

Article

A Simple Modeling of MPPT-based ANN for Photovoltaic System

Evi Nafiatus Sholikhah ^{1*}, Aulia Rahma Annisa ², Muhammad Rizani Rusli ³, and Mentari Putri Jati⁴

¹ Department of Marine Engineering, Politeknik Perkapalan Negeri Surabaya, Surabaya, Indonesia

² Department of Marine Electrical Engineering, Politeknik Perkapalan Negeri Surabaya, Surabaya, Indonesia

³ Department of Electrical Engineering, Politeknik Elektronika Negeri Surabaya, Surabaya, Indonesia

⁴ Department of Electro-Optical Engineering, National Taipei University of Technology, Taipei City, Taiwan

* Correspondence: evinafiatus@ppns.ac.id

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Abstract: This research describes a simple modeling technique for Maximum Power Point Tracking based on Artificial Neural Network (MPPT-based ANN) for photovoltaic (PV) systems. The proposed ANN model utilizes a feed-forward backpropagation architecture. The PV system was developed and tested in a simulation environment under uniform irradiation levels of 1000 W/m², 800 W/m², and 600 W/m², and rapidly varying irradiation changes. The simulation results demonstrate that the MPPT-based ANN accurately tracks the MPP, achieving stable power outputs of 98.36 W, 79 W, and 57.45 W, respectively. Although the system experiences initial transient oscillations during the tracking phase, it stabilizes within 80 milliseconds, showcasing rapid convergence and high steady-state accuracy. Under dynamic conditions, the MPPT-based ANN adapts effectively to fast-changing irradiation, restarting the algorithm to track and maintain the system at the updated MPP accurately. These results highlight the reliability, adaptability, and suitability of the MPPT-based ANN for real-time applications in dynamic environments. Nonetheless, further improvements to the ANN model are suggested to minimize transient oscillations and enhance overall performance.

Keywords: MPPT-based ANN, PV System, uniform irradiation.

1. Introduction

The rapid growth of photovoltaic (PV) system installations worldwide underscores their critical role in addressing energy demands sustainably. PV modules are connected in series-parallel arrangements to create PV arrays, convert sunlight into electrical energy through the photovoltaic effect. With the global push to reduce carbon emissions and adopt clean energy solutions, PV systems have become a vital component of renewable energy strategies. Their numerous advantages, including environmental friendliness, minimal maintenance requirements, and scalability, make them a preferred choice across residential, commercial, and industrial sectors. However, environmental factors such as sun irradiance, temperature, and shading conditions all have a substantial impact on PV system efficiency. These variables can lead to suboptimal power output, necessitating innovative solutions to optimize performance[1] [2] [3].

Maximizing energy extraction from PV systems requires operating them at their Maximum Power Point (MPP), the specific point where power output is at its highest. However, the MPP is dynamic and fluctuates with environmental conditions, creating challenges in maintaining optimal performance. To address this, Maximum Power Point Tracking (MPPT) algorithms are vital for ensuring PV systems consistently achieve peak power output, even under variable conditions. Over

time, numerous MPPT techniques have been developed, with traditional methods like Perturb and Observe (P&O) and Incremental Conductance (IncCond) gaining popularity due to their simplicity and reliability. Despite their widespread use, these methods often face challenges such as slower response times, steady-state oscillations, and decreased accuracy in rapidly changing environmental scenarios [4] [5] [6].

To address the shortcomings of traditional MPPT methods, advanced approaches leveraging artificial intelligence have gained prominence. Among these, Maximum Power Point Tracking based on Artificial Neural Networks (MPPT-based ANN) has emerged as a promising solution. ANN-based MPPT algorithms utilize machine learning techniques to model and predict the MPP with high accuracy. By learning from historical data and patterns, these algorithms can adapt swiftly to changes in environmental conditions, significantly enhancing the speed and precision of MPP tracking. Unlike conventional methods, ANN-based approaches are capable of minimizing steady-state oscillations and improving tracking performance in dynamic operating conditions, making them well-suited for real-time applications [7].

This paper focuses on the implementation and evaluation of an MPPT-based ANN algorithm for PV systems. The study aims to highlight the advantages of ANN-based algorithms in terms of efficiency, reliability, and adaptability. The results demonstrate that ANN-based MPPT algorithms not only achieve faster convergence to the MPP but also maintain steady-state accuracy under both uniform and rapidly changing environmental conditions. These findings underscore the potential of ANN-based MPPT as a robust and efficient solution for optimizing PV system performance. With the increasing complexity of environmental challenges, the integration of intelligent algorithms such as MPPT-based ANN represents a significant step toward enhancing the sustainability and reliability of solar energy generation.

2. Materials and Methods

This section discussed research related to the materials and methods to develop the PV system with the MPPT technique, such as PV module characteristic, Buck-Boost Converter, artificial neural network architecture, and MPPT-based ANN algorithm.

2.1 PV Module Characteristic

The equivalent circuit of a PV cell comprises a parallel current source combined with diodes and resistors connected to its output terminals [8]. PV cells are placed in series-parallel configuration to create a PV module, which generates a significant amount of electrical power. The power output of a PV module is heavily dependent on solar irradiation levels, with increased irradiation leading to higher power production. PV modules display non-linear behavior, commonly depicted through I-V and P-V curves. Any variation in irradiation conditions causes the PV module to function at a distinct Maximum Power Point (MPP). In this research, a 100 Wp PV module is employed to test the proposed algorithm and its P-V characteristics depicted in Figure 1.

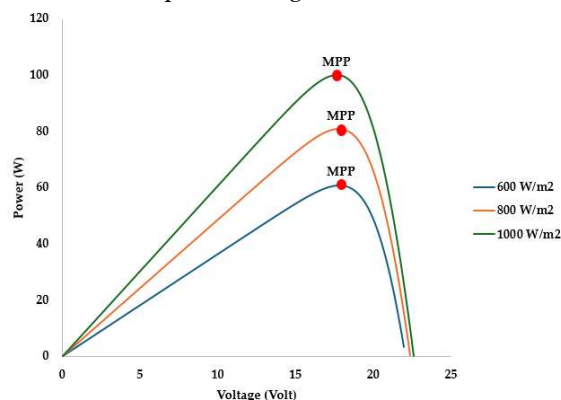


Figure 1. The P-V Characteristic of the PV Module

2.2 Buck-Boost Converter

A Buck-Boost Converter is used to apply the MPPT method between the PV module and the load. The PV module can operate within its Maximum Power Point (MPP) range by regulating the load impedance through changes in the duty cycle of the switching converter. Figure 2 displays the Buck-Boost Converter's circuit diagram, and Table 1 lists the values that were used in this investigation.

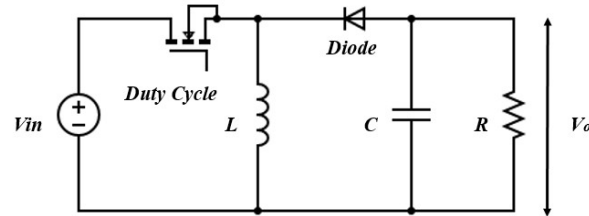


Figure 2. The Topology of the Buck-Boost Converter

Table 1. The parameters of the Buck-Boost Converter

No	Parameter	Variable	Value
1	Switching Frequency	f	40 kHz
2	Inductor	L	200 μ H
3	Capacitor	C	560 μ F
4	Load Resistor	R	40 Ω
5	Input Voltage	V_{in}	10-25 V
6	Output Voltage	V_o	5-225 V

2.3 Artificial Neural Network Architecture

The ANN is trained using 81 datasets that includes the duty cycle of the Buck-Boost Converter (D) as the output and the short-circuit current of the PV module (I_{sc}) as the input using MATLAB's NNTOL program. In this study, several ANN architectures were created with different ANN setting as shown in Table 2. After training process, the best ANN architecture for this study has five neurons in the hidden layer with a tansig function in the output layer and a logsig activation function in the hidden layer, as shown in Figure 3. The best ANN architecture has a regression value of 0.99, which means that the model successfully predicts the target output perfectly, where all predicted values are identical to the target values as shown in the regression plot in Figure 4.

Table 2. The comparison of the ANN Architectures with Different ANN Setting

Architecture	Hidden Layer		Output Layer		MSE
	The Number of Neurons	Function	The Number of Neurons	Function	
1	3	logsig	1	tansig	3.05
2	5	logsig	1	tansig	0.94
3	7	logsig	1	tansig	5.08
4	10	logsig	1	tansig	9.02

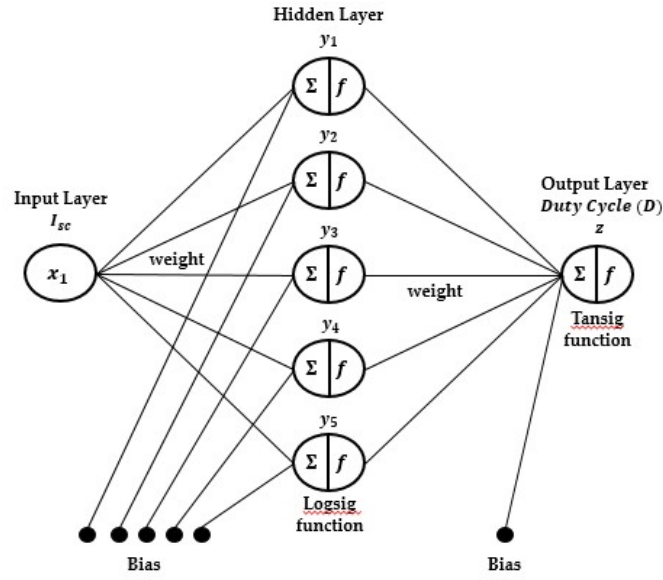


Figure 3. ANN Architecture

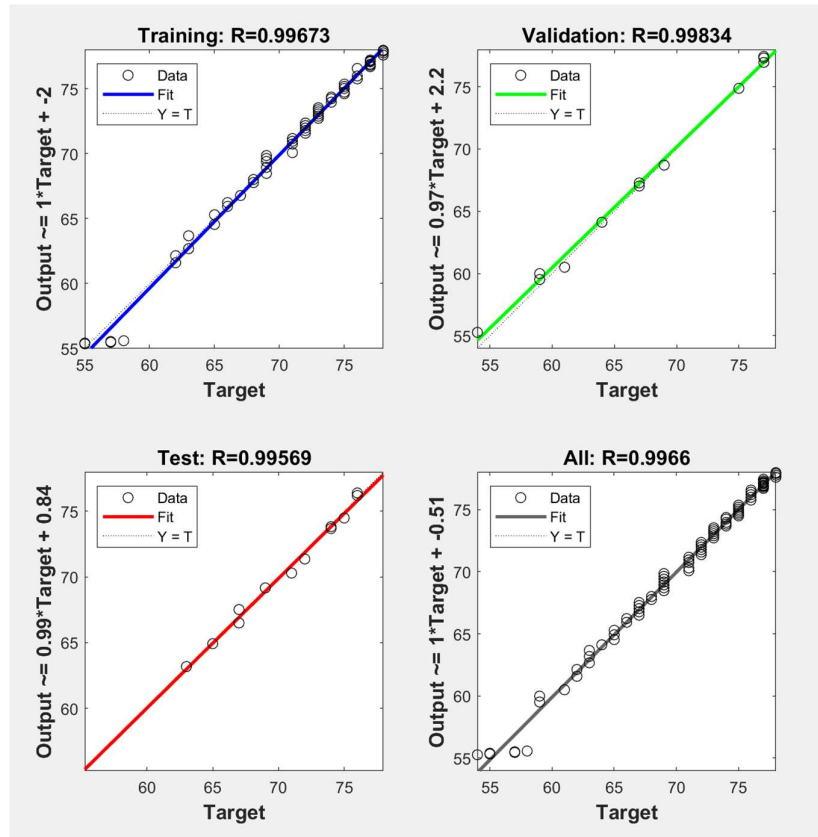


Figure 4. Regression Plot of The Best ANN Architecture

As illustrated in Figure 3, the ANN architecture can be represented as a mathematical model. Within the input layer, the short-circuit current is transformed into a standardized ANN value through a process known as input normalization. The corresponding mathematical model is provided in Equation (1).

$$x_1 = \frac{(I_{sc} - I_{sc,min}) * 2}{(I_{sc,max} - I_{sc,min})} - 1 \quad (1)$$

Here, x_1 represents the normalized input, I_{sc} denotes the short-circuit current, $I_{sc,min}$ is the minimum short-circuit current, and $I_{sc,max}$ is the maximum short-circuit current, both determined from the training data. The value of x_1 is then utilized in subsequent calculations within the hidden layer. The mathematical model is provided in Equation (2).

$$y_n = \frac{1}{(1 + e^{((x_1 * w_{in}) + b_{in}))})} \quad (2)$$

In this context, i denotes the layer index, n represents the number of neurons, y_n is the output from each neuron, w signifies the weight, and b refers to the bias in the ANN. The weight and bias values are optimized during the training process conducted using MATLAB software. The output y_n is subsequently applied in the calculations for the output layer. The mathematical model is expressed in Equation (3).

$$z = \frac{2}{(1 + e^{(-2 * \sum_{n=1}^5 (y_n * w_{in}) + b_{in}))})} - 1 \quad (3)$$

Where z is the result of the output layer. So, the duty cycle as an output can be calculated with Equation (4).

$$D = \frac{(z + 1)(D_{max} - D_{min})}{2} + D_{min} \quad (4)$$

Where D_{max} is the maximum duty cycle and D_{min} is the minimum duty cycle. The value of D_{max} and D_{min} are based on the training data.

2.4 MPPT-based ANN Architecture

The flowchart illustrating the proposed MPPT algorithm utilizing ANN is presented in Figure 5. The process starts with system initialization, during which key parameters, including voltage, current, and ANN settings such as weights and biases, are established. The process starts by measuring the short circuit current (I_{sc}) of the PV system, which serves as an input to the ANN model. Using the measured I_{sc} and predefined equations (Equations (1), (2), (3), and (4)), the ANN model estimates the duty cycle required to operate the PV system at the maximum power point (MPP) area. Next, the system measures the PV voltage (V_{pv}) and current (I_{pv}) at the current operating point. The power output (P_{pv}) at the MPP area is then calculated using $P_{pv} = V_{pv} \times I_{pv}$. The system continuously monitors irradiation levels, if a change in irradiation is detected, the process loops back to measure I_{sc} and re-estimate the duty cycle using the ANN model. If no change is detected, the system maintains the current operating conditions, completing the MPPT process. This iterative process ensures efficient tracking of the MPP under varying irradiation conditions.

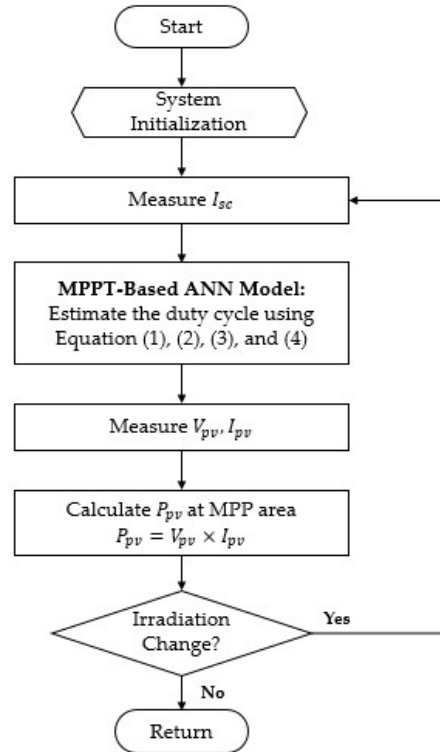


Figure 5. The Flowchart of MPPT-Based ANN

3. Results and Discussion

PSIM software simulations are used to validate the performance of the suggested MPPT-based ANN. As shown in Figure 6, the simulated PV system consists of a PV module connected to a resistive load and a Buck-Boost Converter, utilizing the MPPT-based ANN controller. The effectiveness and dependability of the MPPT-based ANN algorithm are evaluated by testing the system under various uniform irradiation levels and dynamic irradiation fluctuations.

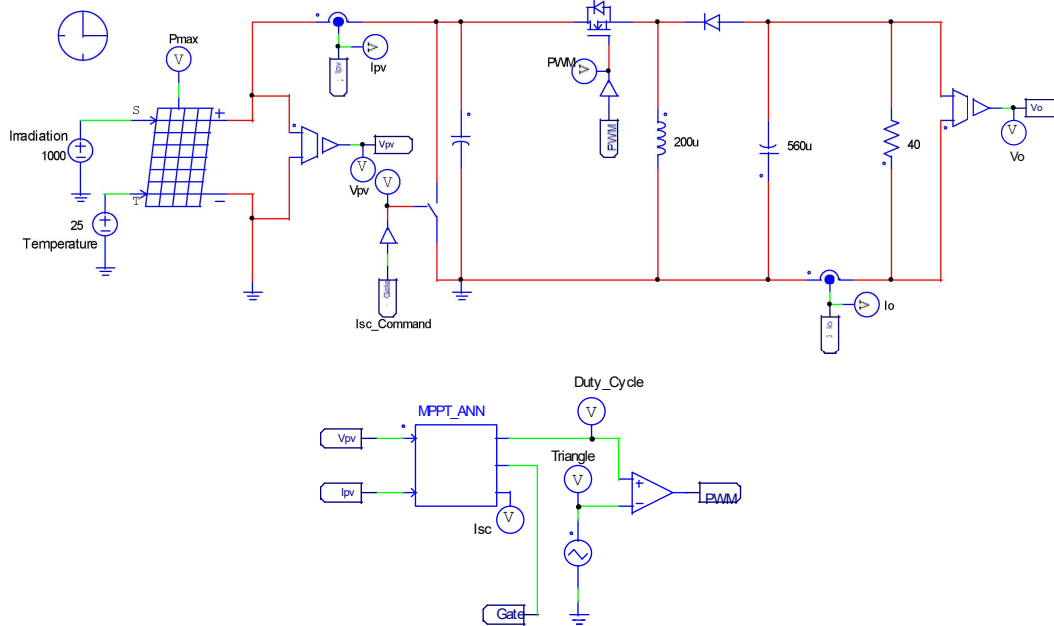


Figure 6. The PV System in PSIM Software

3.1 Under Uniform Irradiation

The PV system is evaluated under various uniform irradiation conditions, including 1000 W/m^2 , 800 W/m^2 , and 600 W/m^2 . Each irradiation situation has a unique maximum power point (MPP) region. The MPPT-based ANN algorithm was validated by comparing it to training data. In case 1, the MPPT-based ANN tested under uniform irradiation 1000 W/m^2 . The simulation result shown in Figure 7. The graph illustrates the performance of MPPT-based ANN algorithm in achieving and maintaining the Maximum Power Point (MPP). The green line represents the real MPP, while the red line shows the MPPT-based ANN algorithm result. Initially, the MPPT-based ANN exhibits oscillations during the tracking phase (0-90 milliseconds) as it adjusts and converges to the MPP at $98,36 \text{ W}$. These oscillations diminish over time, with the system stabilizing at approximately 96 milliseconds, reflecting its ability to achieve steady-state power output efficiently. The ANN-based MPPT demonstrates rapid response times and a high degree of accuracy, maintaining the MPP area once stability is reached.

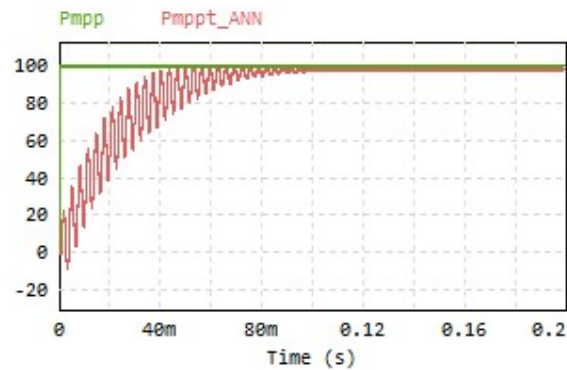


Figure 7. The Result of the Simulation for Case 1

In case 2, the MPPT-based ANN tested under uniform irradiation 800 W/m^2 . The simulation's outcome is displayed in Figure 8. Initially, during the tracking phase (0 to 40 milliseconds), the MPPT-based ANN output exhibits significant oscillations as the system adjusts to track the MPP. The oscillations gradually reduce, and by around 65 milliseconds, the system stabilizes and aligns closely with the MPP at 79 W . This indicates that the ANN model can effectively converge to the MPP with high accuracy in steady-state conditions. In case 3, the MPPT-based ANN tested under uniform irradiation 600 W/m^2 . The simulation result shown in Figure 9. The MPPT-based ANN exhibits oscillations during the tracking phase (0-75 milliseconds) as it adjusts and converges to the MPP at $57,45 \text{ W}$. The MPPT-based ANN can adapt to different environmental conditions, maintaining high accuracy in steady-state operations. However, the transient oscillations observed indicate a need for refinement in the ANN design, such as optimizing its training dataset, architecture, or control parameters. The ANN is appropriate for real-time applications in dynamic contexts due to its quick convergence and dependable performance. Table 3 displays the specific results.

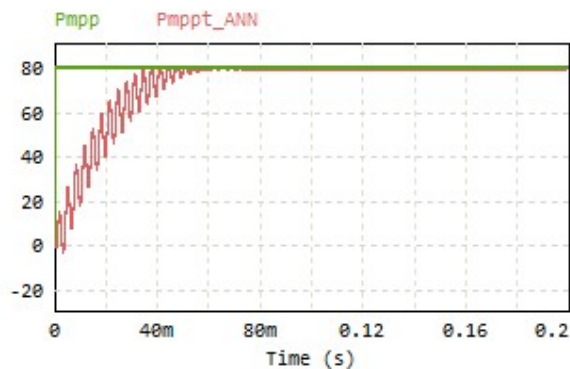


Figure 8. The Result of the Simulation for Case 2

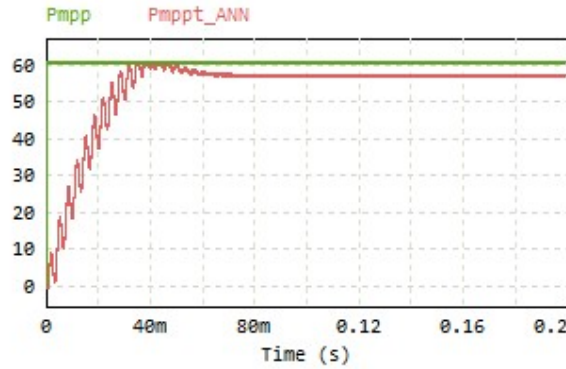


Figure 9. The Result of the Simulation for Case 3

Table 3. The results of MPPT-based ANN

Irradiation (W/m ²)	Training Data		MPPT-based ANN		Accuration (%)	Tracking Time (milliseconds)
	MPP (W)	Duty Cycle (%)	MPP (W)	Duty Cycle (%)		
1000	100	75	98,63	78,46	98,69	96
800	80	72	79	72,73	98,75	65
600	60	69	57,45	70,71	95,75	75

3.2 Under Varying Irradiation Changes

The PV system was also tested under rapidly varying irradiation changes to validate that the MPPT-based ANN can operate under irradiation changes. In this case, the PV system tested under fast varying irradiation changes from 1000 W/m², 800 W/m², to 600 W/m². From the result, as shown in Figure 10, the MPPT-based ANN can adapt to rapidly varying irradiation changes and maintain the system at the MPP area. The MPPT-based ANN will restart the algorithm when the system detects the irradiation changes, so the algorithm will track the new MPP and maintain the system operation at the MPP area.

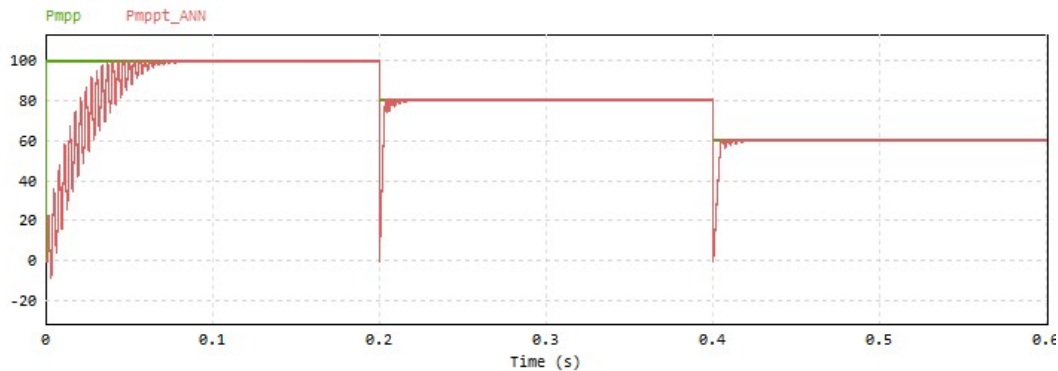


Figure 10. The Simulation Result of the PV System under Varying Irradiation Changes

4. Conclusions

In conclusion, the MPPT-based ANN algorithm exhibits robust performance in tracking and maintaining the Maximum Power Point (MPP) under various uniform and dynamic irradiance conditions. Under uniform irradiances of 1000 W/m², 800 W/m², and 600 W/m², the algorithm effectively converges to the MPP with high accuracy, as demonstrated by the stable power outputs of 98.36 W, 79 W, and 57.45 W, respectively. Despite the initial transient oscillations during the

tracking phase, the system efficiently stabilizes within milliseconds, highlighting the fast response and suitability of the ANN for real-time applications. Furthermore, under rapidly changing irradiance conditions, the MPPT-based ANN successfully adapts to the changes, and dynamically restarts the algorithm to track and maintain operation in the new MPP area. These results underline the reliability, adaptability, and potential of the MPPT-based ANN for improving the efficiency of PV systems. However, further refinement in the training dataset, architecture, or control parameters of the ANN is recommended to minimize transient oscillations and improve overall performance. Future work should focus on improving the ANN architecture for better accuracy, implementing the model in real-time embedded systems, and testing under dynamic conditions such as partial shading. Further studies can also explore hybrid MPPT approaches and integration with intelligent energy management systems.

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