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Research Article

Enhancing Photovoltaic System Performance: A Comparative Study of AI-Based Neural Networks and Traditional MPPT Techniques

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Abstract – The increasing reliance on renewable energy emphasizes the critical need for optimizing photovoltaic (PV) systems to achieve maximum energy output. Traditional Maximum Power Point Tracking (MPPT) methods, such as Perturb and Observe (P&O), are commonly used due to their simplicity. However, they encounter challenges like oscillations around the Maximum Power Point (MPP) and slower adaptation under dynamic environmental conditions. This study addresses these limitations by evaluating AI-based MPPT techniques, particularly Neural Networks (NN), in comparison to the P&O method, highlighting their superior adaptability and efficiency. Using MATLAB simulations, the study analyzes the performance of these methods in an independent PV system featuring a solar array, buck-boost converter, and variable resistive load. Results reveal that AI-based MPPT approaches, especially Neural Networks, deliver smoother power outputs, faster convergence to the MPP, and reduced stress on PV components. By leveraging real-time and historical data, these techniques demonstrate enhanced predictive capabilities, making them highly suitable for regions with fluctuating environmental conditions.

Keywords – Photovoltaic (PV) Systems, Perturb And Observe (P&O) Method, Neural Networks (NN), Maximum Power Point Tracking (MPPT), Buck-Boost Converter.

I. INTRODUCTION

The increasing reliance on renewable energy sources has underscored the importance of solar energy as a sustainable power generation option. Photovoltaic (PV) systems, known for their environmental benefits and accessibility, face challenges in achieving maximum energy output due to their dependence on environmental factors such as sunlight intensity and temperature fluctuations. Addressing these challenges requires effective Maximum Power Point Tracking (MPPT) methods that optimize the energy extraction process. Among conventional techniques, the Perturb and Observe (P&O) method has gained widespread popularity for its simplicity and straightforward implementation. By iteratively adjusting the PV system's voltage and monitoring changes in power output, the P&O method enables the system to converge toward the Maximum Power Point (MPP) [1].

However, traditional MPPT methods like P&O exhibit limitations, including oscillations around the MPP and slower convergence rates, particularly under rapidly changing environmental conditions. These limitations have spurred interest in Artificial Intelligence (AI)-based MPPT techniques, which leverage advanced algorithms to improve tracking efficiency and adaptability. Techniques such as Neural Networks (NN), Fuzzy Logic Controllers (FLC), and optimization methods like Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) have demonstrated superior performance by dynamically learning from real-time and historical data. These AI-driven approaches provide faster convergence, reduced steady-state oscillations, and enhanced robustness in dynamic environments [2][3]. However, their higher computational requirements and complex implementation processes pose significant challenges, particularly in resource-constrained settings [4].

Recent innovations have focused on addressing these challenges through hybrid approaches that combine the strengths of traditional and AI-based methods. For example, Long Short-Term Memory (LSTM) networks have emerged as a promising solution for capturing temporal dependencies in environmental data, enabling precise and adaptive MPPT under fluctuating conditions. Studies demonstrate that LSTM-based systems outperform conventional methods like P&O in both tracking accuracy and response times, particularly in scenarios involving variable irradiance and temperature [5][6]. Furthermore, hybrid systems that integrate AI techniques with traditional methods are gaining traction as a practical solution, balancing performance improvements with manageable complexity [7].Given the typically low efficiency of PV modules—often below 17%—and their sensitivity to environmental conditions, MPPT systems play a critical role in optimizing power extraction. These systems not only address environmental factors such as temperature and irradiance but also consider electrical parameters like current and voltage to maximize PV performance [8][9].

This paper aims to investigate and compare the performance of AI-based MPPT techniques with the P&O method for standalone PV systems. The study employs MATLAB simulations to evaluate both methodologies in terms of tracking accuracy, convergence speed, and overall impact on PV system operation. The simulated framework includes a PV array, a buck-boost converter, and a variable resistive load, with MPPT algorithms optimizing the converter's duty cycle for maximum energy extraction.

II. MATERIALS AND METHOD

This section outlines the modeling approaches and methodologies employed to compare the effectiveness of AI-based MPPT and P&O methods. The objective is to evaluate the efficiency, response time, and adaptability of each technique under varying environmental conditions.

1) A. Photovoltaic (PV) System Model:

Photovoltaic (PV) technology plays a vital role in renewable energy, converting sunlight is converted into electrical energy through the photovoltaic effect. A photovoltaic (PV) module, commonly referred to as a solar panel, consists of interconnected solar cells, usually made from silicon. These cells are arranged in parallel and series configurations to produce the desired voltage and current outputs.

PV cells convert solar energy into electricity via a p-n junction. The single-diode model simplifies the system by representing the cell as an ideal current source with associated resistive losses.

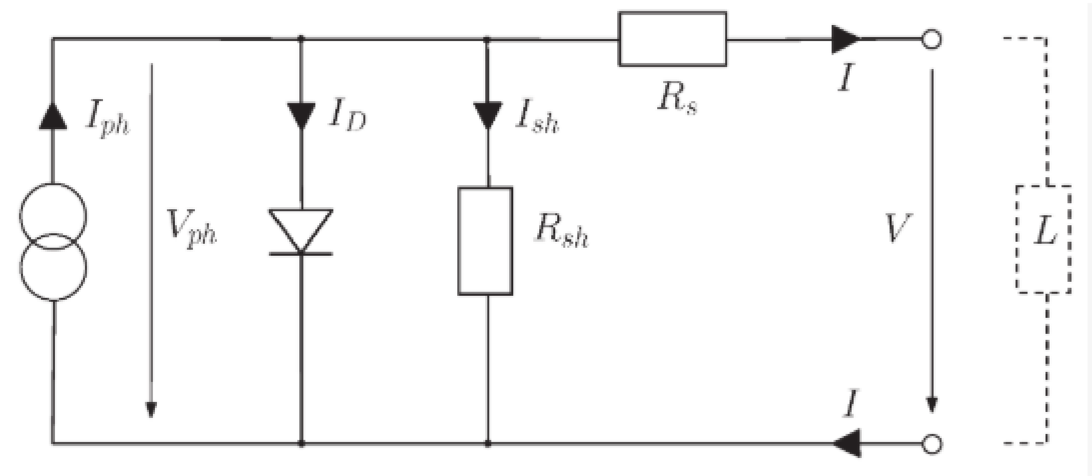


Figure (1) Equivalent Circuit of a Photovoltaic Cell [9]

The calculations for the PV cell, depicted in Figure (1), can be expressed as follows:

$$I_{ph} = G(I_{sc} + \propto \Delta T) \qquad (1)$$

Where:

- I_{ph} the Photocurrent.
- G Represents the solar irradiance or sunlight intensity
- I_{sc} the short circuit current
- $\propto$ Temperature Coefficient of Current
- ΔT Temperature Difference

$$I_{rs} = \frac{I_{sc}}{e^{\left[\frac{qVoc}{N_S KAT_O} - 1\right]}} \qquad (2)$$

- Irs Reverse Saturation Current
- Voc Open-Circuit Voltage
- Ns Number of Series-Connected Cells
- q elementary charge $(1.6 \times 10^{-19} C)$
- k Boltzmann Constant $(1.381 \times 10^{-23} J/K)$
- A Ideality Factor
- To Absolute Temperature

$$I_s = \frac{e^{\left(\frac{|s|\Delta T}{N_S KTA}\right)} \times G[I_{sc} + \propto \Delta T]}{\left(G \times \frac{I_{sc}}{I_{rs}} + 1\right)^{\frac{T_O}{T}} - e^{\left(\frac{|\beta|\Delta T}{N_S KTA}\right)}} \qquad (3)$$

- I_s Represents the saturation current or reverse saturation current
- β Represents the temperature coefficient of voltage or open-circuit voltage.

When substituting from Equation (1) into Equation (3), the resulting expression is derived as follows

$$I = I_{ph} - I_s \left[e^{\left(\frac{qV}{N_S KAT}\right)} - 1 \right] \quad (4)$$

Figure (2) illustrates Overall connections of the modeled equations described. In real-world applications, individual cells are connected in series and parallel combinations to form photovoltaic (PV) modules.

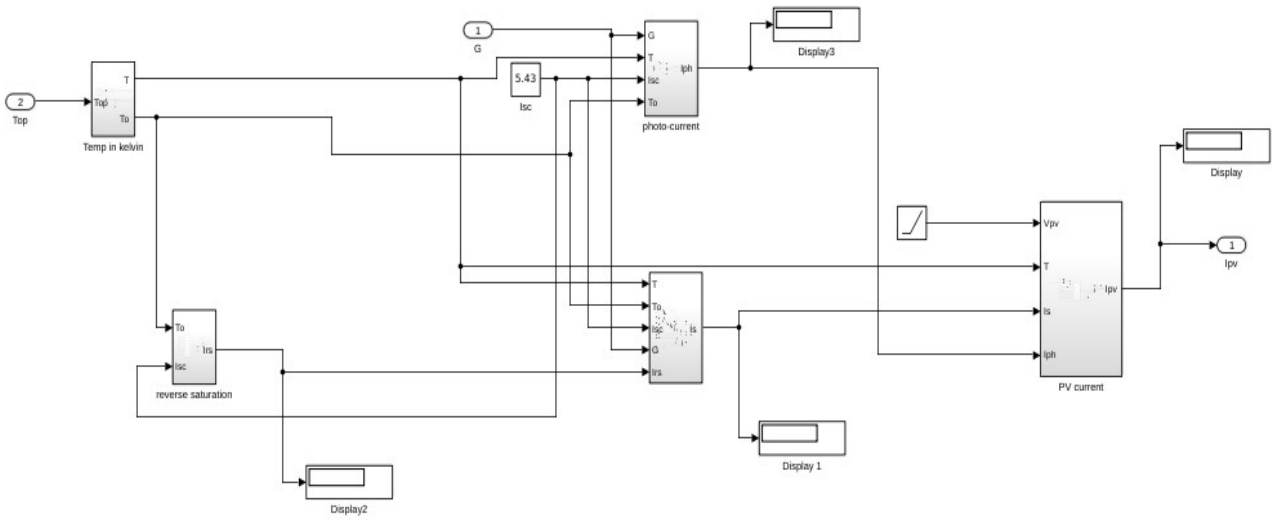
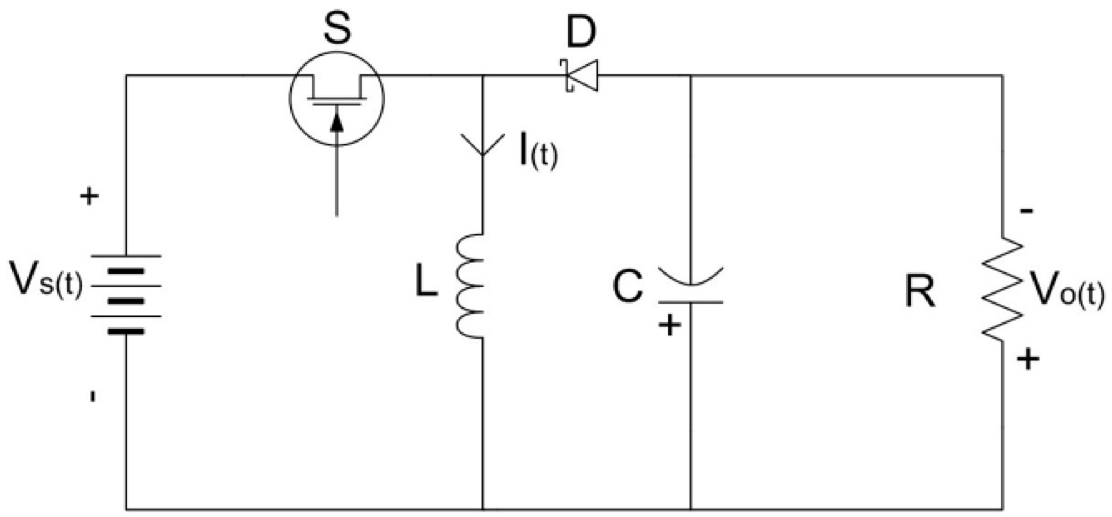


Figure (2) Overall connections of the modeled equations

B. Buck Boost Converter:

A buck-boost current regulator is a type of power converter that adjusts the input voltage to a desired output voltage as illustrated in Figure (3), either increasing or decreasing it. This regulator is particularly useful when the input voltage fluctuates, but a stable output is required for the proper operation of electronic devices.

The main function of the buck-boost regulator is to convert DC voltage from one level to another. It stabilizes the output voltage even when the input voltage varies, improving energy efficiency by minimizing loss during the conversion process. It also protects devices from damage caused by voltage fluctuations.



Figure

Figure (3) illustrates the circuit diagram of the buck-boost converter.

Buck-boost regulators operate in two methods: the boost method and the buck method. In buck mode, when the input voltage is greater than the required output, the regulator reduces the voltage by directing current through inductors and switches. In boost way, when the input voltage is less than needed, the regulator increases the output voltage by storing energy in the inductor. The process involves releasing the switch when it is open and closing it when it is shut.

• When D<0.5D < 0.5, It operates in buck way when the input voltage is higher than the output level.

• When D>0.5D > 0.5, it functions in boost mode, raising the output voltage above the input level.

• For D=0.5D = 0.5, the output voltage matches the input voltage.

These alternating states form the foundation of steady-state analysis, with the output voltage equation derived by equating variations in the input voltage and duty cycle.

The buck-boost converter is extensively used across diverse applications, including portable electronics, renewable energy systems, automotive subsystems, and telecommunications. Its ability to regulate output voltage despite input fluctuations ensures stable power delivery, making it essential for efficient and reliable power systems

The connection between the input voltage (Vin), output voltage (Vout), and other components is described by the following formulas.[10]

$$V_o = -V_s\left(\frac{D}{1-D}\right) \quad (5)$$

Where inductor current iL in the buck-boost converter is given by

$$iL = \frac{V_s D}{R(1-D)^2} \quad (6)$$

The minimum inductance required to maintain continuous conduction mode (CCM) is given by

$$L_{min} = \frac{(1-D)^2 R}{2f} \qquad (7)$$

where f is switching frequency

The output capacitor can be determined using the following equation:

$$C = \frac{V_o \times D}{\Delta V_o R f} \qquad (8)$$

2) C. MPPT Techniques

A. Perturb and Observe (P&O):

The Perturb and Observe (P&O) algorithm serves as a foundational MPPT technique. It works by incrementally adjusting the Photovoltaic voltage and monitoring changes in output power. If the power output rises, the algorithm continues to adjust in a single direction. Conversely, if power reduces, it reverses the direction of perturbation.

In this method, the PV system periodically alters the voltage until the peak power is reached. When a voltage change results in increased power, the system persists in that direction; otherwise, it switches. This dynamic process allows the tracker to continuously search for the optimal operating point.[11] A flowchart illustrating the P&O algorithm is depicted in Figure (4).

Traditional P&O methods, as modeled in MATLAB-Simulink, modify the duty cycle incrementally for performance assessment.

The P&O algorithm is implemented as a baseline method. The algorithm perturbs the voltage and observes the change in power output. If the power increases, the perturbation continues in the same direction; if it decreases, the direction is reversed.

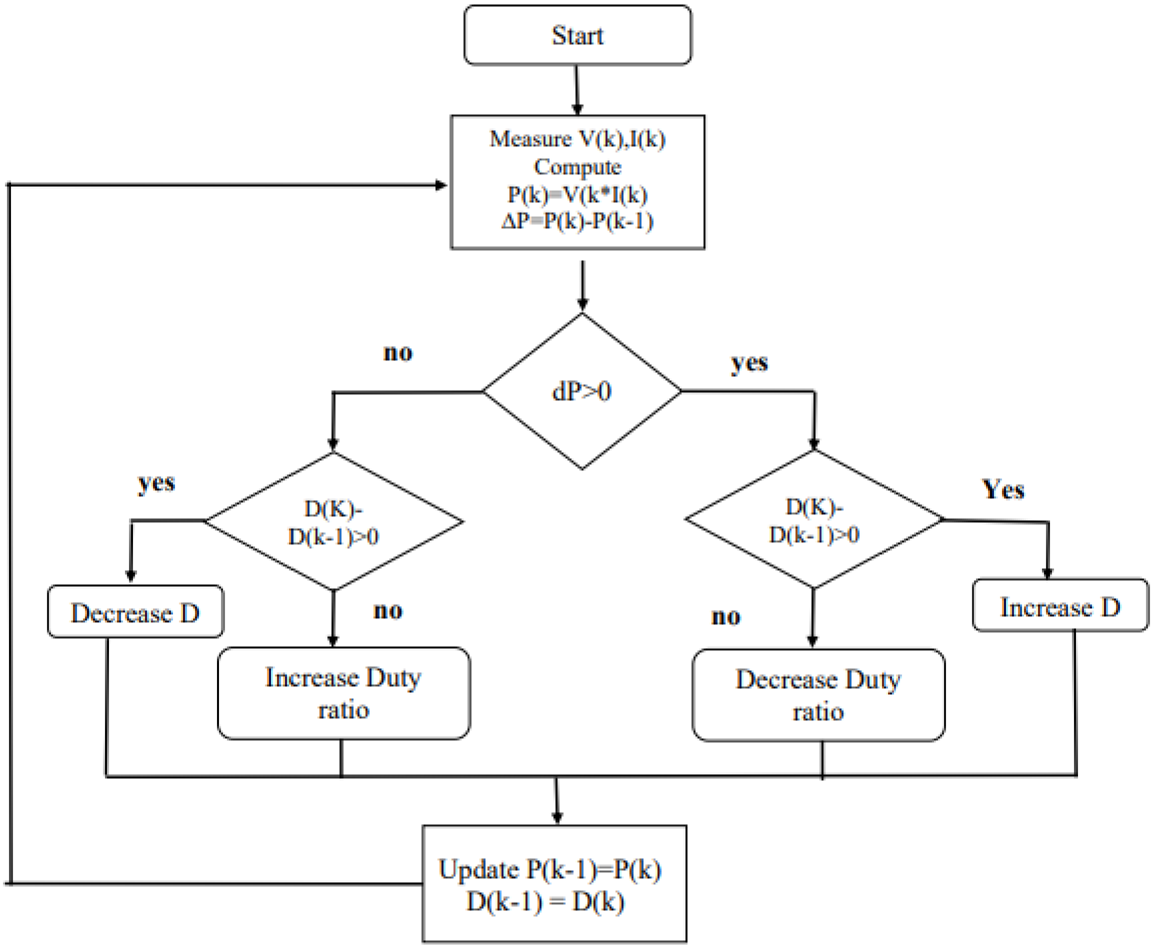


Figure [4] flowchart illustrating the P&O algorithm

B. AI-Based MPPT Techniques:

Neural Networks (NNs), modeled after biological neural systems, are advanced computational tools capable of learning complex input-output relationships. They serve as powerful predictors, particularly effective in applications like MPPT for PV systems. In this study, a NN was implemented using MATLAB. The network, featuring hidden layers with specific configurations of neurons, was trained to predict the required duty cycle adjustments when the PV system encounters rapid variations in solar irradiance.

The data used for training the neural network was sourced from Karabuk a town in Turkey located at a latitude of 41.15°N and a longitude of 32.61°E. This dataset, sourced from NASA's Prediction of Worldwide Energy Resources (POWER) database,[12] provided accurate historical and real-time environmental parameters specific to the region. By leveraging this diverse data, including solar irradiance, temperature, and PV output power, the neural network effectively captured the varying environmental conditions.

To improve the system's predictive accuracy, the NN was trained using this region-specific data, enabling it to estimate the optimal operating point of the PV system under dynamic weather scenarios. The model's performance was evaluated through regression analysis, comparing the NN's predicted outputs with the target values. The results, as shown in Figure (5), demonstrated a perfect correlation, with both the training and target datasets achieving a coefficient of determination (R= 1). This highlights the NN's ability to accurately learn and predict duty cycle adjustments, ensuring optimal power extraction from the PV system despite changing environmental conditions.

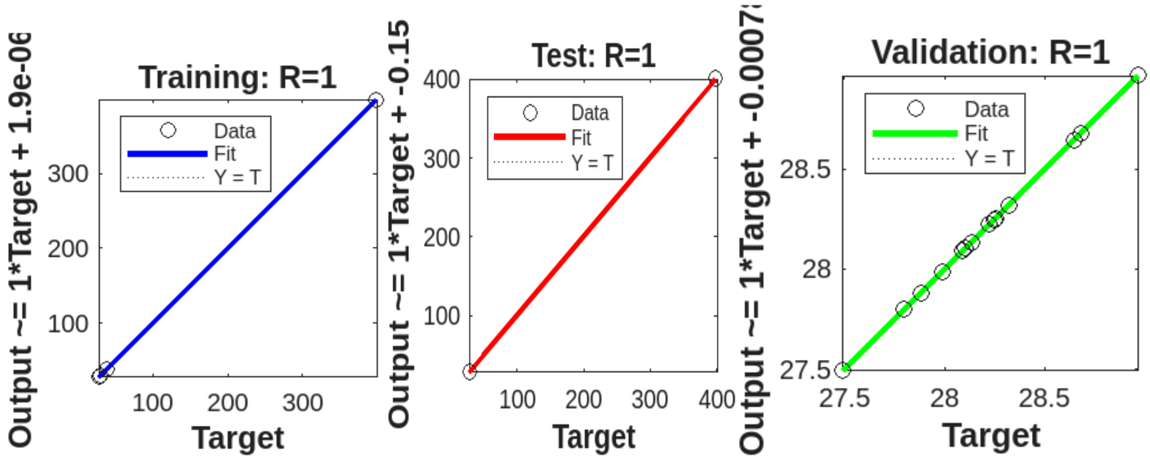


Figure (5) Performance plot of regression analysis for the training, testing, and validation datasets

Figure (5) demonstrates the regression analysis for the training, testing, and validation datasets. This plot highlights the accuracy of the NN in predicting the duty cycle adjustments, ensuring that the PV system operates at maximum efficiency, even during periods of fluctuating solar irradiance.

The Neural Network (NN) training performance depicted in Figure (6) directly supports the effectiveness of the ANN-based MPPT framework described. As the Mean Squared Error (MSE) decreases over epochs. The training error steadily decreases, demonstrating the NN's ability to learn and refine its adjustments for the Proportional-Integral-Derivative (PID) controller. The validation error reaches its lowest point at epoch 71, indicating the model's optimal performance and ability to generalize effectively. Although the test error is slightly higher, it still shows reasonable performance, highlighting the model's adaptability to unseen data.

This well-trained NN minimizes oscillations in the PWM signals applied to the power converter, improving the system's performance. By ensuring low error and robust performance, the NN enables the MPPT framework to adapt effectively to changing weather conditions and obtain maximum power from the PV system, even in dynamic environments.

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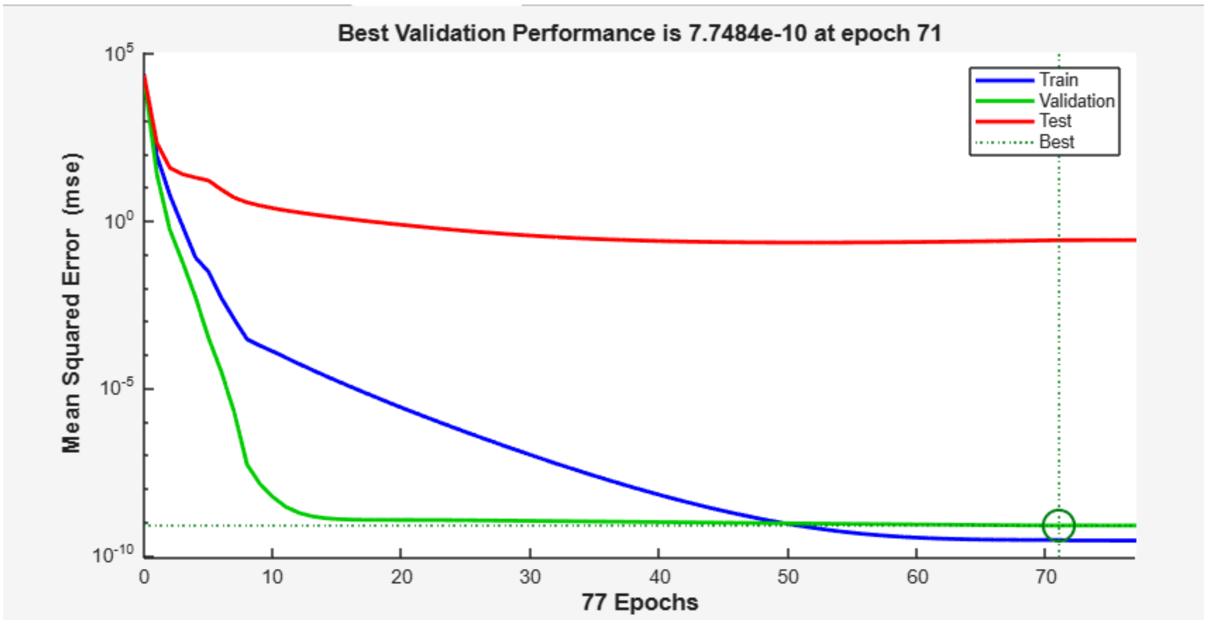


Figure (6) Performance Plot

III. RESULTS AND DISCUSSIONS

This study evaluates the performance of two MPPT methods for photovoltaic systems, the Perturb and Observe (PO) method and a Neural Network (NN)-based approach. The NN model was trained using historical power prediction data from NASA, specific to Karabuk, Turkey, and implemented in MATLAB Simulink for system simulation.

In Figure (8), the input power from the PV array is shown to vary with changing irradiance and temperature environment, as illustrated in the irradiance and temperature data in Figure (12). The PO-based MPPT controller's power output demonstrates oscillations around the MPP, which are characteristic of its iterative search process. These oscillations result in power loss due to continuous perturbations and adjustments.

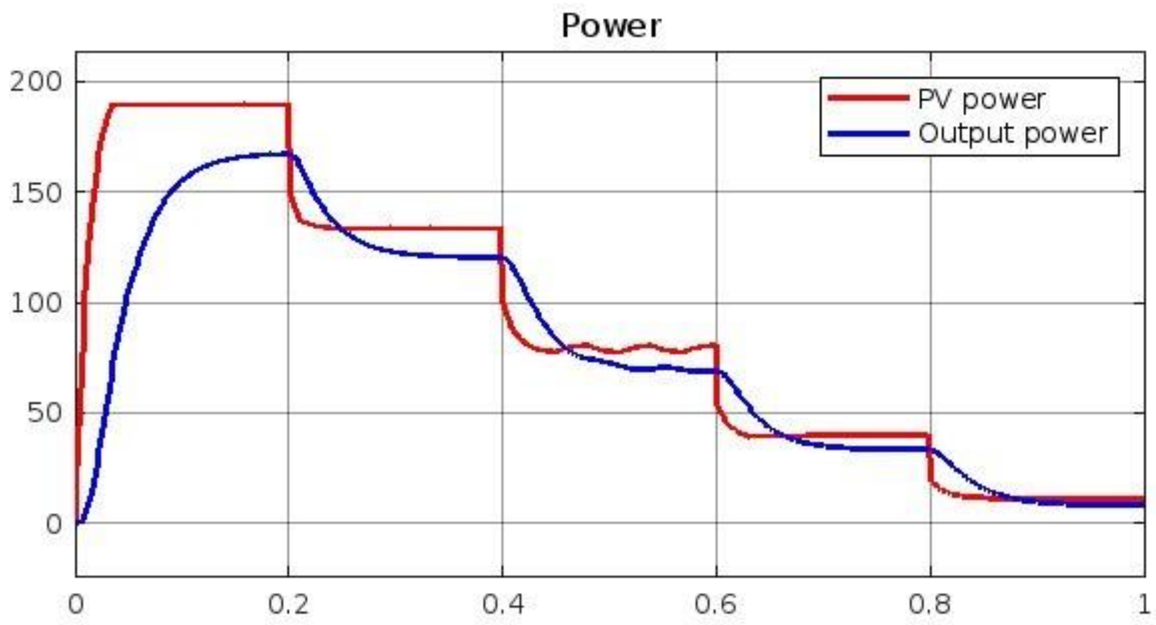


Figure (8) Power Input and Power Output of P&O MPTT

As shown in Figure (9), the PO algorithm introduces continuous perturbations in the input voltage, leading to oscillations, especially during environmental changes such as fluctuating irradiance and temperature. This trial-and-error nature can result in suboptimal transient performance. Although the output voltage stabilizes after finding the MPP, minor variations persist because the algorithm cannot completely eliminate oscillations. This reduces efficiency and increases stress on both the PV modules and the power converter.

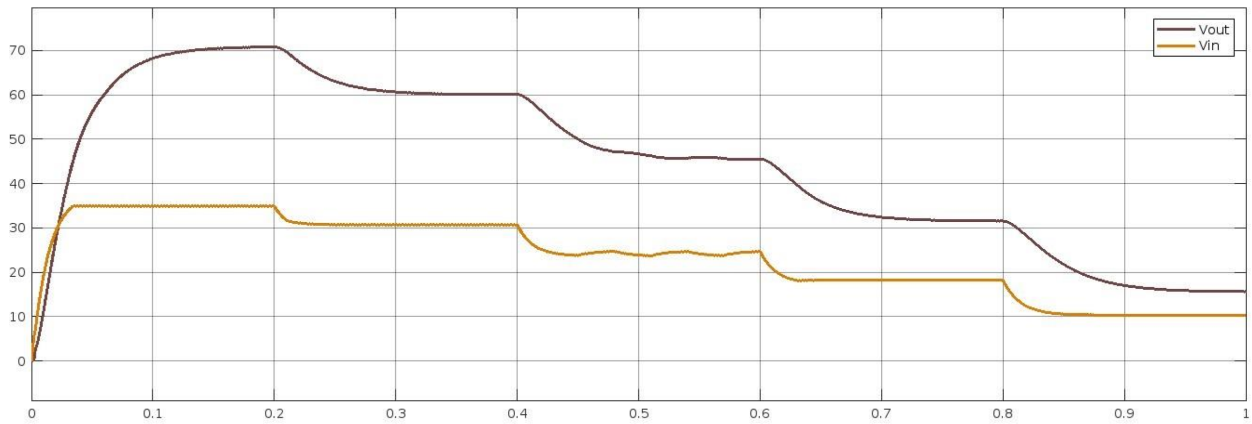


Figure (9) Power Input and Power Output of P&O MPTT

In Figure (10), the input voltage and current from the PV array are shown to vary dynamically as the PO algorithm perturbs the operating point to locate the MPP. While the output voltage stabilizes to some extent, it continues to reflect the dynamic adjustments made by the controller, which indicates suboptimal steady-state performance.

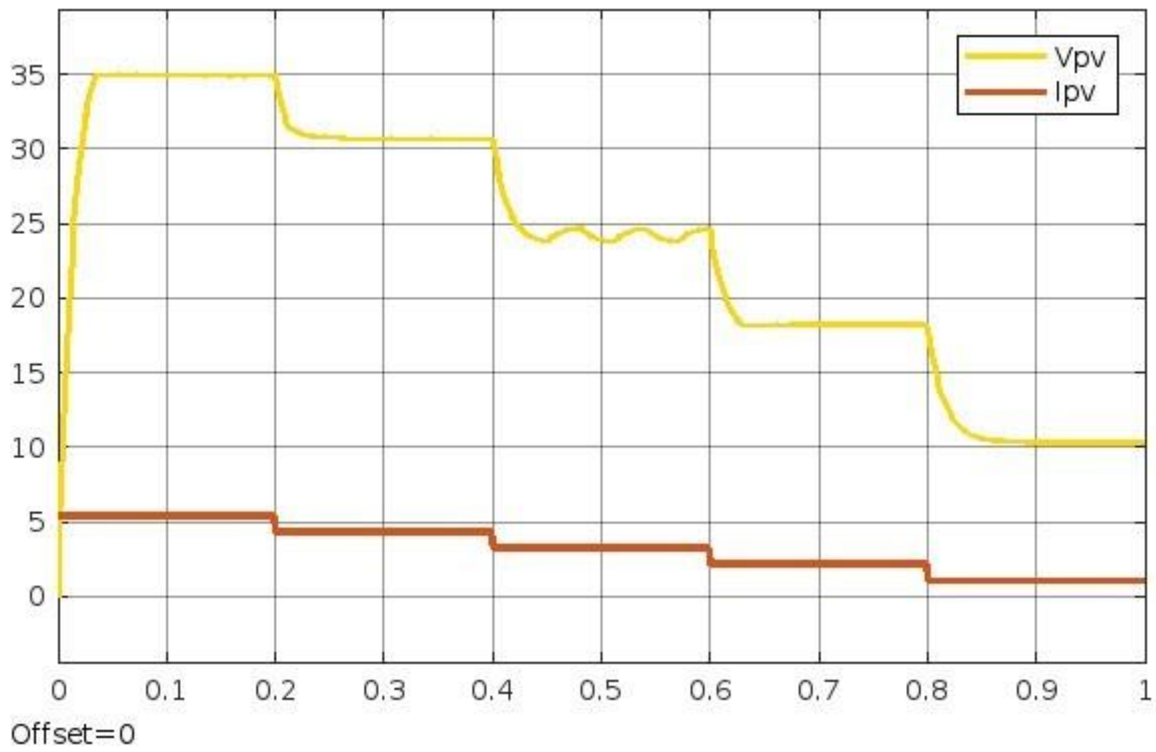


Figure (10) Input Voltage and Input current of P&O MPTT

The duty cycle of the PO algorithm, as shown in Figure (11), undergoes rapid fluctuations due to its continuous perturbation process. This high switching activity increases stress on the power converter and results in reduced overall efficiency.

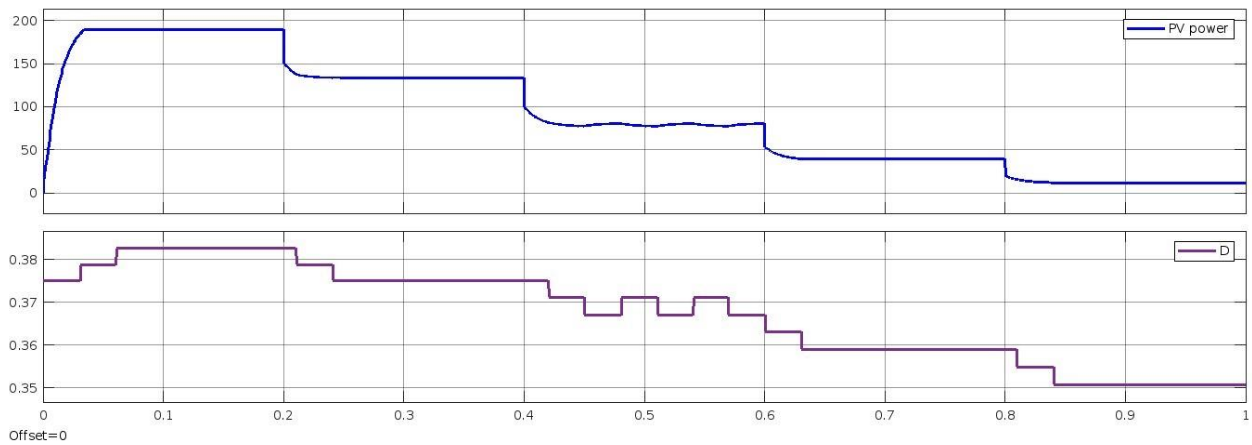
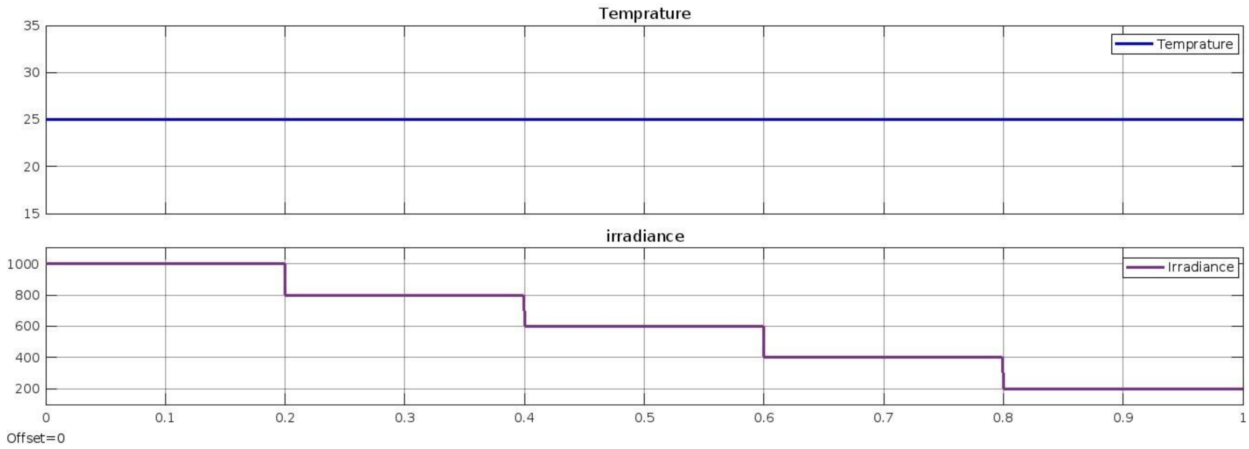


Figure (11) Power Input and Duty cycle of P&O MPTT

Figure 12 represents the variations in temperature and irradiance over a specified time period for a photovoltaic system. The top graph displays the temperature profile, which remains relatively stable, while the bottom graph shows the irradiance levels, characterized by step-wise decreases. These parameters are essential for evaluating the performance of Maximum Power Point Tracking (MPPT) algorithms, as they significantly impact the energy output and efficiency of the PV system. The data is derived from conditions specific to Karabük, providing a realistic context for assessing the effectiveness of different MPPT methods.



Figure

Figure (12) Temprature and Irradiance

Conversely, when using irradiance and temperature data specific to Karabuk, the NN-based MPPT achieves more stable and consistent power input from the PV array. As shown in Figure (13), the power output is smoother and more closely aligned with the true MPP compared to the PO method, demonstrating the NN's enhanced tracking efficiency through its predictive capabilities.

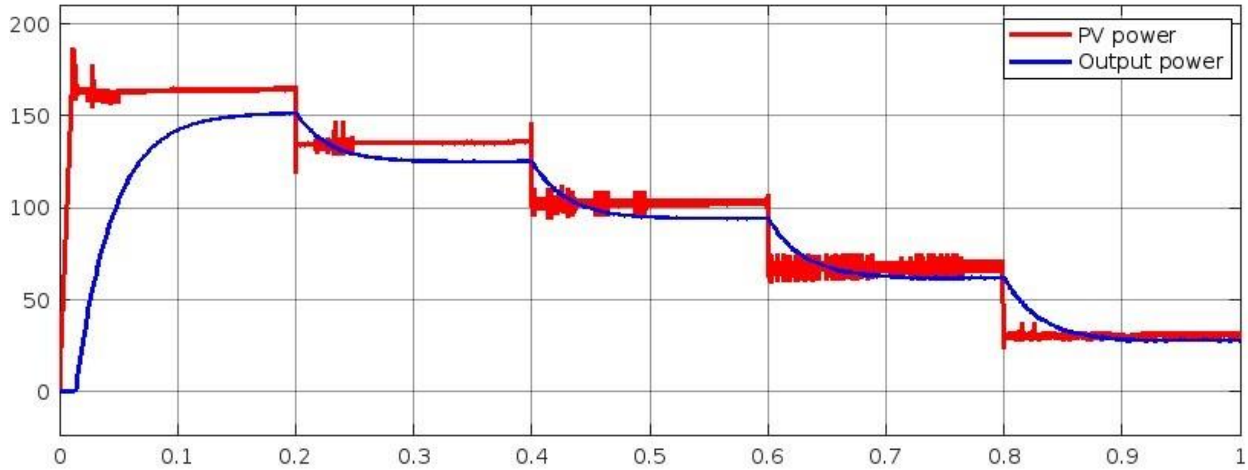


Figure (13) Power Input and Power Output of NN MPTT

In Figure (14), the input and output voltages and currents for the NN-based MPPT exhibit smooth and gradual transitions. This behavior highlights the NN's ability to anticipate and adapt to environmental changes without relying on iterative adjustments. The smoother profiles help reduce stress on the PV modules and the power converter, improving the system's durability and overall performance.

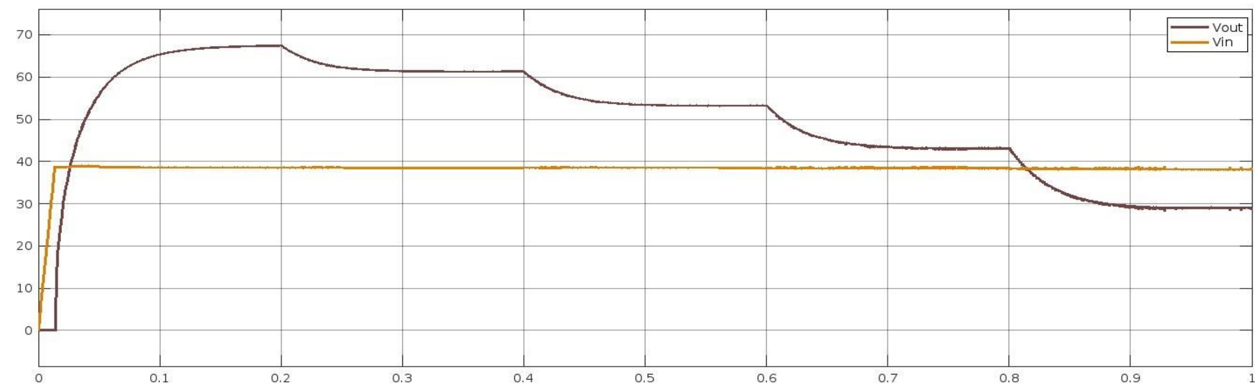


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Figure (14) Input Voltage and output Voltage of NN MPTT

As shown in Figure (15), the NN-based MPPT ensures minimal oscillations and smoother transitions in input voltage. Its predictive capability allows the system to quickly and accurately achieve the optimal operating point, maintaining stability even under dynamic environmental conditions. Similarly, the input current exhibits gradual and stable changes, reflecting the NN controller's capacity to adapt seamlessly to environmental variations. This smooth behavior minimizes stress on the PV array and enhances system efficiency.

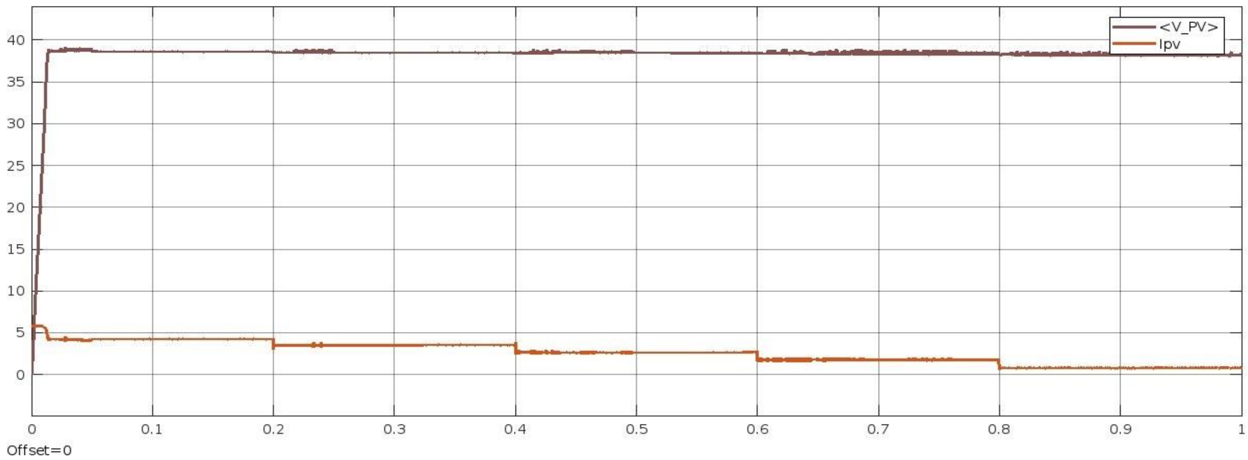

Figure (15) Input Voltage and Input current of NN MPTT

Finally, as illustrated in Figure (16), the duty cycle of the NN-based MPPT shows a significantly smoother trajectory compared to the PO algorithm. This reduced fluctuation results in lower switching losses and improves overall system stability.

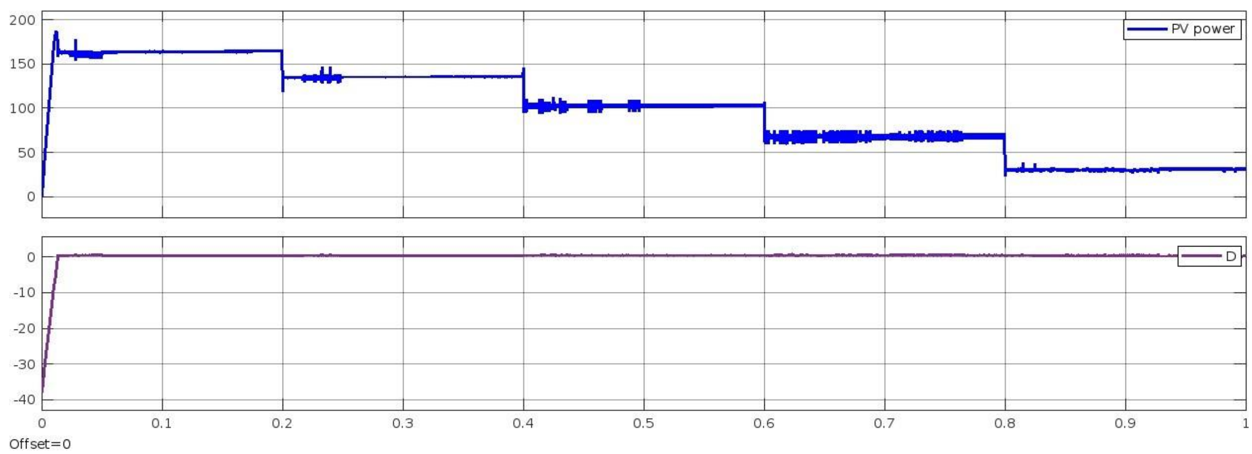

Figure (16) Power Input and Duty cycle of NN MPTT

IV. CONCLUSION

This research demonstrates that the Neural Network (NN)-based MPPT method significantly outperforms the traditional Perturb and Observe (PO) algorithm in terms of efficiency, stability, and adaptability, particularly under dynamic environmental conditions. While the PO algorithm is simple and effective in steady-state scenarios, its inherent oscillations, suboptimal transient behavior, and reduced efficiency in fluctuating conditions limit its overall performance.

In contrast, the NN-based MPPT leverages predictive capabilities to deliver faster, smoother, and more stable tracking of the Maximum Power Point (MPP), even under varying irradiance and temperature. By minimizing oscillations, reducing stress on PV modules and power converters, and enhancing overall efficiency, the NN-based approach proves to be a robust and reliable solution for photovoltaic systems operating in dynamic environments.

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