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Design and Simulation of a Microgrid-Connected Photovoltaic System Using Recurrent Neural Network-Based MPPT Control

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Abstract

This study presents the design and simulation of a micro-inverter system for photovoltaic (PV) energy conversion in microgrid applications using a Recurrent Neural Network (RNN)-based Maximum Power Point Tracking (MPPT) control strategy. The objective is to enhance power conversion efficiency and system responsiveness under dynamic solar conditions. The proposed system integrates a boost converter, micro-inverter, LCL filter, and Phase-Locked Loop (PLL) for grid synchronization. The RNN model is trained using variations in solar irradiance and PV electrical characteristics to determine the optimal duty cycle for controlling the converter. System modeling and simulations were conducted in MATLAB to assess performance. Simulation results demonstrate that the RNN-MPPT algorithm significantly improves the system's ability to track the maximum power point accurately and rapidly, achieving a peak efficiency of 99.9% at 1000 W/m^2 irradiance. The system delivers a stable output power of 2096 W with a rise time of only 0.123 seconds. These results confirm the feasibility and effectiveness of AI-based control strategies in smart PV energy systems.

Keywords: maximum power point tracking (MPPT), micro-inverter, photovoltaic (PV) system, recurrent neural network (RNN), smart grid integration

I. Introduction

Solar energy has gained significant attention as a sustainable alternative in the global movement to reduce reliance on fossil fuels and lower greenhouse gas emissions. Among various renewable sources, photovoltaic (PV) systems are particularly appealing due to their abundant availability, low operational costs, and ease of integration into microgrid networks [1], [2]. These PV-based microgrids offer an efficient and autonomous means of supplying electricity, especially in remote or decentralized settings [3]. However, their performance is closely tied to the effectiveness of energy management systems, which must dynamically balance energy production and consumption in real-time [4], [5].

Within such PV systems, micro-inverters serve a crucial function by transforming the direct current (DC) output of solar panels into alternating current (AC) that can be used by loads or synchronized with the grid [6], [7]. Importantly, these devices must maintain not only high conversion efficiency but also the ability to respond swiftly to changing environmental parameters such as irradiance and temperature. To achieve optimal operation under such conditions, the integration of Maximum Power Point Tracking (MPPT) techniques is essential [8], [9].

Traditional MPPT algorithms like Perturb and Observe (P&O) and Incremental Conductance (INC) have been extensively applied due to their simplicity and relatively straightforward implementation [10], [11]. Despite this, their performance tends to degrade during abrupt changes in solar irradiance, often resulting in suboptimal power output and noticeable energy losses. This has driven interest toward more adaptive and precise control techniques [12], [13].

Artificial intelligence (AI) has recently emerged as a compelling solution to enhance MPPT performance, particularly under dynamic operating conditions. Recurrent Neural Networks (RNNs), known for their capacity to process sequential data and recognize temporal patterns, have shown great promise in this context [14], [15]. These networks are capable of learning the temporal relationships between input variables—such as solar irradiance and ambient temperature—and the resulting power output, making them effective for real-time prediction and control of the maximum power point [16].

This research explores the development and simulation of a micro-inverter system equipped with an RNN-based MPPT controller, tailored for use in solar-powered microgrids. The main aim is to improve the overall efficiency and operational stability of microgrids by employing a control strategy that can intelligently adapt to rapid environmental fluctuations, thereby maximizing solar energy utilization.

II. Methods

A. System Design

In the system design, there will be a micro inverter design that will be implemented in the micro grid, as well as establishing the technical specifications and operational parameters needed to ensure optimal performance. The micro inverter system design may include PV model, converter design and micro inverter design. The block diagram design is represented in Fig. 1.

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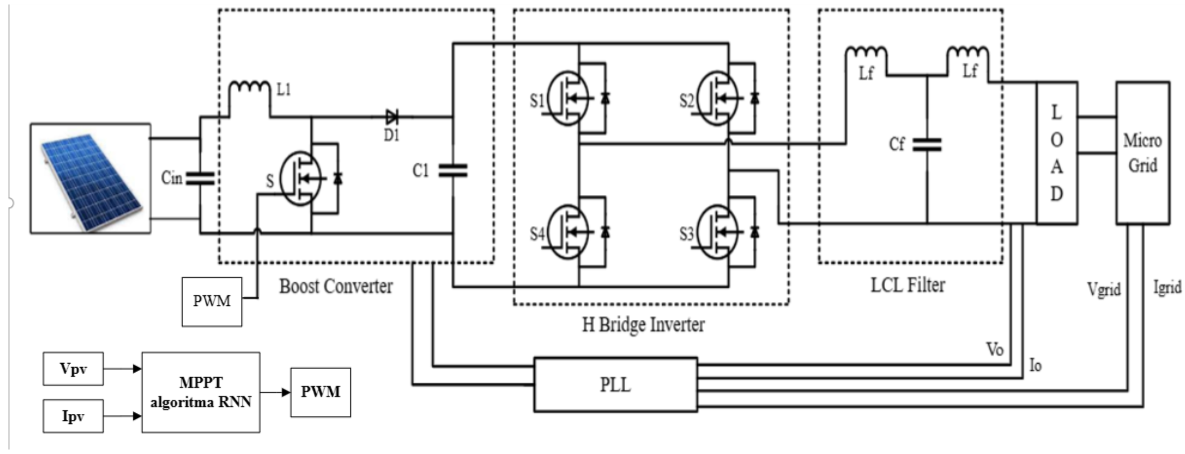

Fig. 1. System Design Block Diagram

This research focuses on designing an energy conversion system that integrates photovoltaic (PV) energy using a boost converter and micro inverter to enhance power efficiency. An RNN-based MPPT algorithm processes PV voltage (Vpv) and current (Ipv) to determine the optimal duty cycle for controlling the MOSFET in the boost converter. The system aims to maximize power output using micro inverter technology, supported by an LCL filter for noise reduction and a PLL for synchronization with the microgrid.

B. *Modeling Photovoltaic Specifications*

The photovoltaic data specification used is the JKM350M-72 model shown in Table PV panel characteristic value.

TABLE 1. PV PANEL CHARACTERISTIC VALUE

Parameter	Value
Rated Maximum Power (Pmax)	350 W
Maximum Power Voltage (Vmp)	39.1 V
Maximum Power Current (Imp)	8.94 A
Open-Circuit Voltage (Voc)	47.5 V
Short-Circuit Current (Isc)	9.88 A
Operating Temperature (°C)	Minus 40 to 85
Maximum System Voltage	1500 Vdc
Maximum Series Fuse Rating	20 A
Nominal Operating Cell Temperature (NOCT)	45±2°C
Cell Type	Mono-Crystalline
Weight	22,5 Kg
Dimension	1956*992*40 mm
Photovoltaic Connection	6 Series

The photovoltaic output power specification used is 350 Wp, the research used 6 photovoltaic modules arranged in series to get a higher Vmpp. With the series configuration, the voltage from each module will be summed up with a maximum power voltage (Vmpp) of 234.6 V with a power capacity of 2100 Wp. This characteristic curve test uses different irradiation values ranging from 100 W/m^2 to 1000 W/m^2 irradiation. As for the temperature on the panel is considered ideal unchanged with a value of 25 °C.

C. *Boost Converter Modeling*

The system topology that will be used in this research is a boost converter connected to the photovoltaic input source. Design of DC-DC converter topology boost converter with output power of 2 kW. In the process of designing the converter, the value of the parameters to be used is required. The parameters that make up the converter are duty cycle, capacitor value, inductor value, MOSFET and diode.

1) Duty Cycle Calculation: From the equation can determine the duty cycle value which aims to determine how many RNN output duty cycles must be entered into the system.

2) Inductor Value Calculation: Determination of the inductor value is influenced by the large ripple current and switching frequency. With the switching frequency used 5 KHz.

3) Calculation of Capacitor Value: In addition to determining the amount of voltage on the capacitor, it is necessary to determine the value of the capacitor.

D. *Design of Micro Inverter and Phase Locking Loops*

The dc-bus voltage of the boost converter is converted into AC voltage using an H-bridge inverter. In a grid-tied micro inverter, each panel can be connected to the grid independently of each other. Therefore, each panel must monitor the mains voltage instantly and correctly. The algorithm that performs this operation is called a Phase Locking Loop (PLL).

The AC voltage shape obtained from the inverter output is far from sinusoidal shape due to the use of switching. Therefore, the signal obtained from the inverter output should be used to simulate a sine waveform and the use of filters to eliminate the effects of harmonics. The purpose of the filter is to suppress current and voltage signals that occur at one or more frequencies and will impact the main waveform.

TABLE 2. PARAMETER OF H-BRIDGE INVERTER

Inverter Parameter	Value
Inverter switching frequency (Fs)	10 kHz
Line Frequency (Fg)	50 Hz
DC voltage (VDC)	400 V
System output voltage (RMS) (Vg)	220 V

E. Recurrent Neural Network (RNN) Integration

Artificial Neural Network (ANN) as an algorithm implemented for MPPT approach. The ANN method used in this research is Recurrent Neural Network (RNN) with Lavenberg Marquardt learning. The RNN architecture design process and learning process are carried out by utilizing the NNStart feature in MATLAB. In this study, a search for learning data was carried out first through MATLAB software. The process of the RNN algorithm to obtain MPP is represented in the flowchart in Fig. 2.

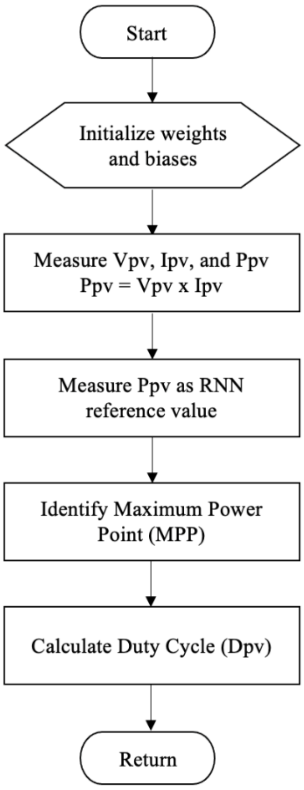

Fig. 2. Flowchart of RNN Algorithm

1) RNN Architecture Design: The RNN architecture for PV MPPT, as shown in Fig. 3, consists of three layers: an input layer receiving PV power (Ppv), a hidden layer with up to 5 neurons for performance evaluation, and an output layer generating the duty cycle to control the DC-DC converter. The model is trained using 100 data variations representing PV voltage and current under irradiance levels from 100 W/m^2 to 1000 W/m^2, with the target output being the optimal duty cycle for maximum power. The goal is for the RNN to learn the relationship between input conditions and optimal duty cycle values to ensure efficient PV system operation. Training is conducted using MATLAB, with weight and bias connections between layers. The training data consists of 100 variations of data, with input being pairs of PV voltage and current values, and the target output being the corresponding duty cycle value for each irradiance condition, as represented in Table RNN MPPT PV Learning Data. This data was used as learning data in MATLAB software to ensure the PV operates at the MPP.

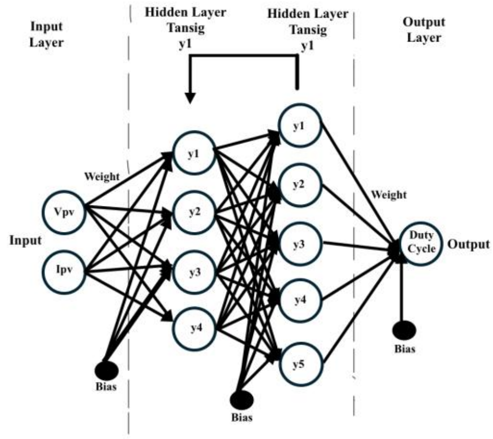

Fig. 3. RNN Architecture for PV MPPT

TABLE 3. RNN MPPT PV LEARNING DATA

Tem pera ture	Irradiance (W/m^2)	Duty Cycle (%)	Voltage (V)	Current (A)	Power
25	1000	37.50%	234.6	8.94	2097.3
25	900	35%	234.13	8.046	1883.8
25	800	32.50%	233.66	7.152	1671.1
25	700	30%	233.19	6.258	1459.3
25	600	27.50%	232.72	5.364	1246.3
25	500	25%	232.25	4.47	1038.1
25	400	22.50%	231.78	3.576	828.86
25	300	21%	232.32	2.682	620.39
25	200	17%	320.85	1.788	412.75
25	100	10.50%	230.35	0.894	205.96

2) RNN Learning Process: The RNN MPPT model was trained using MATLAB's NNStart feature, reaching convergence at epoch 181 in about 30 seconds. The final performance value was very low (9.91e-11), with a gradient reduction from 1.11 to 9.93e-08 and a decrease in mu from 0.001 to 1e-08, indicating training stability and optimal learning. Six validation checks confirmed the model's optimal condition.

3) Computational Flow Translator of the RNN Algorithm: The planned architecture of the RNN network involves 4 stages. This sub-chapter will explain the 4 stages of the mathematical modeling process of the RNN calculations based on the designed network architecture:

a) Sequential Data Input (Time Series Input): In a Recurrent Neural Network (RNN) system, before the input data is processed by the network, normalization is first performed to convert the raw data such as voltage, current, and irradiance into a standard numerical range that is easier for the network's activation function to process.

b) Hidden Layer 1 Process: The hidden layer in an RNN consists of four main elements: weights, bias, netsum, and the activation function. Weights are divided into two types: W for the current input and U for the previous hidden state. The bias (b) serves as an additional value to make the neuron's activation more flexible. The netsum is passed through an activation function such as tanh or sigmoid, which provides non-linear properties, allowing the network to capture complex patterns in sequential data.

c) Hidden Layer 2 Process (Output Layer): The second hidden layer in the artificial neural network consists of several key components: weights, bias, netsum, and the activation function tansig. The computational process in this layer involves three main stages: multiplying the input by the weights, adding the result of the multiplication with the bias to form the netsum, and then transforming it through the activation function to produce the neuron's output.

d) Output Process: Once the prediction process has been completed by the RNN model, the predicted result, which has already undergone normalization, needs to be converted back to its original scale. This process is done using the Mapminmax Reverse function, which reverses the normalization so that the output value from the network can be represented in its original units, namely the duty cycle.

III. Results and Discussion

This section discusses the performance of the proposed system through the simulation results of Maximum Power Point Tracking (MPPT) on a photovoltaic system integrated

with a boost converter and micro-inverter, modeled according to the specifications in the previous chapter, and analyzed based on the collected data. This includes testing photovoltaic characteristics and efficiency analysis.

A. Photovoltaic Characteristics Testing

The solar panel characteristics were tested to evaluate the performance of the PV model used. In this study, the JKM350W-72 PV module was employed, as described in Table RNN MPPT PV Learning Data in Methods. The testing involved varying the load resistance to generate variations in output voltage and current from the panel. These variations in resistance provided different voltage (V) and current (I) data, which were used to form the characteristic curve of the solar panel.

The curve in Fig. 4 illustrates the relationship between voltage, current, and power, enabling the identification of key parameters such as maximum power voltage (Vmpp), maximum current (Impp), and maximum power (Pmpp). The results are shown in Table Photovoltaic Characteristics Testing. Simulations were carried out with load variations from 20 Ω to 80 Ω and solar irradiance varying from 100 W/m^2 to 1000 W/m^2. The test results produced the characteristic curve of the solar panel as shown in Fig. 4.

TABLE 4. Photovoltaic Characteristics Testing

Irradiance (W/m^2)	Voltage (V)	Current (A)	Power (W)
1000	234.6	8.94	2097
900	234.412	8	1892
800	235.201	7.17	1686
700	235.808	6.26	1478
600	235.825	5.37	1268
500	235.264	4.48	1056
400	234.722	3.59	843
300	230.429	2.69	620
200	226.762	1.799	408
100	220.829	0.89	198

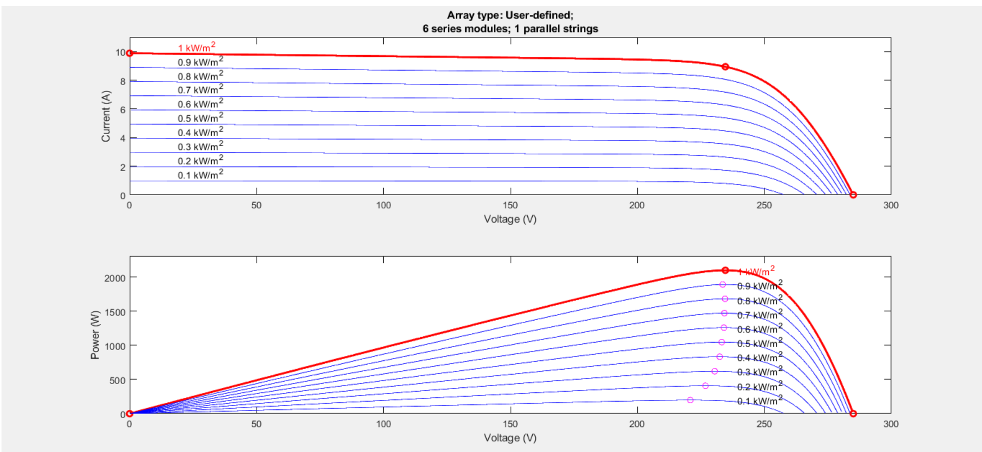

Fig. 4. PV Power (P-V) and Voltage (I-V) Characteristic Curves

B. Simulation Testing in Steady State

The steady-state simulation test aims to analyze the performance of the power conversion system when the system has reached operational stability. The analysis is conducted on several important parameters, such as voltage gain, duty cycle response, and the efficiency of the DC-DC converter circuit in the inverter used. The test is conducted using a 250 V voltage source with a duty cycle setting of 37.5%, connected to a 20 Ω load, resulting in an output voltage (Vout = 400 V).

1) RNN Architecture Design: The simulation results are shown in Fig. 5, representing the output voltage waveform of the boost converter in a steady-state condition with a duty cycle of 37.5%. The boost converter topology is widely used in solar power systems to increase the output voltage of the PV panel to meet the system's load requirements. Based on the PWM signal obtained from the simulation, it is found that the 37.5% duty cycle means that the MOSFET switch is active (ON) for 37.5% of one PWM signal period, and inactive (OFF) for 62.5%. When the PWM signal is in a high logic state (value 1), the MOSFET switch conducts current from the PV panel to the inductor, storing energy in the inductor. Meanwhile, the diode is in reverse bias, preventing current from flowing to the load. Conversely, when the PWM signal is in a low logic state (value 0), the MOSFET is turned off (OFF), allowing the energy stored in the inductor to be released through the diode, which is now in forward bias, to the load.

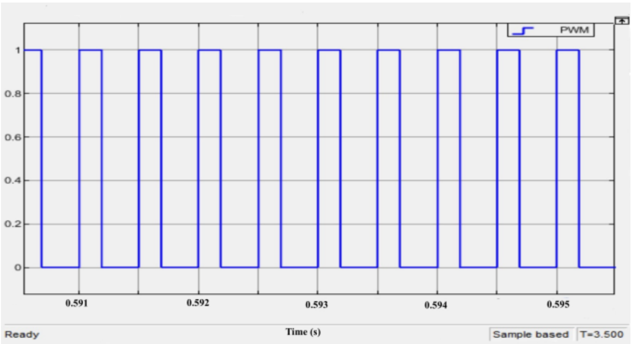

Fig. 5. Duty Cycle Signal Response Simulation Results

2) Testing the inductor signal response on the converter: Testing of the inductor signal is carried out under full load conditions to evaluate the dynamic characteristics during the switching cycle of the boost converter. The purpose of this test is to understand the process of charging and discharging energy in the inductor. As represented in Fig. 6, the simulation results show the inductor in continuous conduction mode (CCM) condition with the test conducted at a switching frequency of 5 kHz. Charge mode occurs when the MOSFET is in the conduction state, which is during the active duty cycle. Based on the simulation results, the maximum inductor current (IL) recorded reaches 18 A, which indicates that the inductor works optimally in storing and transferring energy during the switching cycle.

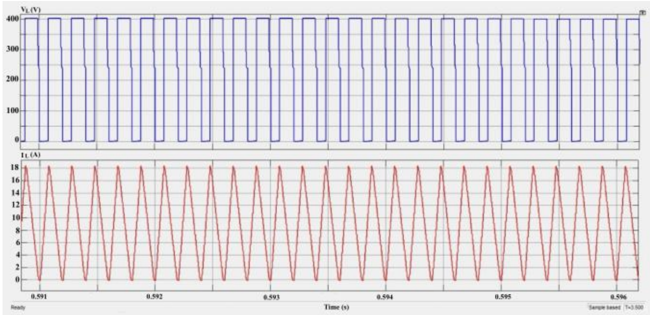

Fig. 6. Inductor current and voltage Waveforms

3) Testing the Output Signal Response of the Converter: This test is carried out to compare the output voltage value of the boost converter between the design stage and the implementation stage. At the design stage, simulations are carried out using component models to predict converter performance and ensure that each component used has met the specified technical specifications. Based on the simulation results shown in Fig. 7, the boost converter produces an output voltage of 400 V and an output current of 20 A. These values indicate that the converter is able to provide output in accordance with the design target. The test results also show that this conversion system is able to maintain the stability of the output voltage and current despite working under full load conditions. This shows that the converter design has been successfully implemented and is able to operate reliably.

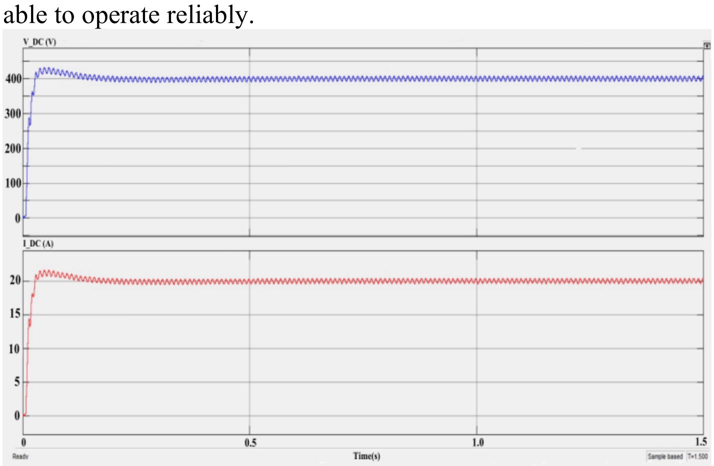

Fig. 7. Voltage and current response of the converter output

4) Testing the Output Signal Response on the Micro Inverter: This test is carried out to compare the output voltage value of the micro inverter between the implementation and design stages. In the design stage, simulations are carried out using component models to predict inverter performance and ensure that each component used is in accordance with the technical specifications designed. Represented in Fig. 8, the simulation results show that the micro inverter is capable of producing an output voltage of 220 V and a current of 100 A. Under implementation conditions, when the system is loaded with a resistance of 5.9 Ω, the resulting output current is 38 A.

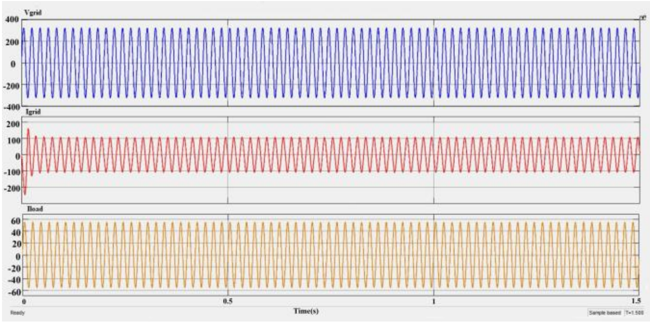

Fig. 8. Micro-Inverter Output Response

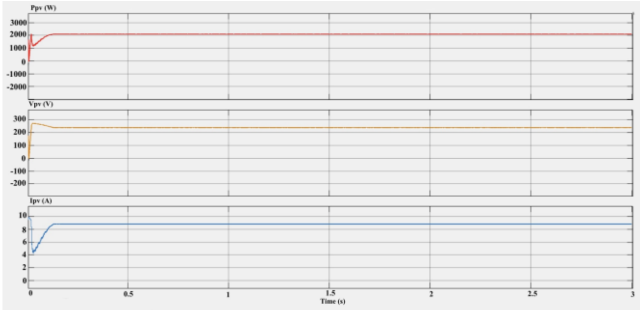

Fig. 10. Simulation results of voltage, current, and PV power of RNN algorithm (Irradiation 1000 W/m^2)

C. *MPPT Testing of RNN Algorithm with changes in PV Irradiation and Fixed Temperature*

Maximum power point tracking (MPPT) is a technique used to maximize the power extracted from solar panels (PV). One of the innovative MPPT methods is using Recurrent Neural Network (RNN) algorithm, which is a part of Artificial Intelligence (AI). The RNN algorithm is able to overcome the weaknesses of conventional methods such as P&O more effectively under dynamic conditions.

1) PV Radiation Testing Scheme 1000 W/m^2: In the research, the testing scheme was carried out with changing irradiation with constant temperature to show the performance of MPPT RNN algorithm in optimizing the power from PV. The test was conducted with an irradiation value of 1000 W/m^2 with a temperature of 25°C represented in Fig. 9. These conditions reflect a standard setup with maximum sunlight intensity at an ideal temperature to ensure that the temperature factor does not significantly affect the system performance. The purpose of this test is to observe how the RNN algorithm can adjust and optimize the output power of the solar panel under high irradiation conditions, which are more commonly encountered under direct sunlight exposure during the day. Fig. 9 provides a visual representation of the effect of irradiation on system performance, which forms the basis for further analysis of the effectiveness of the MPPT RNN algorithm under such conditions.

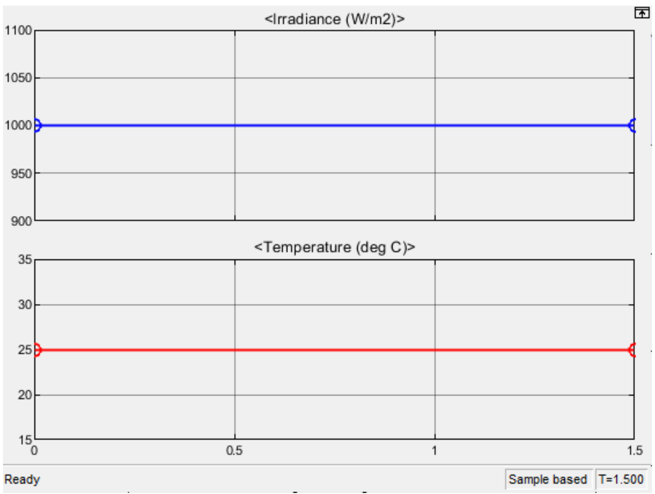

Fig. 9. Change in response of MPPT RNN Irradiation 1000 W/m^2 and temperature 25°C

The simulation results of RNN algorithm testing in Fig. 10 on the power signal (Ppv), it can be seen that the system reaches a steady-state value at a value of 2096 W with a short rise time of 0.123 seconds. This reflects that the system has a fast initial response to changes in conditions. The initial fluctuations that occur are very small and immediately damped, the system still maintains power stability efficiently. While the PV voltage graph (Vpv) shows that the voltage rises very quickly and stabilizes at 234.6 V, the results show that the panel voltage control is very stable. Likewise, the PV current (Ipv), the current rises to steady-state at a value of 8.934 A with a very fast transient response. The response to the simulation results can be analyzed that RNN has the advantage of reducing oscillations when compared to conventional algorithms.

The following are the complete results of the RNN algorithm simulation with changes in PV irradiation and fixed temperature.

TABLE 5. SIMULATION RESULTS OF THE RNN ALGORITHM UNDER VARYING IRRADIANCE AND FIXED TEMPERATURE

Irradiance	**P_pv_rated (W)**	**P_pv_rnn (W)**	**Efficiency (%)**	**Vo (V)**	**Io (A)**	**Po (W)**
1000	2097	2096	99.9	325	54.6	17745
900	1883.8	1866	99.9	325	54.8	17810
800	1671.1	1668	99.8	325	54.6	17745
700	1459.3	1450	99.3	325	54.59	17741.75
600	1246.3	1224	98.2	325	54.59	17741.75
500	1038.1	1037	99.8	325	54.53	17722.25
400	828.86	818	98.6	325	54.47	17702.75
300	620.39	613	98.8	325	54.47	17702.75
200	412.75	410	99.3	325	54.68	17771
100	205.96	201	97.5	325	54.68	17771

IV. CONCLUSION

This study concludes that the implementation of a Recurrent Neural Network (RNN)-based Maximum Power Point Tracking (MPPT) algorithm significantly enhances the performance of a micro-inverter system in photovoltaic (PV) energy conversion. By effectively processing input data from PV voltage and current to determine optimal duty cycles, the proposed system successfully maximizes power output under varying irradiance conditions. Simulation results show that that the system achieves a peak efficiency of 99.9% at 1000 W/m^2 irradiance, delivering a stable output power of 2096 W with a rise time of only 0.123 seconds, indicating high accuracy and responsiveness in MPPT control. The integration of a boost converter, micro-inverter, and supporting components such as an LCL filter and PLL further ensures system stability, grid compatibility, and power quality. The purpose of this research—to develop an intelligent and responsive energy conversion system—has been achieved, demonstrating both technical feasibility and efficiency improvements. This contribution is particularly relevant to the advancement of smart renewable energy technologies and offers a scalable solution for improving energy management in distributed PV systems.

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