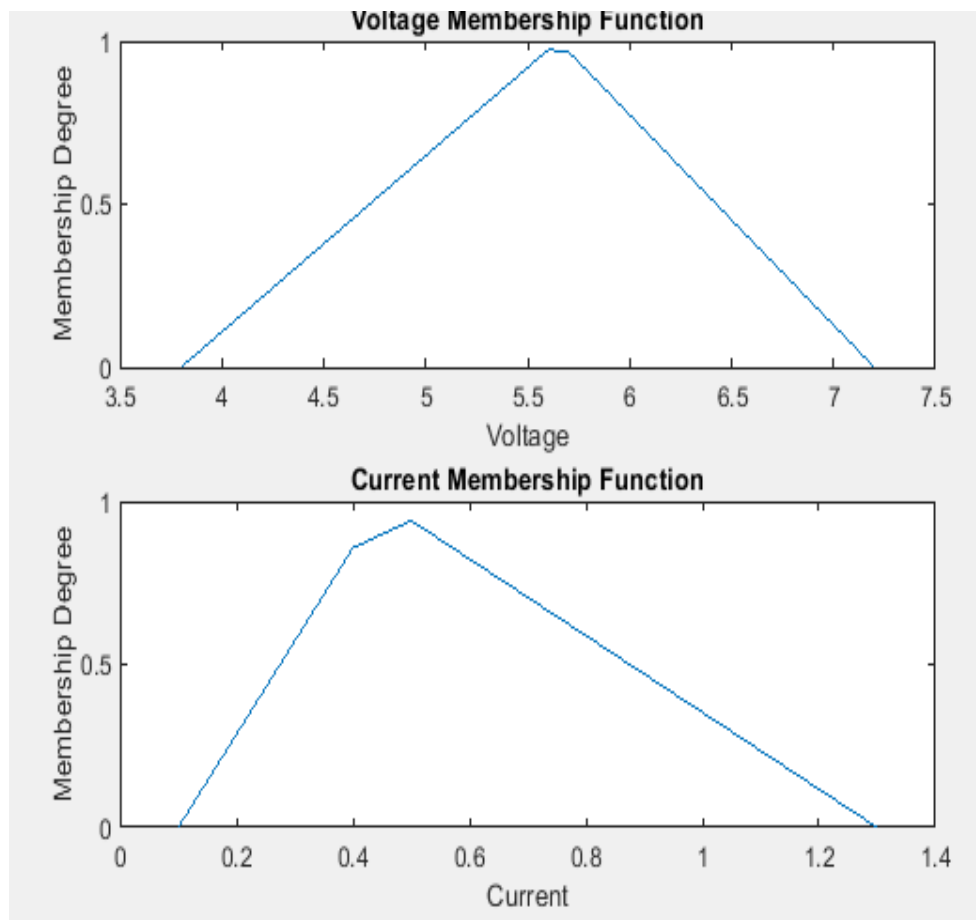


Figure 5. MPPT Fuzzy.

4.2. MPPT Ann when 2 Is Pressed

The MPPT (Maximum Power Point Tracking) algorithm is implemented using an artificial neural network (ANN). The neural network here is considered the main control unit in achieving the maximum power point of the solar energy system. The main steps for the operation of the MPPT neural network are:

1. Determine the number of data points based on 24 hours and hourly data reading frequency.
2. Input voltage and current data for solar energy system.
3. Convert the data into a format suitable for the artificial neural network.
4. Convert values to desired range (eg -1 to 1) using mapminmax function.
5. Set target values for the MPPT (optimum duty cycle) system and convert them to the desired range.
6. Create an artificial neural network using newff and specify the number of layers and active functions for each layer.
7. Train the artificial neural network using trainlm and specify the number of trainings fields.as Figure 2
8. Applying artificial neural network to voltage and current data using SIM.
9. Display the results with a graph, where the actual voltage, current and results of the artificial nerve network are displayed.

It should be noted that using a neural network in this case is an alternative approach to other strategies used in MPPT algorithms. Achieving satisfactory performance may require training the neural network on a wide range of data collected under various operating conditions and potential variations

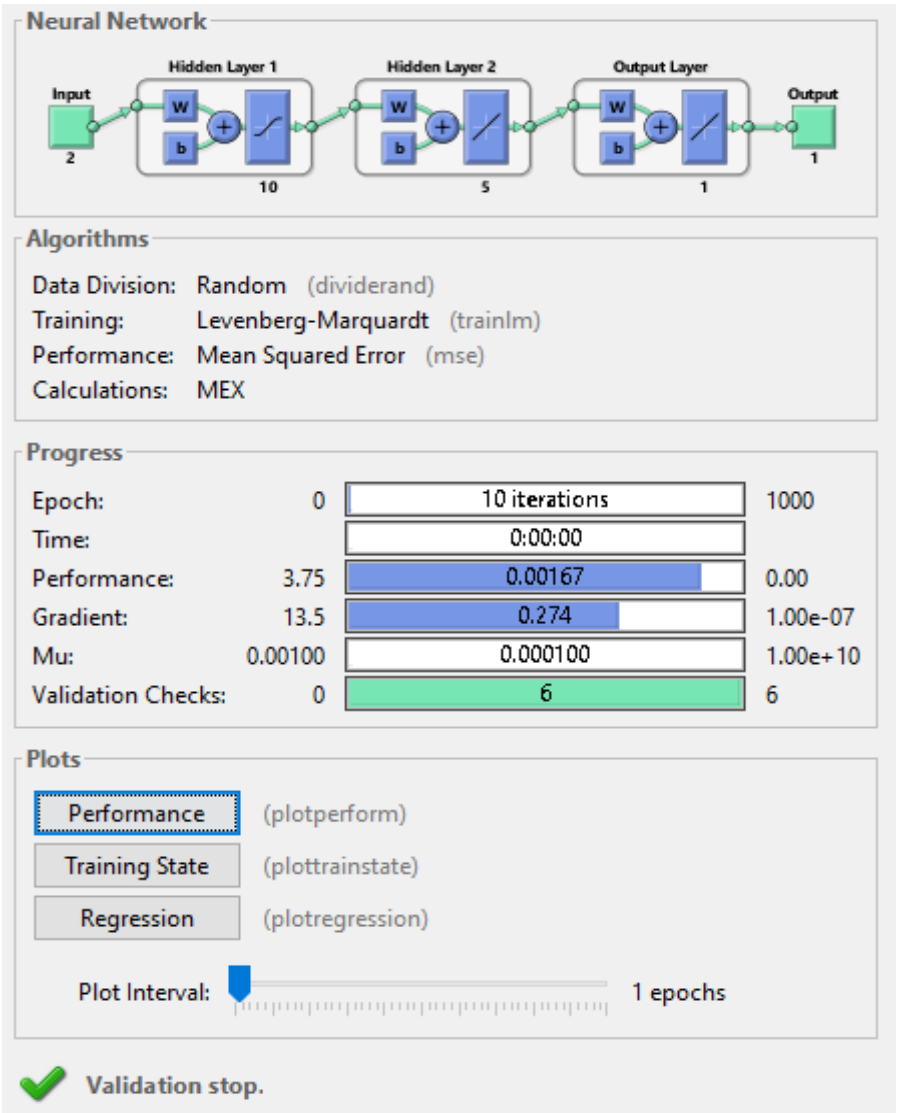


Figure 6. Training process by ANN.

Results for voltage and current in the solar system are plotted over a 24-hour period. The results express the actual values measured during the operation of the solar system.

For voltage, the measured values are stored in the “voltage” array which contains 24 values representing the voltage measured over the different clocks. These values are plotted in red in the graph.

For current, the measured values are stored in the “current” array which also contains 24 values representing the current measured over the different clocks. These values are plotted in blue in the graph. As Figure 3.

Voltage and current are displayed on the x-axis and the measured values on the y-axis. This gives an idea of the voltage and current changes during the given time period and the neural network is used to estimate the optimal duty cycle values for the MPPT system. The optimal duty cycle target values are represented in the matrix “dutyCycleOptimal” and are also converted to the desired range. The rated duty cycle output is plotted in green in the graph and these graphs provide an overview of the performance of the solar system and its ability to achieve maximum generated power capacity. There may be discrepancies between the measured values and the optimal values estimated by the neural network.

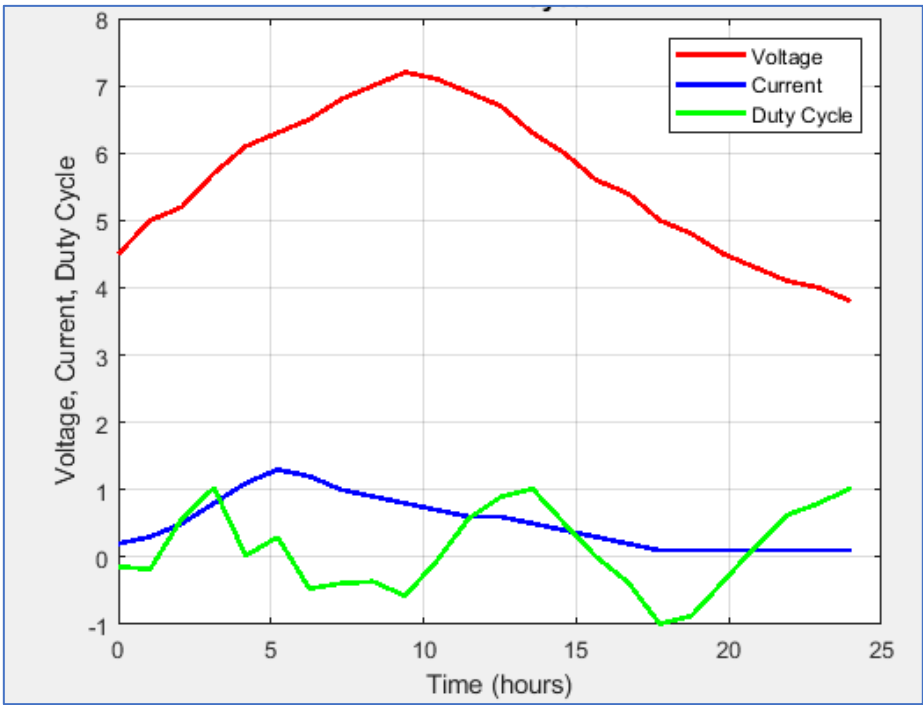


Figure 7. MPPT ANN.

4.3. Hybrid System MPPT when 3 Is Pressed

A hybrid system is a system that combines an Artificial Neural Network (ANN) and Fuzzy Logic to achieve Maximum Power Point (MPPT) in a solar energy system.

The hybrid system consists of two inputs, namely voltage and current, and the ranges of permissible values for each input are defined. The ranges of values were divided into fuzzy partitions, such as “Low”, “Medium”, and “High”, using fuzzy distributions such as “trapmf” and “trimf”, and the partitions were defined using appropriate parameters.

The output, which is the DutyCycle, is then determined and the permissible range of values is set. The domain is also partitioned into fuzzy partitions with the partitions defined and using fuzzy distributions.

Fuzzy knowledge bases are created based on the input and output knowledge shared in this system. Fuzzy knowledge rules are defined in the ruleList array, where each input and output are assigned a rule.

Using fuzzy defined rules, they are applied to values computed from a neural network (ANN) using the evalfis function. This generates the final DutyCycle results of the hybrid system.

Finally, the results are plotted using a graph. Voltage and current are displayed at the top of the graph and are represented in red and blue respectively. There is also a neural network under the graph that represents the results calculated from the neural network. As Figure 4.

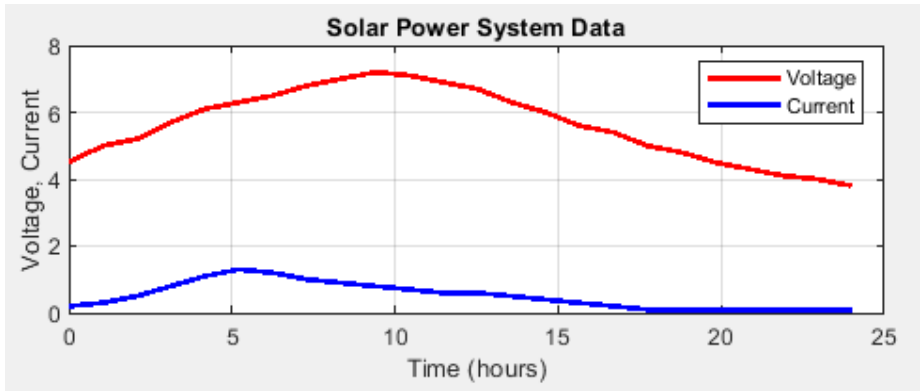


Figure 8. ybrid system MPPT.

The results of the hybrid system implemented in the code can be considered the best in the context of the maximum power point (MPPT) of the solar energy system. The hybrid system combines the power of an artificial neural network (ANN) in analyzing data and learning patterns, and the flexibility of fuzzy knowledge bases (Fuzzy Logic) in dealing with ambiguity and changes in surrounding conditions.

These better results can be demonstrated by the ability of the hybrid system to achieve maximum efficiency in extracting energy from the solar panels. This is achieved by adjusting the Duty Cycle to be in the optimal range for solar panel performance under different radiation conditions. Hence, maximum efficiency can be achieved in converting solar energy into usable electrical energy.

5. Simulation

The simulation system MPPT (Maximum Power Point Tracking) and fuzzy MPPT are both methods used in photovoltaic (PV) systems to optimize the power output of solar panels by tracking the maximum power point (MPP) under varying environmental conditions.

5.1. Simulation System MPPT

Simulation-based MPPT methods involve creating a mathematical model of the PV system and simulating its behavior under different operating conditions. These methods use the model to estimate the MPP and adjust the operating parameters of the system accordingly. Common simulation-based MPPT techniques include Perturb and Observe (P&O), Incremental Conductance (IncCond), and Fractional Open Circuit Voltage (FOCV).

P&O: This method perturbs the operating point of the PV system and observes the resulting change in power output. Based on the observed change, it adjusts the operating point towards the MPP.

IncCond: This method calculates the incremental conductance of the PV system and compares it with zero. By adjusting the operating point based on the sign of the incremental conductance, it tracks the MPP.

FOCV: This method utilizes the fractional open-circuit voltage to estimate the MPP. It calculates the fractional voltage value corresponding to the MPP and adjusts the operating point accordingly.

Simulation-based MPPT methods offer good accuracy and can be implemented using mathematical models and simulation software.

5.2. Fuzzy MPPT

Fuzzy MPPT is a control approach that utilizes fuzzy logic to track the MPP. Fuzzy logic allows for the incorporation of linguistic rules and human-like decision-making into the MPPT algorithm. It uses input variables such as PV voltage, PV current, and their rates of change to determine the appropriate adjustment to the operating point.

Fuzzy MPPT algorithms typically involve defining a set of fuzzy rules that map the input variables to the adjustment needed for the operating point. These rules are based on expert knowledge and experience. By using linguistic variables such as "low," "medium," and "high" to describe the input and output variables, fuzzy MPPT algorithms can handle the uncertainties and nonlinearities of the PV system.

The advantage of fuzzy MPPT is its adaptability to changing environmental conditions and its ability to handle partial shading and other non-ideal operating conditions. However, fuzzy MPPT algorithms may require more computational resources compared to traditional MPPT methods.

Both simulation-based MPPT and fuzzy MPPT techniques aim to optimize the power output of PV systems by tracking the MPP. The choice of method depends on factors such as system complexity, computational resources, and the desired level of adaptability to changing operating conditions. as Figure 5.1.

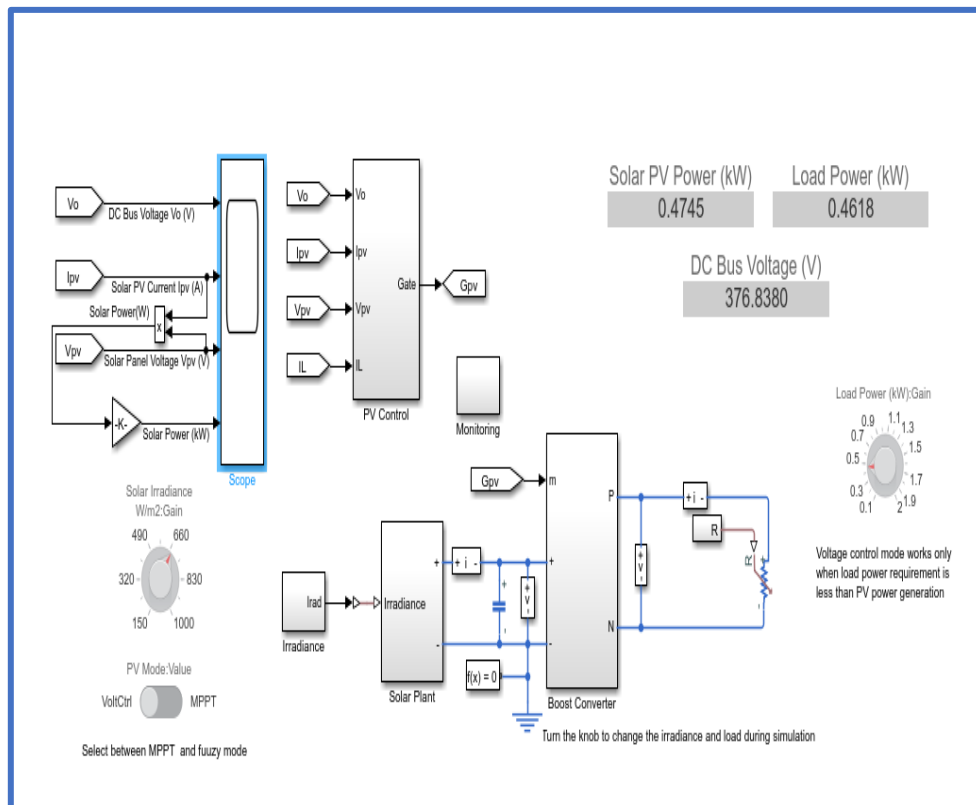


Figure 9. Simulation system MPPT and fuzzy MPPT.

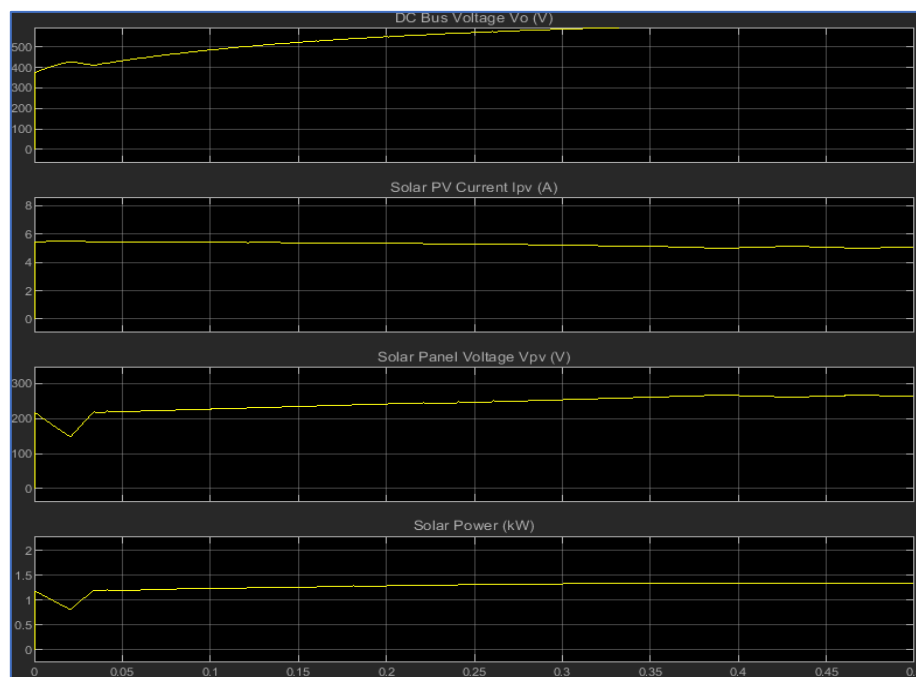


Figure 10. Results of the normal MPPT simulation system.

5.3. ANN MPPT

MPPT nervous network is a system that uses synthetic nervous network technologies to improve the performance of MPT system in solar energy systems. This circuit uses the principle of work that it quotes from the function of the human brain to learn and adapt behavior.

The circuit depends on the Multilayer Neural Network, as it consists of multiple layers of the nodes (Neurons) that are linked to each other through weighted Connections. The network receives the input information from the sensors in the MPT system such as the solar plate effort and its current, and it processes and generates it to output signals that express the voltage and current required to obtain the maximum ability.

The work of the nervous network is done through training and learning, where the values of the weight of communications between the contract in the network are changed based on the reference data and notes available on the performance. This weight is adapted to reduce the error between the targeted sign (maximum) and the actual signal generated from the system.

Using this model, the circuit can work smart to adjust the current and effort of the system so that the maximum energy point is reached accurately and effectively, which improves the performance of the solar energy system and increases its efficiency.

The circuit is designed using control rings to simulate an artificial neuron (ANN) in a way called "the loop modification" or "reactionary nutrition". This approach includes the inclusion of a control circuit in the system, which monitors the performance of the model that simulates the nerve network and modernizes parameters or weight to improve performance.

In this case, the control ring can include an observer to know the amount of energy generated by the MPT system and how to change weight (transactions) in the nervous network to ensure the desired goal, which is to reach the maximum energy point with the utmost efficiency.

After each control cycle, the control episode analyzes the current performance of the model and weight modification (transactions) in the nerve network based on the difference between the targeted values and the actual calculated values. This work is done continuously, and the update and modification processes are done to ensure better performance of the system.

This type of design is an effective technology to improve the performance of the MPT system, as the system can adapt to the changes of environmental conditions and operating conditions better, ensuring the maximum efficiency of energy generated from solar cells in all circumstances.

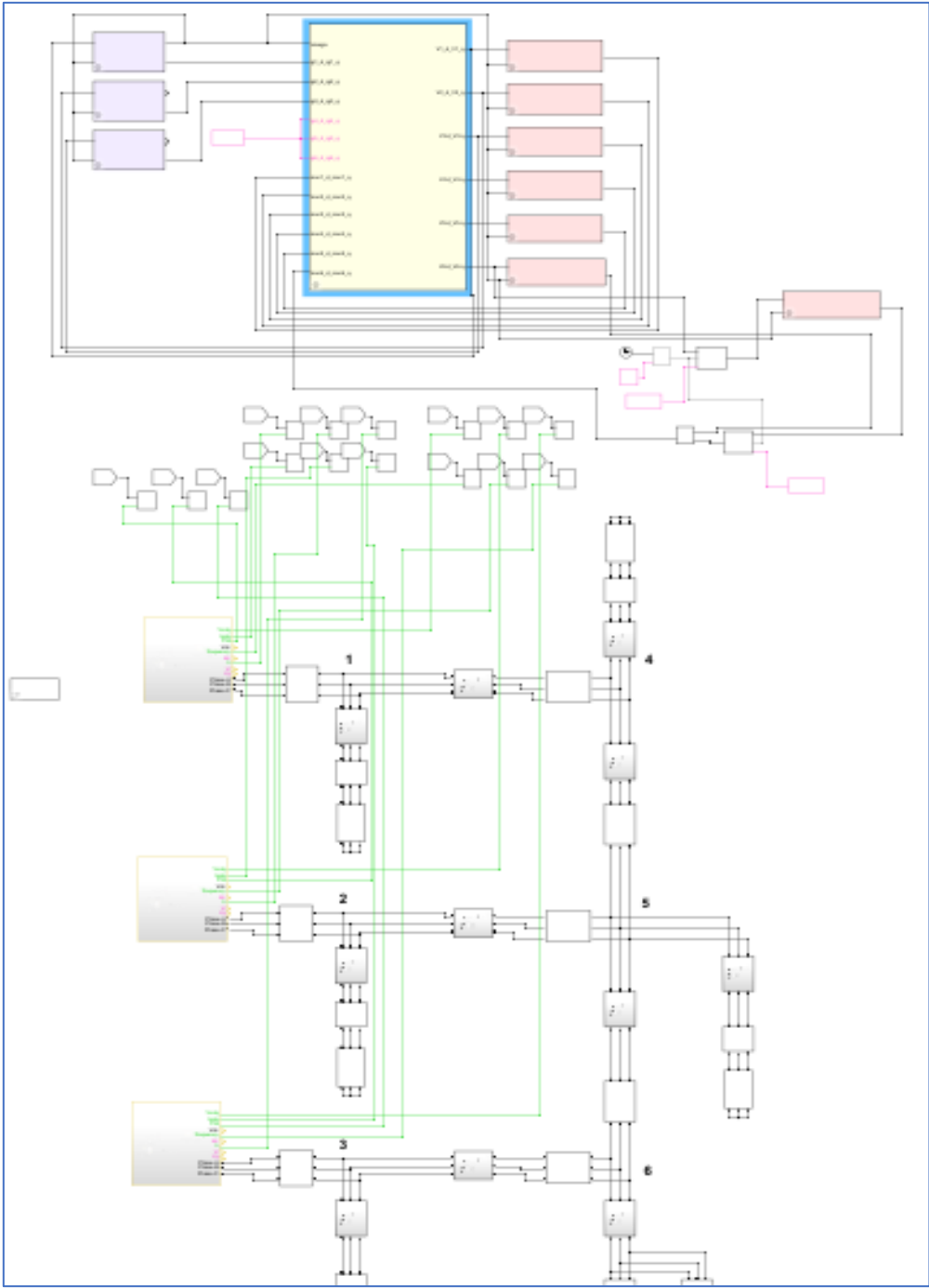


Figure 11. ANN MPPT circuit design.

5.3.1. Results of the First Section: MPPT Simulation System

The results of the MPPT simulation system are based on the mathematical model of the solar system and simulate its behavior under different operating conditions. These methods are used to estimate the maximum power point (MPP) and adjust the operating parameters of the system based on the estimation. Common MPPT simulation techniques include methods such as Perturb and Observe (P&O), Incremental Conductance (IncCond), and Fractional Open Circuit Voltage (FOCV).

- P&O: This method changes the operating point of the solar system and monitors the resulting change in electrical power. Based on the observed change, the operating point is adjusted towards MPP.

- IncCond: This method calculates the differential conductivity of the solar system and compares it to zero. By adjusting the operating point based on the sign of the differential conductance, the MPP is tracked.

- FOCV: This method uses partial open voltage to estimate MPP. The relative value of the voltage corresponding to the MPP is calculated and the operating point is adjusted according to this value.

MPPT simulation methods offer good accuracy and can be implemented using mathematical models and simulation software.

5.3.2. Results of the Second Section: Fuzzy MPPT

Fuzzy MPPT is based on a control approach that uses fuzzy logic to track the MPP. Fuzzy logic allows linguistic rules and human-like decision-making process to be incorporated into the MPPT algorithm. It uses input variables such as the solar cell's voltage, current, and rates of change to determine the appropriate adjustment of the operating point.

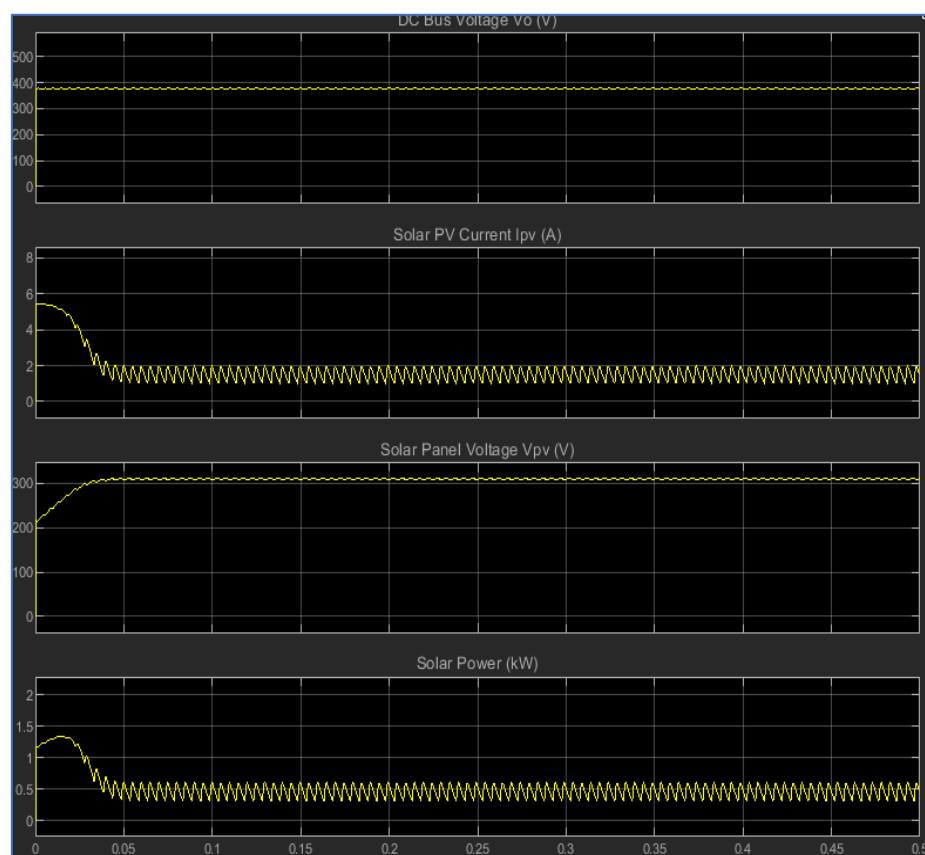


Figure 12. Results of the fuzzy MPPT simulation system.

5.3.3. ANN MPPT

MPT nervous network is a system that uses synthetic nervous network technologies to improve the performance of MPT system in solar energy systems. This circuit uses the principle of work that it quotes from the function of the human brain to learn and adapt behavior.

The circuit depends on the Multilayer Neural Network, as it consists of multiple layers of the nodes (Neurons) that are linked to each other through weighted Connections. The network receives the input information from the sensors in the MPT system such as the solar plate effort and its current, and it processes and generates it to output signals that express the voltage and current required to obtain the maximum ability.

The work of the nervous network is done through training and learning, where the values of the weight of communications between the contract in the network are changed based on the reference

data and notes available on the performance. This weight is adapted to reduce the error between the targeted sign (maximum) and the actual signal generated from the system.

Using this model, the circuit can work smart to adjust the current and effort of the system so that the maximum energy point is reached accurately and effectively, which improves the performance of the solar energy system and increases its efficiency.

The circuit is designed using control rings to simulate an artificial neuron (AnN) in a way called "the loop modification" or "reactionary nutrition". This approach includes the inclusion of a control circuit in the system, which monitors the performance of the model that simulates the nerve network and modernizes parameters or weight to improve performance.

In this case, the control ring can include an observer to know the amount of energy generated by the MPPT system and how to change weight (transactions) in the nervous network to ensure the desired goal, which is to reach the maximum energy point with the utmost efficiency.

After each control cycle, the control episode analyzes the current performance of the model and weight modification (transactions) in the nerve network based on the difference between the targeted values and the actual calculated values. This work is done continuously, and the update and modification processes are done to ensure better performance of the system.

This type of design is an effective technology to improve the performance of the MPPT system, as the system can adapt to the changes of environmental conditions and operating conditions better, ensuring the maximum efficiency of energy generated from solar cells in all circumstances.

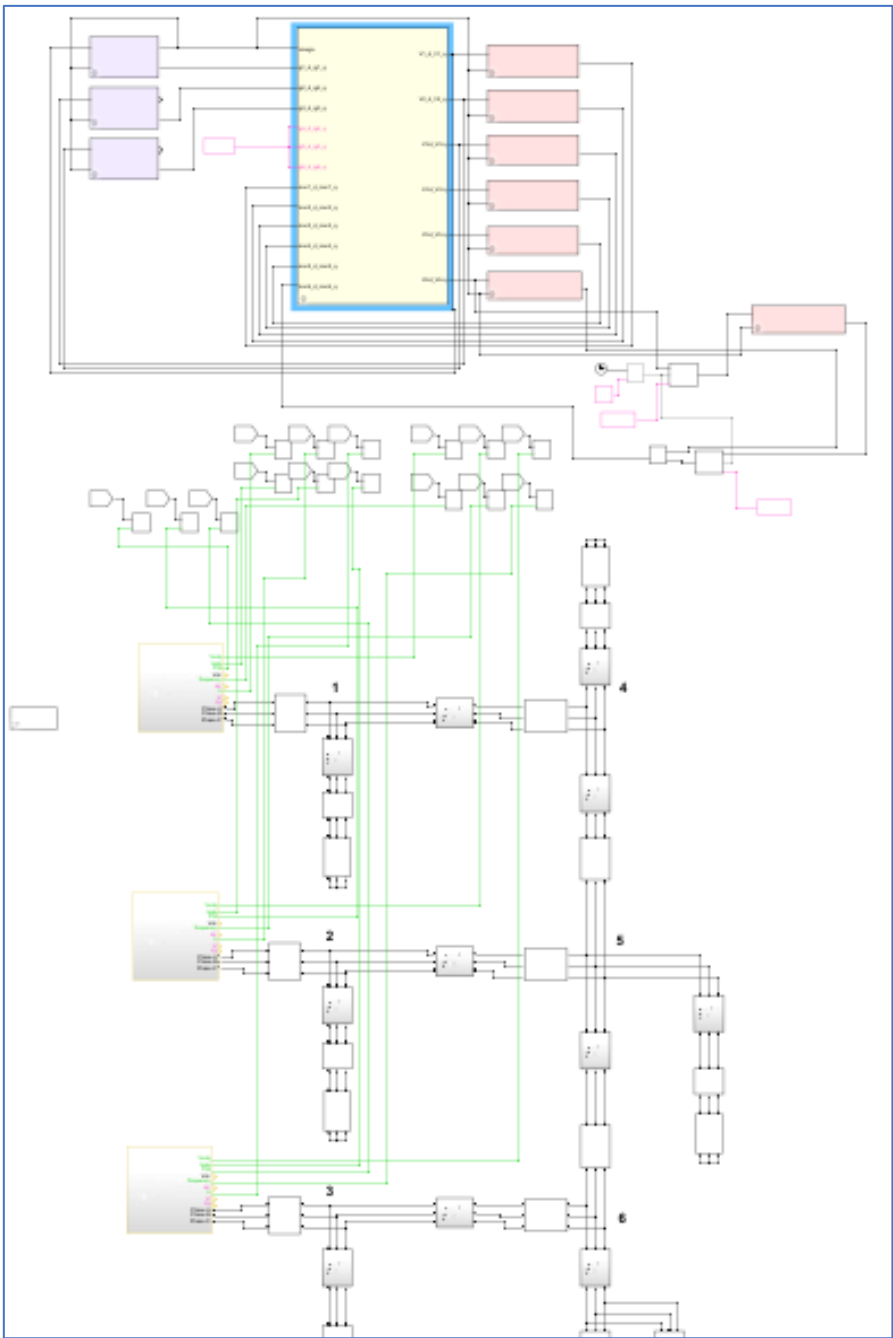


Figure 13. Ann MPPT circuit design.

5.4. Results of the First Section: MPPT Simulation System

The results of the MPPT simulation system are based on the mathematical model of the solar system and simulate its behavior under different operating conditions. These methods are used to estimate the maximum power point (MPP) and adjust the operating parameters of the system based on the estimation. Common MPPT simulation techniques include methods such as Perturb and Observe (P&O), Incremental Conductance (IncCond), and Fractional Open Circuit Voltage (FOCV).

- P&O: This method changes the operating point of the solar system and monitors the resulting change in electrical power. Based on the observed change, the operating point is adjusted towards MPP.

- IncCond: This method calculates the differential conductivity of the solar system and compares it to zero. By adjusting the operating point based on the sign of the differential conductance, the MPP is tracked.

- FOCV: This method uses partial open voltage to estimate MPP. The relative value of the voltage corresponding to the MPP is calculated and the operating point is adjusted according to this value.

MPPT simulation methods offer good accuracy and can be implemented using mathematical models and simulation software.

5.5. Results of the Second Section: Fuzzy MPPT

Fuzzy MPPT is based on a control approach that uses fuzzy logic to track the MPP. Fuzzy logic allows linguistic rules and human-like decision-making process to be incorporated into the MPPT algorithm. It uses input variables such as the solar cell's voltage, current, and rates of change to determine the appropriate adjustment of the operating point.

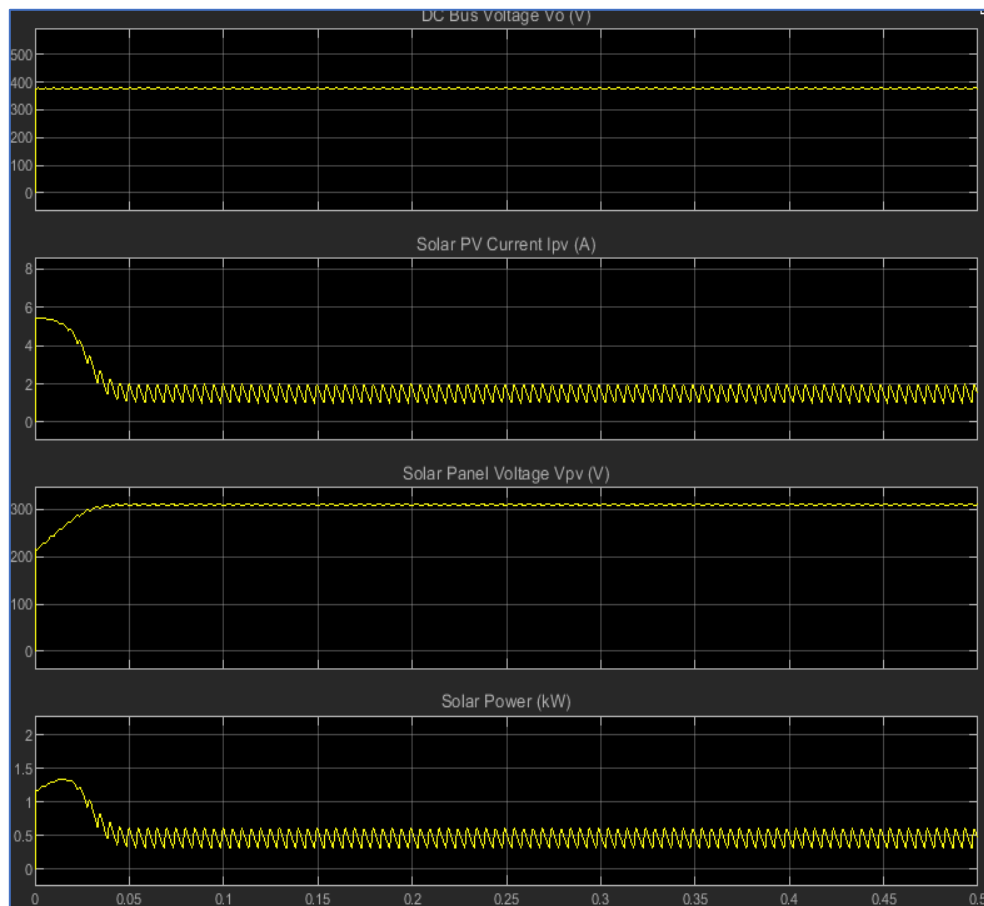


Figure 14. Results of the fuzzy MPPT simulation system.

Fuzzy MPPT algorithms usually involve defining a set of fuzzy rules that relate the input variables to the necessary adjustment of the operating point. These rules are based on expert knowledge and experience. By using linguistic variables such as "low", "medium" and "high" to describe input and output variables, Fuzzy MPPT algorithms can deal with instability and nonlinearity in a solar cell system.

The advantage of Fuzzy MPPT is its ability to adapt to changes in environmental conditions and its ability to handle partial shade and less than ideal operating conditions. However, Fuzzy MPPT algorithms may require more computational resources than traditional MPPT methods.

In general, both sections aim to improve the power output of solar cell systems by tracking the MPP. Choosing the appropriate method depends on factors such as system complexity, computational resources, and the required level of adaptation to changing operating conditions.

5.6. Results of the Second Section: ANN MPPT

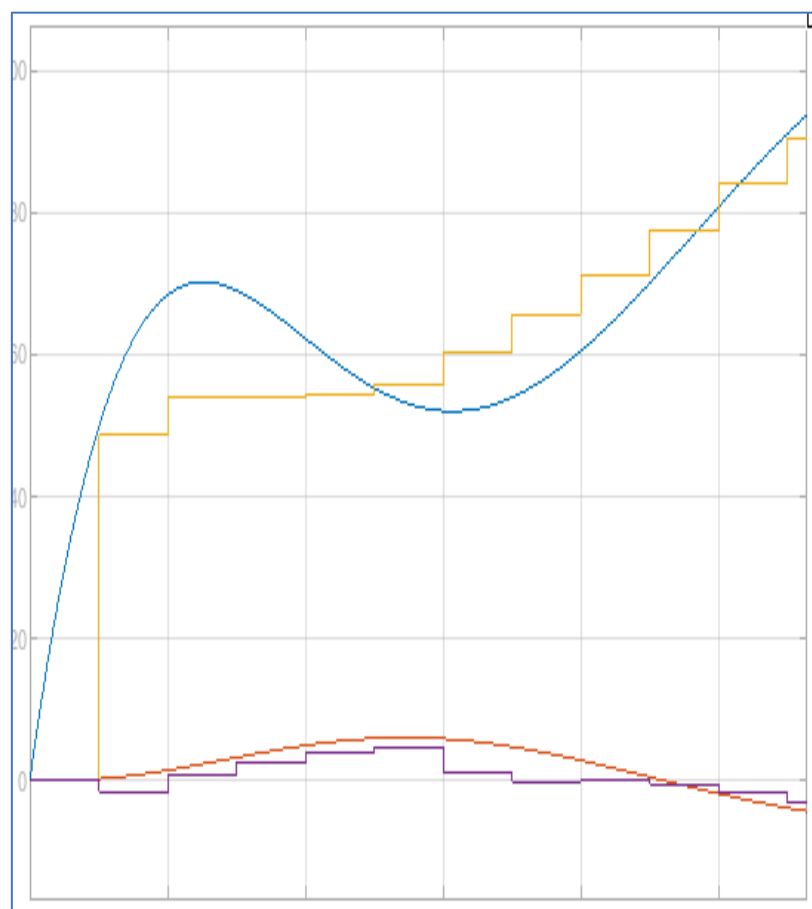
DC output out of the Ann MPPT is generated based on the signals from the circuit control episode. This output is the required current and voltage to reach the maximum Power Point from solar cells.

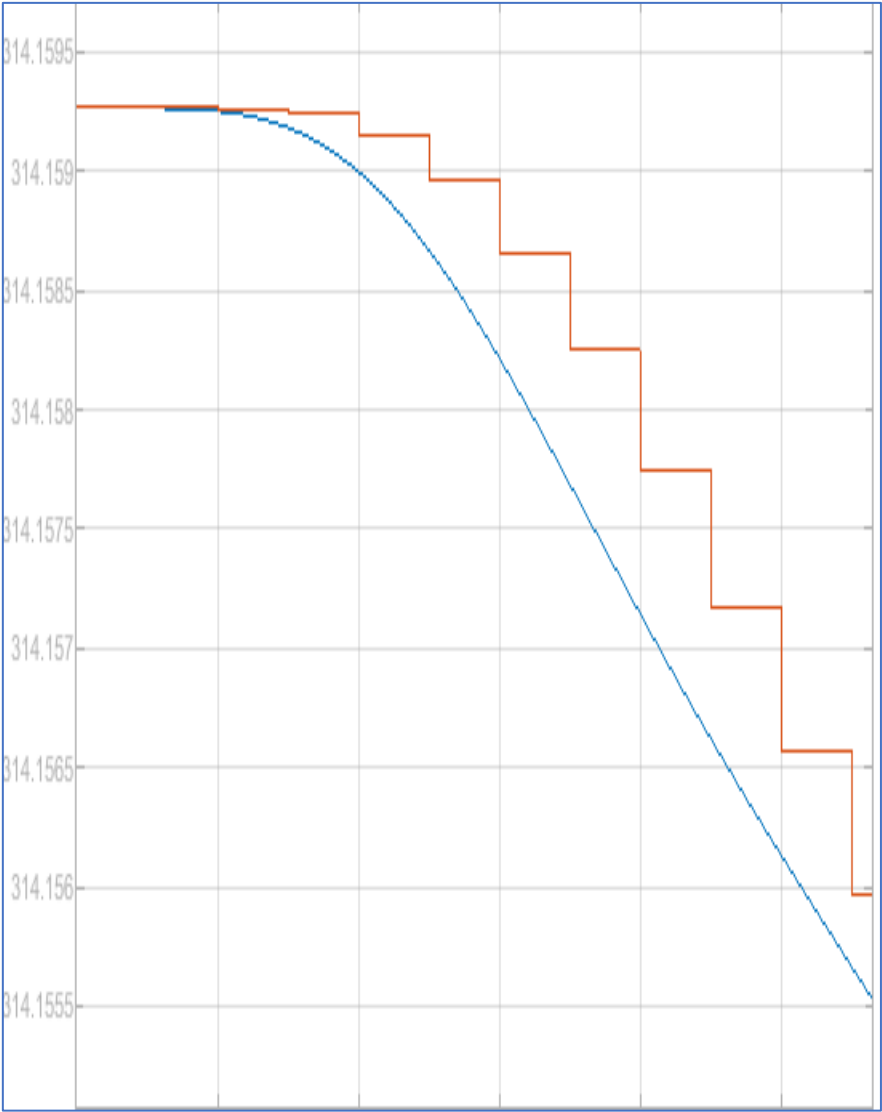
Usually, the Ann MPPT is adjusted to ensure the generation of a stream and effort that achieves the highest possible efficiency of the solar system in different environmental conditions. This is done by constantly adjusting the nerve network parameters based on the extent of the variation between the targeted values and the actual values of the current and the effort generated by the solar cells.

Thus, the DC output resulting from the Ann MPPT is improving to achieve the maximum benefit from the energy generated by solar cells, by providing the current and the appropriate effort to achieve the maximum point of energy in all the circumstances and surrounding changes.

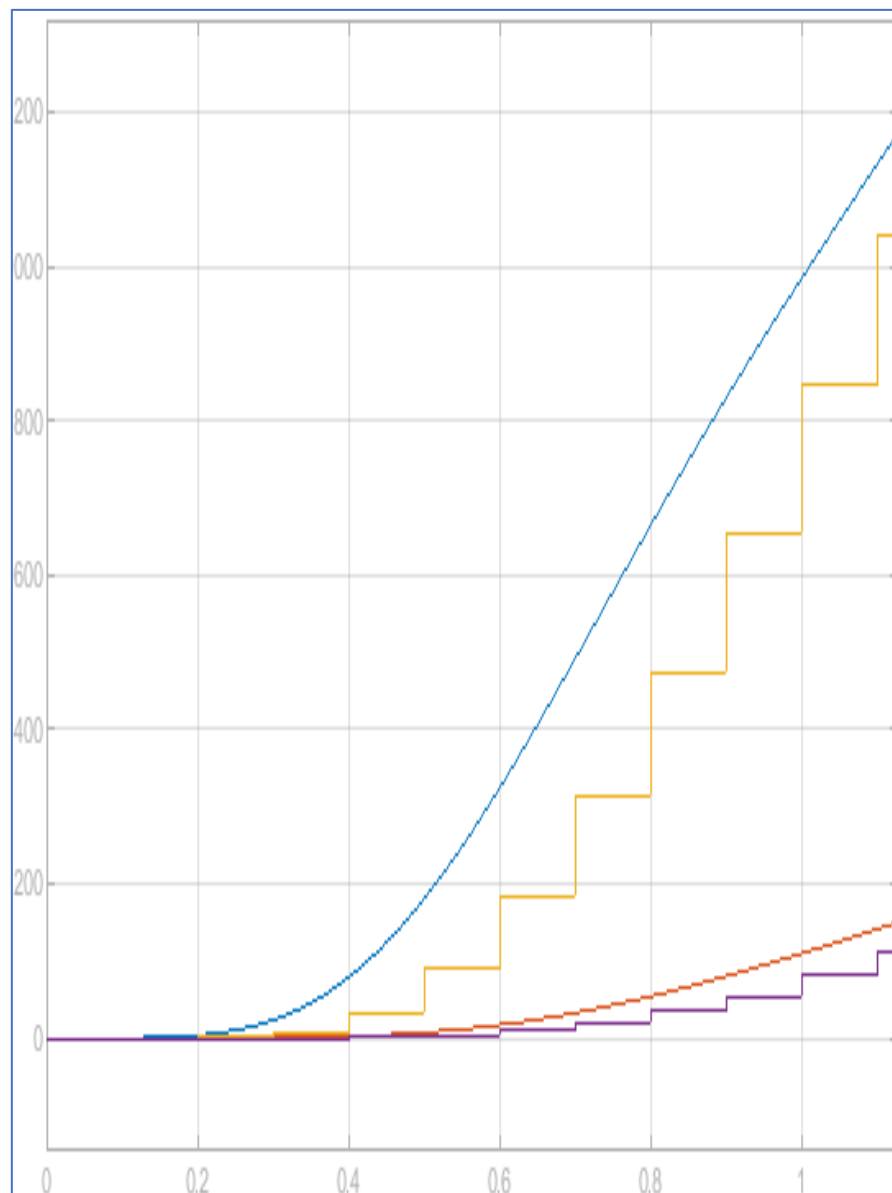
Understanding the appearance of PWM impulses in the Figure facilitates observers noting the improvement in the generation of the DC as a result of the application of the artificial neurons (ANN). I will explain the possible way to represent this in the form:

1. The original PWM signal: The original PWM signal is represented as a square wave, where high periods (High) appear representing the key operation (ON) and low periods (LOW) representing the OFF.
2. The effect of the AnN on PWM pulses: After the artificial neural network, changes in the PWM wave can appear. You may see frequencies or operating times (ON) and stop (Off) different due to the neural network adjustments to reach the maximum point of the capacity.
3. Comparison of the resulting DC: Next to the form of PWM impulses, a graph of the resulting DC can be included after applying the artificial neurons. It will appear that the DC was significantly improved after the Ann application, which shows the potential benefits of this technology in improving the performance of the MPT system.





-b-



-C-

Figure 15. DC results by ANN.

6. Conclusions

In conclusion, it can be concluded that there are two systems proposed to evaluate and improve the performance of the solar energy system, which are the solar neural network system and the fuzzy controller system. Both systems have their specific advantages and uses.

A solar neural network system relies on the ability of neural networks to analyze data and gain knowledge about optimal conditions for solar energy generation. System performance can be improved using neural network models and making the most of solar energy.

The fuzzy controller system relies on the principles of fuzzy logic and fuzzy inference rules to make decisions. It uses imprecise values of variables, allows representation of ambiguity and uncertainty in data, and can handle nonlinear and heteroscedastic variables.

Regardless of the system chosen, it should be chosen according to the specific application requirements, the level of complexity of the specific problem, and the availability of data and resources required.

A detailed analysis should be carried out and other factors specific to your requirements should be taken into account before a final decision is made.

In short, a neural network system relies on the ability of neural networks to learn and uses digital data, while a fuzzy controller system relies on fuzzy logic and uses imprecise values.

From Table 1, it can be seen that each system has its own cost, performance speed and reliability, but the performance speed and reliability may vary depending on the implementation, size and application of the systems.

Based on the presented results, an MPPT system can be designed using a solar neural network system or a fuzzy controller system or combining them into a hybrid system. MATLAB can be used to implement these systems and compare the results, which is the optimal system

References

1. S. Marlin and S. Jebaseelan, "A comprehensive comparative study on intelligence based optimization algorithms used for maximum power tracking in grid-PV systems," *Sustain. Comput. Informatics Syst.*, vol. 41, p. 100946, 2024.
2. S. A. Sarang *et al.*, "Maximizing solar power generation through conventional and digital MPPT techniques: a comparative analysis," *Sci. Rep.*, vol. 14, no. 1, p. 8944, 2024.
3. M. Bilal, A. A. Algethami, and S. Hameed, "Review of computational intelligence approaches for microgrid energy management," *IEEE Access*, 2024.
4. H. Husin and M. Zaki, "A critical review of the integration of renewable energy sources with various technologies," *Prot. Control Mod. power Syst.*, vol. 6, no. 1, pp. 1–18, 2021.
5. S. T. Blesslin, G. J. J. Wessley, V. Kanagaraj, S. Kamatchi, A. Radhika, and D. A. Janeera, "Microgrid optimization and integration of renewable energy resources: innovation, challenges and prospects," *Integr. Renew. Energy Sources with Smart Grid*, pp. 239–262, 2021.
6. Y. Liu and C. Feng, "Promoting renewable energy through national energy legislation," *Energy Econ.*, vol. 118, p. 106504, 2023.
7. P. A. Østergaard, N. Duic, Y. Noorollahi, and S. Kalogirou, "Renewable energy for sustainable development," *Renew. energy*, vol. 199, pp. 1145–1152, 2022.
8. A. G. Olabi and M. A. Abdelkareem, "Renewable energy and climate change," *Renew. Sustain. Energy Rev.*, vol. 158, p. 112111, 2022.
9. C. Breyer *et al.*, "On the history and future of 100% renewable energy systems research," *IEEE Access*, vol. 10, pp. 78176–78218, 2022.
10. M. R. Javed, A. Waleed, U. S. Virk, and S. Z. ul Hassan, "Comparison of the adaptive neural-fuzzy interface system (ANFIS) based solar maximum power point tracking (MPPT) with other solar MPPT methods," in *2020 IEEE 23rd international multitopic conference (INMIC)*, 2020, pp. 1–5.
11. L. Shang, H. Guo, and W. Zhu, "An improved MPPT control strategy based on incremental conductance algorithm," *Prot. Control Mod. Power Syst.*, vol. 5, no. 2, pp. 1–8, 2020.
12. A. O. Baatiah, A. M. Eltamaly, and M. A. Alotaibi, "Improving photovoltaic MPPT performance through PSO dynamic swarm size reduction," *Energies*, vol. 16, no. 18, p. 6433, 2023.
13. A. Gupta and O. Singh, "Grid connected PV system with MPPT scheme using particle swarm optimization technique," *Int. J. Intell. Netw.*, vol. 2, no. 02, 2021.
14. M. H. Ibrahim, S. P. Ang, M. N. Dani, M. I. Rahman, R. Petra, and S. M. Sulthan, "Optimizing step-size of perturb & observe and incremental conductance MPPT techniques using PSO for grid-tied PV system," *IEEE access*, vol. 11, pp. 13079–13090, 2023.
15. M. J. Khan, L. Mathew, M. A. Alotaibi, H. Malik, and M. E. Nassar, "Fuzzy-logic-based comparative analysis of different maximum power point tracking controllers for hybrid renewal energy systems," *Mathematics*, vol. 10, no. 3, p. 529, 2022.
16. M. J. Khan and L. Mathew, "Artificial neural network-based maximum power point tracking controller for real-time hybrid renewable energy system," *Soft Comput.*, vol. 25, no. 8, pp. 6557–6575, 2021.
17. S. D. Al-Majidi, M. F. Abbod, and H. S. Al-Raweshidy, "Maximum power point tracking technique based on a neural-fuzzy approach for stand-alone photovoltaic system," in *2020 55th International Universities Power Engineering Conference (UPEC)*, 2020, pp. 1–6.
18. Z. Ali, S. Z. Abbas, A. Mahmood, S. W. Ali, S. B. Javed, and C.-L. Su, "A study of a generalized photovoltaic system with MPPT using perturb and observer algorithms under varying conditions," *Energies*, vol. 16, no. 9, p. 3638, 2023.
19. M. M. V. Reddy and S. Sivanantham, "DC MICROGRID USING PHOTOVOLTAIC IMPROVED INCREMENTAL CONDUCTANCE ALGORITHM FOR TRACKING THE MPP IN A STAND-ALONE MINIMIZING ENERGY STORAGE UTILIZATION," 2023.

20. M. L. Katche, A. B. Makokha, S. O. Zachary, and M. S. Adaramola, "A comprehensive review of maximum power point tracking (mppt) techniques used in solar pv systems," *Energies*, vol. 16, no. 5, p. 2206, 2023.
21. S. Annam, S. Srikrishna, S. R. Prabandhankam, and G. Sivarajan, "A prospective study on perturb observe MPPT methods for photovoltaic systems," *Instrumentation, Mes. Metrol.*, vol. 22, no. 2, p. 73, 2023.
22. S. Danyali, M. Babaeifard, M. Shirkhani, A. Azizi, J. Tavoosi, and Z. Dadvand, "A new neuro-fuzzy controller based maximum power point tracking for a partially shaded grid-connected photovoltaic system," *Heliyon*, vol. 10, no. 17, 2024.
23. M. Derbeli, C. Napole, and O. Barambones, "A Fuzzy Logic Control for Maximum Power Point Tracking Algorithm Validated in a Commercial PV System," *Energies*, vol. 16, no. 2, p. 748, 2023.
24. K. A. Al Sumarmad, N. Sulaiman, N. I. A. Wahab, and H. Hizam, "Energy management and voltage control in microgrids using artificial neural networks, PID, and fuzzy logic controllers," *Energies*, vol. 15, no. 1, p. 303, 2022.
25. B. S. Sudarshan, A. Chitra, W. Razia Sultana, P. R. Chandrasekhar, T. Ganguli, and I. Sahu, "Maximum Power Point Tracking Techniques for Photovoltaic Systems—A Comprehensive Review From Real-Time Implementation Perspective," *Smart Grids Green Energy Syst.*, pp. 159–196, 2022.
26. A. Amoh Mensah, X. Wei, D. Otuo-Acheampong, and T. Mbuzi, "Maximum power point tracking techniques using improved incremental conductance and particle swarm optimizer for solar power generation systems," *Energy Harvest. Syst.*, vol. 11, no. 1, p. 20220120, 2024.
27. M. Kumar, K. P. Panda, J. C. Rosas-Caro, A. Valderrabano-Gonzalez, and G. Panda, "Comprehensive review of conventional and emerging maximum power point tracking algorithms for uniformly and partially shaded solar photovoltaic systems," *Ieee Access*, vol. 11, pp. 31778–31812, 2023.
28. L. Bhukya, N. R. Kedika, and S. R. Salkuti, "Enhanced maximum power point techniques for solar photovoltaic system under uniform insolation and partial shading conditions: a review," *Algorithms*, vol. 15, no. 10, p. 365, 2022.
29. J. Li, Y. Wu, S. Ma, M. Chen, B. Zhang, and B. Jiang, "Analysis of photovoltaic array maximum power point tracking under uniform environment and partial shading condition: A review," *Energy Reports*, vol. 8, pp. 13235–13252, 2022.
30. S. A. Rizzo and G. Scelba, "A hybrid global MPPT searching method for fast variable shading conditions," *J. Clean. Prod.*, vol. 298, p. 126775, 2021.
31. M. Y. Worku *et al.*, "A comprehensive review of recent maximum power point tracking techniques for photovoltaic systems under partial shading," *Sustainability*, vol. 15, no. 14, p. 11132, 2023.
32. M. Awais, L. Khan, S. Ahmad, S. Mumtaz, and R. Badar, "Nonlinear adaptive NeuroFuzzy feedback linearization based MPPT control schemes for photovoltaic system in microgrid," *PLoS One*, vol. 15, no. 6, p. e0234992, 2020.
33. A. M. Jasim, B. H. Jasim, V. Bureš, and P. Mikulecký, "A novel cooperative control technique for hybrid AC/DC smart microgrid converters," *IEEE Access*, vol. 11, pp. 2164–2181, 2023.
34. E. Alipour, A. Dejamkhooy, M. Hosseinpour, and A. Vahidnia, "Enhanced frequency control of a hybrid microgrid using RANFIS for partially shaded photovoltaic systems under uncertainties," *Sci. Rep.*, vol. 14, no. 1, p. 22846, 2024.
35. C. Hussaian Basha, M. Palati, C. Dhanamjayulu, S. M. Muyeen, and P. Venkatareddy, "A novel on design and implementation of hybrid MPPT controllers for solar PV systems under various partial shading conditions," *Sci. Rep.*, vol. 14, no. 1, p. 1609, 2024.
36. G. Zhou, Q. Bi, Q. Tian, M. Leng, and G. Xu, "Single sensor based global maximum power point tracking algorithm of PV system with partial shading condition," *IEEE Trans. Ind. Electron.*, vol. 69, no. 3, pp. 2669–2683, 2021.
37. Z. Xie and Z. Wu, "A flexible power point tracking algorithm for photovoltaic system under partial shading condition," *Sustain. Energy Technol. Assessments*, vol. 49, p. 101747, 2022.
38. F. A. Eshete, D. P. Samajdar, and A. Kumar, "Implementation of modified P&O and an adaptive fuzzy logic controller based MPPT tracking system under partial shading and variable environmental conditions," *Phys. Scr.*, vol. 99, no. 6, p. 65212, 2024.
39. S. N. V. B. Rao, Y. V. P. Kumar, M. Amir, and F. Ahmad, "An adaptive neuro-fuzzy control strategy for improved power quality in multi-microgrid clusters," *IEEE Access*, vol. 10, pp. 128007–128021, 2022.
40. A. S. Kumar, S. Ramesh, P. Arukula, and M. A. S. Parveen, "Analyzing PV power systems using MPPT based on Artificial Neural Networks," *Nanotechnol. Perceptions*, pp. 792–797, 2024.
41. M. N. Ali, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "An efficient fuzzy-logic based variable-step incremental conductance MPPT method for grid-connected PV systems," *Ieee Access*, vol. 9, pp. 26420–26430, 2021.
42. S. Allahabadi, H. Iman-Eini, and S. Farhangi, "Fast artificial neural network based method for estimation of the global maximum power point in photovoltaic systems," *IEEE Trans. Ind. Electron.*, vol. 69, no. 6, pp. 5879–5888, 2021.

43. N. Bhoj and R. S. Bhadoria, "Time-series based prediction for energy consumption of smart home data using hybrid convolution-recurrent neural network," *Telemat. Informatics*, vol. 75, p. 101907, 2022.
44. M. Merai, M. W. Naouar, I. Slama-Belkhodja, and E. Monmasson, "A systematic design methodology for DC-link voltage control of single phase grid-tied PV systems," *Math. Comput. Simul.*, vol. 183, pp. 158–170, 2021.
45. R. Srinivasan and C. Ramalingam Balamurugan, "Deep neural network based MPPT algorithm and PR controller based SMO for grid connected PV system," *Int. J. Electron.*, vol. 109, no. 4, pp. 576–595, 2022.
46. Z. Ullah, F. Al-Turjman, L. Mostarda, and R. Gagliardi, "Applications of artificial intelligence and machine learning in smart cities," *Comput. Commun.*, vol. 154, pp. 313–323, 2020.
47. S. Vanti, P. R. Bana, S. D'Arco, and M. Amin, "Single-stage grid-connected PV system with finite control set model predictive control and an improved maximum power point tracking," *IEEE Trans. Sustain. Energy*, vol. 13, no. 2, pp. 791–802, 2021.
48. I. Kapur, D. Jain, A. Jain, and R. Garg, "Adaptive Neuro Fuzzy Inference System for MPPT in Standalone Solar Photovoltaic System," in *2020 IEEE 17th India Council International Conference (INDICON)*, 2020, pp. 1–6.
49. M. Khan *et al.*, "Modeling of intelligent controllers for solar photovoltaic system under varying irradiation conditions," *Front. Energy Res.*, vol. 11, p. 1288486, 2023.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.