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DESIGN AND ANALYSIS OF A FUZZY LOGIC CONTROLLED PHOTOVOLTAIC SYSTEM WITH A BIDIRECTIONAL DC-DC CONVERTER

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Abstract: This paper presents a detailed model of a photovoltaic (PV) system integrated with a bidirectional DC-DC converter, employing the Adaptive Neuro-Fuzzy Inference System (ANFIS) for intelligent control. The model considers two key input variables: time and ambient temperature. By incorporating ANFIS, the system adapts dynamically to environmental fluctuations, enhancing its overall performance. Key performance indicators such as voltage stability, current fluctuation mitigation, and battery charge optimization are analyzed to assess system effectiveness. Simulations are carried out in the MATLAB/Simulink environment, providing a robust framework for evaluating system behavior under varying operating conditions. Results indicate that the integration of ANFIS significantly improves energy flow management, enhances stability, and ensures a higher quality of power output. Furthermore, the model demonstrates adaptability to changing external conditions, making it a viable solution for real-world renewable energy applications and intelligent PV power management.

Keywords:photovoltaic panel, fuzzy logic, fuzzy controller, ANFIS, MATLAB/Simulink modeling, bidirectional converter, MPPT, renewable energy.

1. Introduction

The accurate modeling of photovoltaic (PV) systems is vital in advancing renewable energy technologies. These systems are inherently nonlinear and highly sensitive to external parameters such as solar irradiance and ambient temperature. Achieving optimal performance requires not only the physical modeling of components but also the integration of advanced control strategies and power converters.

Recent advancements in PV system research span various domains, including component-level electrical modeling, intelligent control algorithm development, and forecasting techniques. Several studies have addressed these aspects comprehensively.

For example, [1] examines how shading affects electrical mismatches in PV systems, particularly highlighting the role of bypass diodes in reducing power loss and reverse voltage. However, it notes inefficiencies under light shading, where current splits between the module and diode. In [2], a support vector machine (SVM)-based algorithm predicts PV output based on weather classification into four categories (clear, cloudy, foggy, and rainy). This model, validated on a 20 kW system, achieved high accuracy in power forecasting, showing promise for grid-connected applications. DC-DC converters are integral to PV efficiency. Study [3] introduces a converter design utilizing a coupled inductor in both series and parallel modes, yielding greater voltage gain than traditional configurations. In [4], an improved PI-controlled boost converter model simplifies control circuit design while enhancing voltage regulation.

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Maximum Power Point Tracking (MPPT) remains a cornerstone of PV optimization. A fuzzy logic-based MPPT method in [5] demonstrated 94.8%–99.4% accuracy across varying irradiance (700–1000 W/m^2) and temperature (25–60°C). Similarly, [6] presents a PV model combined with a bidirectional energy storage system, validating the PI algorithm for effective energy flow control. Study [7] explores solar radiation modeling using clearness index and time-based diurnal patterns to refine converter duty cycles. In [8], bifurcation analysis uncovers nonlinear instability phenomena, emphasizing the necessity for robust control schemes. These findings affirm the centrality of converter control, intelligent methods (e.g., ANFIS, fuzzy logic controllers, SVM), and advanced MPPT techniques in PV research [9]. Recent developments further reveal the superiority of AI-based MPPT algorithms. Deep learning models, such as LSTM, achieve up to 30% higher efficiency in variable light conditions compared to traditional perturb and observe (P&O) and ANN methods [10].

Innovations in converter design are also noteworthy. For example, [11] introduces a three-phase interleaved boost converter directly interfacing with Li-ion batteries, eliminating the need for separate charging circuits. Adaptive strategies like ASGAO-RBFN not only improve MPPT accuracy but also enhance converter efficiency [12]. Moreover, integrating PV and wind systems into the grid calls for advanced energy management techniques. Study [13] shows that battery systems with controlled reverse energy flows can stabilize operation and reduce losses, especially in regions with limited infrastructure. Building upon this body of research, the present study proposes a MATLAB/Simulink-based model of a PV system equipped with a bidirectional DC-DC converter. The model employs the ANFIS algorithm to achieve high-precision control in the face of variable external conditions, making it a promising candidate for further development and real-world deployment.

2. Photovoltaic Network Modeling

Photovoltaic systems are complex and nonlinear by nature, with their performance strongly influenced by environmental conditions such as solar radiation and ambient temperature. At their core, PV cells convert sunlight into electricity and are organized into modules and arrays to meet specific voltage and power requirements. Modern modeling approaches aim to reflect the dynamic behavior of PV systems under real-world operating conditions. These include considerations such as partial shading, non-uniform temperature profiles, component aging, and the influence of inverters and other electronic components on system performance. Simulation platforms like MATLAB/Simulink play a critical role in this process. They allow for detailed system design, performance analysis, and the testing of various control strategies—most notably MPPT algorithms. As a result, PV network modeling serves as a foundational tool in optimizing energy conversion, improving system reliability, and supporting the integration of renewable technologies into the electrical grid [14].

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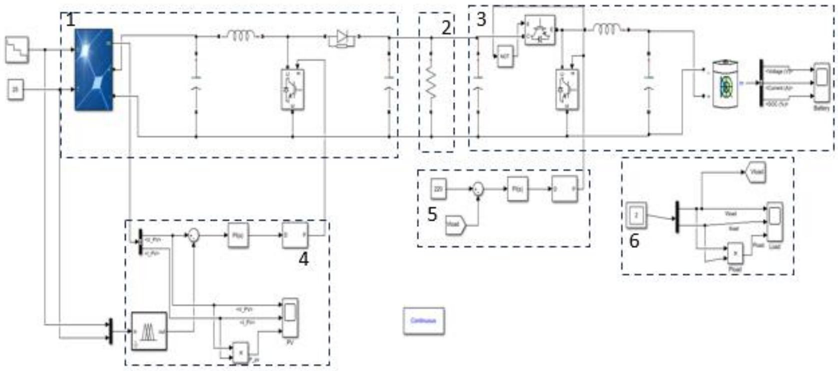

Figure 1. Simulation of a photovoltaic panel with a DC-DC converter

The modeled photovoltaic system consists of the following key components: Photovoltaic Panel (PV Panel), Electrical Load. Battery Storage, Fuzzy Logic Controller, Proportional-Integral (PI) Controller, Measuring Instruments

1. Photovoltaic Panel (PV Panel): The photovoltaic panel converts incident solar radiation into electrical energy. It provides a DC voltage output whose magnitude is influenced by environmental conditions, particularly ambient temperature and solar irradiance over time. The panel serves as the primary energy source for the system.

2. Bidirectional DC-DC Converter: The DC-DC converter manages power flow between the PV panel, the load, and the battery. It functions in two operational modes:

Boost Mode: Increases the voltage from the PV panel to match the system's power requirements.

Buck Mode: Decreases the voltage to facilitate energy transfer to either the battery or the load, depending on system demand.

3. Converter Components: Inductor (L): Smooths the current flow by limiting rapid changes, thereby reducing current ripples. Capacitors (C1, C2): Filter the voltage to stabilize output during switching operations. Switching Elements (Diodes and Transistors): Enable mode transitions (boost/buck) through controlled switching actions. MPPT Algorithm: The Maximum Power Point Tracking algorithm generates the control signals for converter switching. It ensures that the PV panel consistently operates at its optimal power output point, enhancing efficiency.

4. Battery: The battery stores excess electrical energy produced by the PV panel during periods of high generation. It discharges stored energy when generation is insufficient to meet the load demand, ensuring system reliability and power continuity.

5. Load: The system supplies power to a connected electrical load. The load represents the real-time energy consumption component and is powered either directly from the PV panel or via stored energy from the battery.

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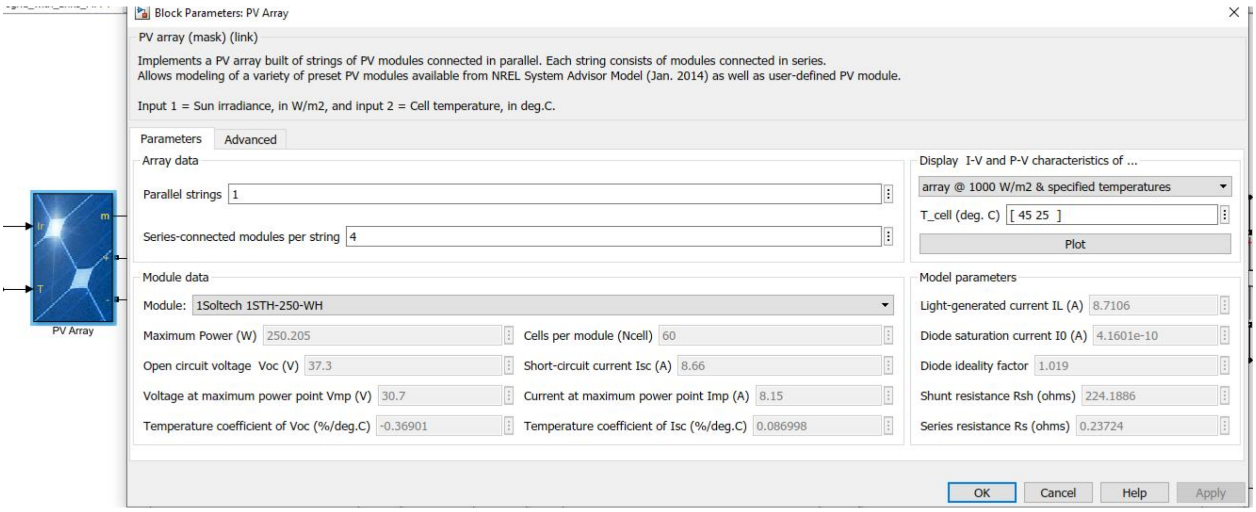

Figure 2. Initial PV data.

The calculation of the algorithm for modeling the photoelectric system is shown in the table below.

To enter the initial conditions, we will set 2 input parameters-temperature and amplitude, as well as the response time of the model.

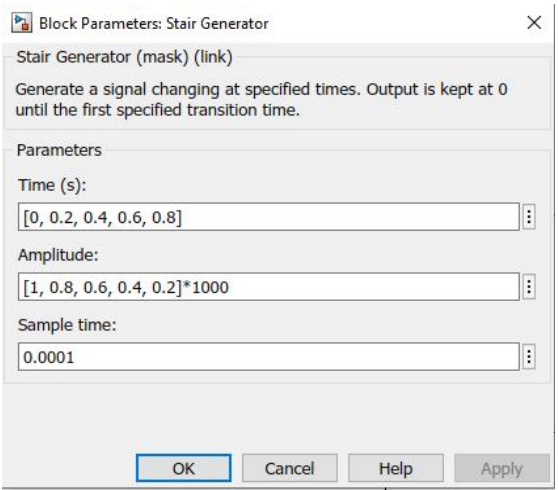

Figure 3. Block parameters: Stair generator

The block generates a signal that initially starts at zero. At specified time points (set in the "Time" parameter: 0, 0.2, 0.4, 0.6 and 0.8 seconds), the signal value changes abruptly according to the corresponding amplitude (defined in the "Amplitude" parameter). The amplitude varies between 1000 and 200. The continuous signal is then sampled at a given time step (specified by the "Sample time" parameter) to generate a sequence of discrete digital values.

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```
clear all
ISCS=8.66;          %% Short circuit current at Panel name plate detalies
IMPS=8.15;          %% Maximum current at from panel name plate detalies
VOCS=37.3;          %% Open circuit voltage from panel name plate detalies
VMPS=30.7;          %% Maximum voltage from panel name plate detalies
alpha=0.086998;     %% Current temperature coeefficient from manufacture
betta=-0.36901;     %% Voltage temperature coeefficient from manufacture
Gs=1000;            %% Sandart Irraniance 1000 W/m2
Ts=25;              %% Sandart tamperature 25 dagrees
for i=1:1000
    Tmin=15;
    Tmax=35;
    T=(Tmax-Tmin)*rand+Tmin; %% Temperature
    Gmin=0;
    Gmax=1000;
    G=(Gmax-Gmin)*rand+Gmin; %% Irradiance
    IMP(i)=IMPS*(G/Gs)*(1+(alpha*(T-Ts)));    %% Maximum current of the given
irrandiance and Temperature
    VMP(i)=VMPS+(betta*(T-Ts));                %% Maximum voltage of the
given irrandiance and Temperature
    PMP(i)=VMP(i)*IMP(i);                     %% Maximum Power of the given
irrandiance and Temperature
    input(i,:)=[G, T];
    output (i,1)=4*VMP(i);
    output1(i,1)=IMP(i);
    output2(i,1)=PMP(i);
    data(i,:)=[G T output(i,1)];
end
```

Figure 4. Database collection

3. ANFIS Algorithm

In the simulation of a photovoltaic panel operating at maximum power under varying environmental conditions (temperature and solar radiation), a fuzzy logic-based controller was developed. The MATLAB Simulink environment was used to model a solar panel circuit with a DC-DC converter, where the ANFIS algorithm was applied.

In MATLAB, ANFIS is implemented through the Fuzzy Logic Toolbox, enabling the modeling of complex nonlinear relationships between inputs and outputs. ANFIS operates as an adaptive neural network using either Mamdani or Sugeno fuzzy inference systems. Its structure consists of five layers: input membership functions, normalization, linear combination, and final output computation. Various software tools, such as MATLAB and Python libraries, provide implementations of this algorithm, simplifying its practical application.

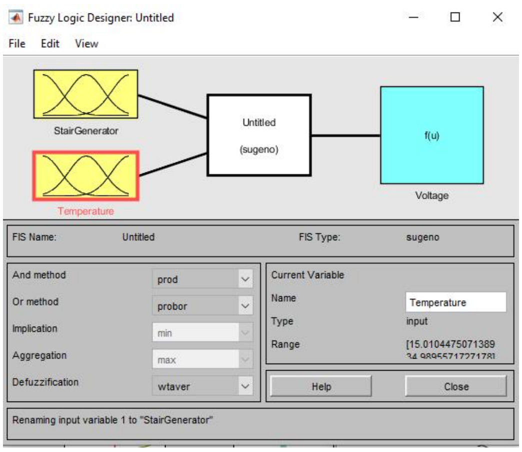

Figure 5. Simulation of a photovoltaic panel and a DC-DC converter using ANFIS neuro-fuzzy logic

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Data collection and fuzzy rule formation for anfis system.

The adaptive neuro-phasic inference system (ANFIS) is a combination of artificial neural networks and phasic logic systems. This system is an effective tool for processing, analyzing and drawing conclusions about various types of data. This article analyzes the process of data collection in the ANFIS system, the formation of their fuzzy dependencies and their management through sigmoid activation mechanisms.

When constructing an anfis model of data collection in ANFIS system, the input parameters are converted into fuzzy logical variables. The main input parameters in this study include: Stair generator-phase State of the generator and step performance parameter; Temperature-ambient temperature; Voltage-output parameter.

The data is formed by connection functions in the form of a sigmoid for the main parameters of the Stair generator and Temperature. This separation helps to accurately describe the dependency functions presented in Figures 5 and 6.

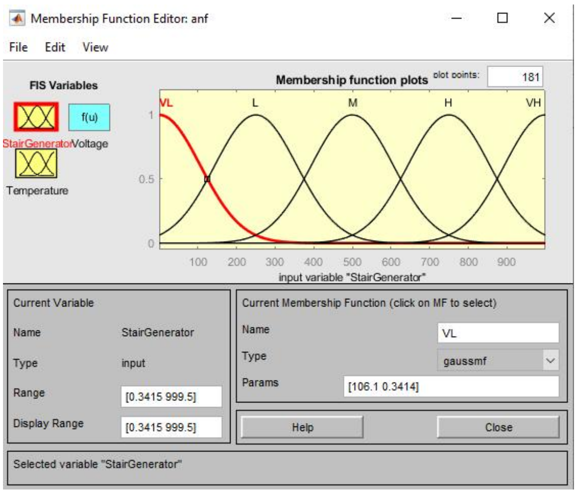

Figure 6. MATLAB membership function editor for the Stair generator input variable.

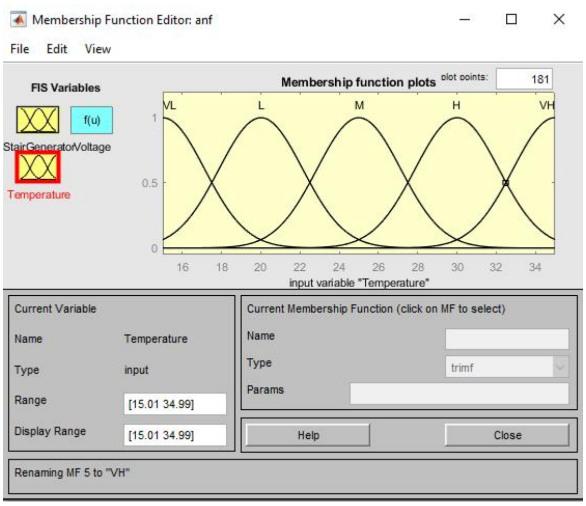

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Figure 7. MATLAB membership function editor for the Temperature input variable.

The advantage of such classification is that the data is more accurately decomposed into phasic structures and the results are significantly improved.

Affects the Stair generator → Voltage;

Related to Temperature → Voltage.

On the basis of dependencies, sigmoid activation functions are used. The Sigmoid function is given by:

$$S(x) = \frac{1}{1 + e^{-(ax+b)}}$$

Here:

x=Stairgenerator+Temperaturex = Stair generator + Temperature;

a-severity parameter;

b-absorption value.

Fuzzy rule formation (rules) fuzzy logical systems are governed by rules. Since there are two main input parameters, they are combined and 25 rules are formed:

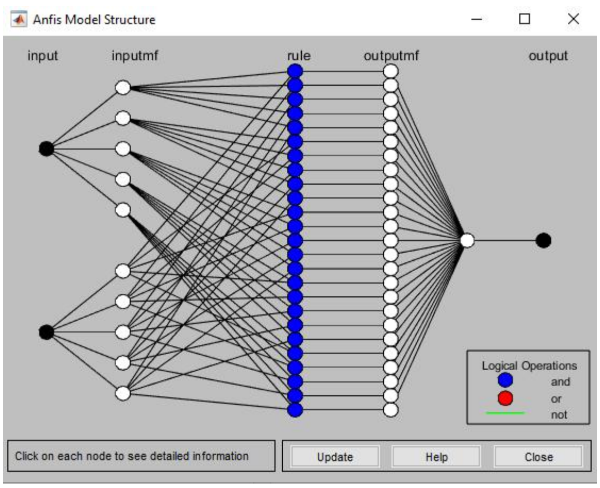

Figure 8. Anfis Model Structure

1. A dark circle is circled around the input layer, on which the input parameters are indicated (for example, a stair generator and temperature).

2. Fuzzy Auxiliary Functions (inputmf) – The input signals are transmitted to the fuzzy view according to the corresponding auxiliary functions.

3. Rule layer - The blue circles show that fuzzy forms 25 rules based on membership functions. These rules represent the relationship between the two input parameters.

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4. Output of fuzzy membership functions (outputmf) – a result is generated for each rule.

5. Assembly level (output data) – the action of all rules is combined to obtain a single output result (voltage values).

Table 1. Table of rules for controlling a step generator depending on temperature

	Temperature					
		VL	L	M	H	VH
Stair generator	VL	VL	L	L	L	M
	L	L	L	L	M	M
	M	L	L	M	M	H
	H	L	M	M	H	H
	VH	M	M	H	H	VH

In fuzzy systems, input parameters are interpreted through linguistic variables using fuzzy dependencies and activation mechanisms such as sigmoid membership functions. For instance, variables such as the stair-step generator signal and ambient temperature are classified into linguistic categories: very low, low, medium, high, and very high. This linguistic representation facilitates adaptive control in the presence of environmental variability.

The use of neuro-fuzzy logic, specifically the Adaptive Neuro-Fuzzy Inference System (ANFIS), provides significant advantages. It enables the system to dynamically adapt to fluctuating environmental conditions and varying photovoltaic panel characteristics. Furthermore, neuro-fuzzy systems exhibit high tolerance to measurement noise and sensor errors, improving reliability. Their ability to learn from data allows for highly accurate converter control, and their implementation is supported by mature, readily available software tools.

Initial system instability observed at the beginning of the simulation—evident through sharp voltage, current, and power fluctuations—corresponds to the stabilization phase. As the simulation progresses, these parameters stabilize, reflecting proper functioning of the power conversion and control architecture. A gradual decrease in the battery's State of Charge (SOC) indicates that stored energy is being utilized to supply the load. Despite generally stable voltage and power delivery to the load, these parameters may still be influenced by network asymmetry, which can result in additional power losses and reduced efficiency [15], [16].

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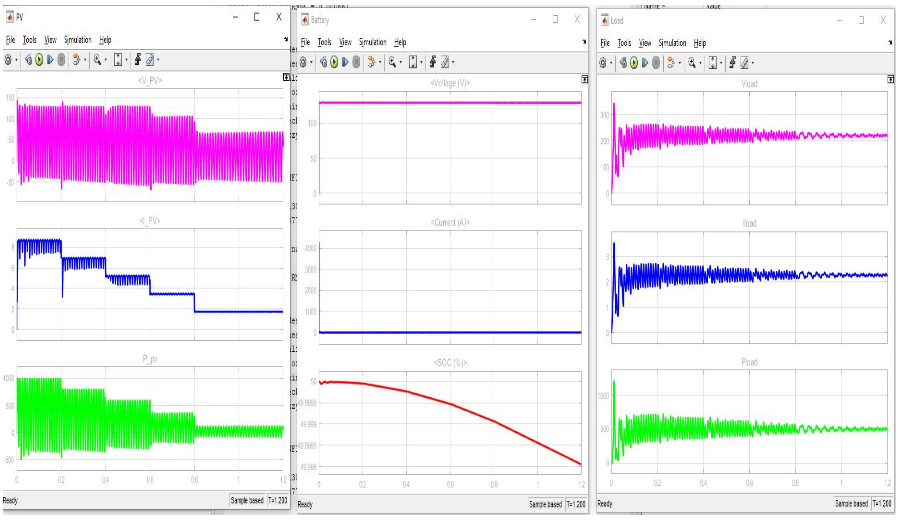

Figure 9. Output characteristics of the solar panel, battery and load before applying neuro-fuzzy logic

In recent developments, fuzzy logic has also been effectively applied to other critical energy system challenges, including grid monitoring and management. For example, [17] examines fuzzy logic-based models for improving power distribution networks, emphasizing its superiority in reactive power compensation and voltage control compared to conventional methods. Another study [18] presents a methodology using fuzzy logic to evaluate electrical network performance, considering parameter uncertainties. This approach enhances the accuracy of analyses related to power quality, supply reliability, and energy loss. The use of Mamdani-type membership functions and control algorithms enables a more nuanced and flexible decision-making framework. The integration of neuro-fuzzy logic into the PV system results in several performance improvements: Enhanced efficiency, due to more precise and adaptive converter control; Reduced mechanical and thermal stress on components, owing to smoother and more consistent operation; Greater system robustness against disturbances and external variability; Improved operational reliability across diverse climatic conditions and varying solar irradiance levels.

These improvements position neuro-fuzzy control as a promising approach for advanced photovoltaic system design and broader applications in renewable energy infrastructure.

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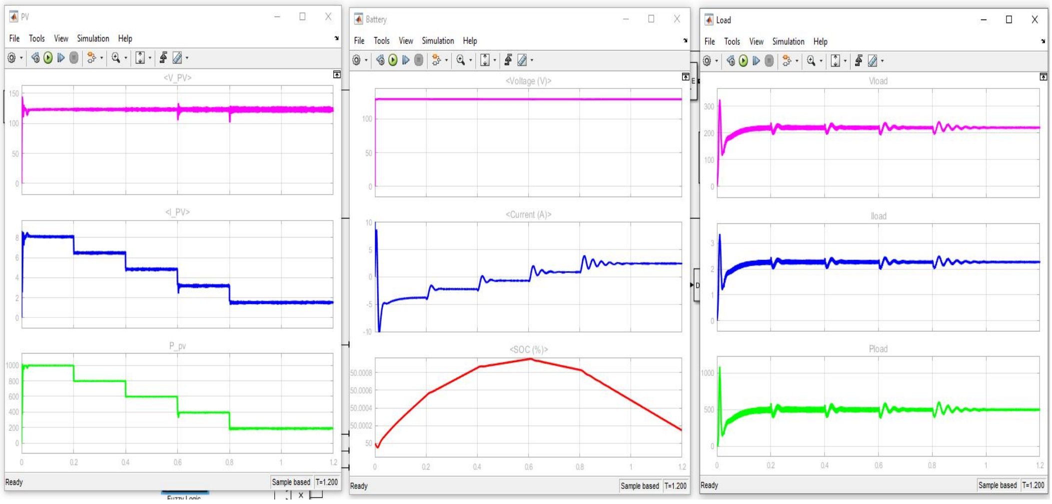

Figure 10. Output characteristics of the solar panel, battery, and load after applying neuro-fuzzy logic

The main distinguishing feature of this research work from others is that the neuro-fuzzy logic of ANFIS has been added to this model ANFIS. A comparison of the simulated photovoltaic network with the absence and presence of Fuzzy Logic of the ANFIS element is shown in the table below.

Tab.2. Characteristics of output parameters before and after ANFIS application

pparametr	Without ANFIS	With ANFIS
PV	Voltage algorithm (VPV): Significant fluctuations during the entire simulation time. Current (IPV): Non-linear behavior, with clear stepwise changes, which indicates the presence of jumps in the load. Power (PPV): It has more significant swings and fluctuations.	Voltage (VPV): More stable voltage with minimal fluctuations. Current (IPV): Noticeably improved smoothness of current changes, without sudden jumps. Power (PPV): Stable behavior with less loss.
Bbattery	Voltage: Almost stable. Battery Current: Irregular surges are observed. Battery Level (SOC): A gradual decrease characteristic of system	Battery Voltage: Almost perfect stability, which means less impact on the system. Battery Current: Reduces surges, which improves battery life. Battery Level (SOC): A smoother change that

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	operation.	indicates optimized power usage.
Lload	Load voltage (Vload): Fluctuations of relatively high amplitude. Load current (Iload): A lack of stability is observed. Load power: load fluctuations due to changes in system operation.	Load voltage (Vload): A significant reduction in the amplitude of vibrations. Load current (Iload): Stable behavior, which indicates an improvement in the quality of system operation. Load capacity (Pload): Almost stable power, which indicates a more efficient transfer of energy to the load.

The practical implementation of a fuzzy logic-based controller in real-world photovoltaic (PV) systems involves the integration of several key hardware and software components. These include microcontrollers or digital signal processors (DSPs) with adequate computational capabilities to process fuzzy logic algorithms in real time, along with digital voltage and current sensors to ensure precise measurement of system inputs. Additionally, bidirectional DC-DC converters with adaptive control logic are essential, supported by development platforms such as MATLAB/Simulink with the Fuzzy Logic Toolbox or embedded libraries tailored for real-time controller deployment.

While the Adaptive Neuro-Fuzzy Inference System (ANFIS) offers significant benefits—such as improved adaptability to variable solar irradiance and environmental conditions—it also presents several practical challenges. These include: High computational complexity, necessitating robust processing hardware; Model training requirements, which demand historical performance data to accurately calibrate the system; Latency in decision-making, potentially longer than that of heuristic-based algorithms; Increased system cost, driven by the need for high-performance controllers and precision sensors.

Despite these challenges, ANFIS remains a promising solution for enhancing the efficiency and intelligence of PV energy systems. To objectively evaluate its effectiveness, it is useful to perform a comparative analysis of ANFIS against other Maximum Power Point Tracking (MPPT) methods—such as Perturb & Observe (P&O), Incremental Conductance (IncCond), and Artificial Intelligence (AI)-based algorithms—based on key performance metrics like tracking accuracy, response time, and computational load.

Below is a conceptual comparison framework:

MPPT Method	Accuracy	Response Time	Computational Complexity
ANFIS	High	Moderate	High
Perturb & Observe	Low to Moderate	Fast	Low

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MPPT Method	Accuracy	Response Time	Computational Complexity
Incremental Conduction	Moderate to High	Moderate	Moderate
AI-Based (e.g., ANN, DNN)	Very High	Fast to Moderate	Very High

This table provides a high-level overview of the trade-offs involved in selecting an appropriate MPPT strategy. While ANFIS provides superior accuracy and adaptability, especially under dynamic conditions, its complexity may be prohibitive for systems with limited processing resources or cost constraints.

Table 3. Comparison of MPPT methods

MPPT Method	Accuracy	Response Time	Computational Complexity	Shading Tolerance
Perturb & Observe (P&O)	Medium	Fast	Low	Poor Adaptation
Incremental Conductance (IncCond)	High	Medium	Medium	Tolerates Slo Changes
AI (NN, GA, etc.)	Very High	Medium	High	Good Adaptatio
ANFIS	Very High	Medium	High	Excellent Adaptation

This table is a summary of information from a number of scientific studies listed in [19]-[25]. Despite the computational complexity and the need for advanced training, ANFIS demonstrates excellent adaptability to changing lighting conditions, which is especially important for photovoltaic systems operating in unstable environments.

A study published [26] provides the following indicators for various MPPT methods with illumination of 1000 W/m2 and a maximum power of 250 W:

P&O: Average power of 237.4 W, efficiency of 94.96%, convergence time of 0.004 s.

IncCond: Average power of 239.1 W, efficiency of 95.60%, convergence time of 0.006 s.

ANFIS: Average power 244.4 W, efficiency 97.76%, convergence time 0.046 s.

Neural networks: Average power 244.6 W, efficiency 97.84%, convergence time 0.205 s.

Hybrid method: Average power 247 W, efficiency 98.80%, convergence time 0.2005 s. Comparing the presented MPPT methods, it can be noted that ANFIS demonstrates high

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efficiency (97.76%) and close to maximum output power (244.4 W), surpassing the classical P&O and IncCond methods. Although its convergence time (0.046 s) is longer than that of these methods, it is significantly lower than that of neural networks and the hybrid method. This makes ANFIS the optimal compromise between efficiency and speed, providing more accurate tracking of maximum power with an acceptable response time.

Conclusion:

This study presents the modeling of a photovoltaic (PV) system integrated with a bidirectional DC-DC converter in the MATLAB/Simulink environment, with a primary focus on implementing an Adaptive Neuro-Fuzzy Inference System (ANFIS) for intelligent control. The simulation results confirm the high accuracy and effectiveness of the proposed approach across a wide range of operating conditions.

A comparative analysis with traditional Maximum Power Point Tracking (MPPT) methods—including Perturb & Observe (P&O), Incremental Conductance (IncCond), and artificial intelligence (AI)-based techniques—demonstrates that ANFIS offers superior adaptability to variations in solar irradiance and ambient temperature. This capability is particularly valuable for PV systems deployed in regions with unstable or unpredictable climatic conditions.

Despite its increased computational requirements and the necessity of preliminary training on historical data, ANFIS provides several critical advantages over conventional control methods:

Enhanced System Stability: ANFIS significantly reduces fluctuations in voltage, current, and power on both the generation and load sides. It ensures consistent system behavior even under rapidly changing environmental conditions.

Improved Energy Efficiency: The algorithm enables adaptive management of power flows between the solar panel, battery, and load, resulting in more effective utilization of the available energy. Enhanced MPPT accuracy minimizes energy losses and boosts overall system performance.

Higher Power Quality: Systems controlled by ANFIS exhibit lower harmonic distortion and reduced signal ripple, contributing to improved quality of the delivered electrical energy.

The results strongly indicate that ANFIS is a viable and promising solution for advanced PV systems requiring high levels of precision, adaptability, and operational stability. Future research should explore strategies to reduce the computational burden of ANFIS and develop embedded hardware solutions capable of supporting its real-time implementation in commercial solar energy systems.

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