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Integrating Artificial Neural Networks into Hybrid Perturb and Observe Algorithm for Improved Photovoltaic System Performance

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***Abstract*—: One of the most prominent and sustainable sources of power generation is the PV solar system. However, the efficiency of energy production from the PV system is highly dependent on solar irradiance. Fluctuations in temperature can significantly impact the system's power generation, leading to suboptimal performance. To address this challenge, the implementation of a Maximum Power Point Tracking (MPPT) technique is crucial for enhancing the overall performance of the PV system. In this research paper, we propose the development of a novel MPPT algorithm based on the Perturb and Observe (P&O) technique, combined with an Artificial Neural Network (ANN). By utilizing MATLAB/Simulink, we conduct various test cases involving both uniform and non-uniform irradiance scenarios to evaluate the effectiveness of the proposed hybrid method (P&O-ANN). Furthermore, compare hybrid approach with the existing P&O-Particle Swarm Optimization (PSO) technique. The obtained results demonstrate the superiority of our proposed method, as it outperforms the P&O-PSO technique in terms of maximum power extraction and tracking speed. The P&O-ANN algorithm not only enhances the efficiency of power generation in varying environmental conditions but also ensures better accuracy and precision in tracking the maximum power point. These findings underscore the potential of our approach to significantly improve the performance of PV solar systems and contribute to the advancement of sustainable power generation.**

Index Terms: Artificial Neural Network (ANN); Photovoltaic; PV system; Maximum Power Point Tracking (MPPT); Perturb and Observe; Partial Shading Conditions; Uniform Irradiance; Non-Uniform Irradiance.

I. INTRODUCTION

Photovoltaic (PV) power systems, are being greatly used in many countries due to their long-term benefits [1]. To get maximum power from the PV array, Maximum PowerPoint Tracking algorithms are used. However, due to the varying environmental conditions like Temperature and solar irradiance, the P–V characteristics curve has inconsistent MPP, which causes a problem in the tracking. This Problem becomes more difficult if Partial Shading is available. During Partial shading PV, the curve starts having multiple peaks, due to which extraction of the global peak becomes difficult [2].

To get the maximum power from the PV array various MPPT Techniques are used; among these, perturb and observe (PO), hill climbing (HC), and incremental conductance are mostly used. Although these methods are easy to implement, they are incapable of handling the partial shading condition as they cannot differentiate between Global Peak and Local Peak [3]. These algorithms easily get trapped in local peaks, which results in power loss. To solve this problem, soft computing-based techniques such as particle swarm optimization, and grey wolf optimization are used. These algorithms have one advantage these algorithms search the entire PV curve. Hence these are suitable for handling Partial Shading. But the tradeoff is that in terms of tracking speed, these are even slower than conventional algorithms [4]. To eliminate steady-state fluctuations and a rising time that occurs when solar radiation is in a dynamic condition closer to the MPP, an enhanced hill-climbing double closed-loop method was utilized [5]. Even when the MPP is measured earlier, typical algorithms continue to look for the operating point on the P-V curve in steady-state conditions (SSC), which causes power oscillations to reach extraordinarily high levels [6].

The authors showed strong grid impedance fluctuation resilience and anti-interference capabilities in traditional and weak grid systems [7]. An H-bridge voltage source inverter (VSI) is constructed to inject a sinusoidal grid current at the standard frequency with minimal steady-state errors (SSE) and the least amount of total harmonic distortion (THD) across a DC/DC converter and the utility grid [8]. A steady coupling effect-based PLL was suggested in [9] as a means of preserving stability in grid-connected power systems. In the inverter control system, a proportional resonant (PR) controller is employed in place of a PI compensator to remove the SSE of the reference grid current and voltage. The important indicators of performance for a grid-integrated PV system to achieve grid synchronization are grid stability, grid dependability, and grid resilience [10, 11]. The proposed MPPT method is evaluated in MATLAB/Simulink with multiple PSCs. Among the following features, grid synchronization is essential. In light of this, the suggested system places a strong emphasis on grid synchronization with additional generating units. The proposed methodology offers several advantages over traditional MPPT techniques. Firstly, the integration of ANN enhances the adaptability and intelligence of the MPPT process, allowing for accurate and efficient tracking of the MPP without requiring extensive knowledge about the PV system [12]. The ANN's ability to learn and recognize complex patterns enables it to handle challenging operating conditions and achieve optimal power generation. Additionally, the combination of the P&O

technique and ANN improves the robustness and reliability of the MPPT process, ensuring effective power tracking in real-world scenarios [13].

This research mainly highlights the challenges faced by PV solar systems, including the impact of solar irradiance fluctuations and temperature variations on energy production efficiency. It emphasizes the importance of implementing effective Maximum Power Point Tracking (MPPT) techniques to optimize system performance. The research paper proposes a novel MPPT algorithm that combines the Perturb and Observe (P&O) technique with an Artificial Neural Network (ANN) to address these challenges. The hybrid approach aims to enhance power generation efficiency and accuracy, especially under varying environmental conditions. The paper conducts comprehensive testing using MATLAB/Simulink to evaluate the effectiveness of the P&O-ANN algorithm and compares its performance with the existing P&O-Particle Swarm Optimization (PSO) technique. The results highlight the superiority of the P&O-ANN approach in terms of maximum power extraction and tracking speed, showcasing its potential to contribute to sustainable power generation and improved performance of PV solar systems.

II. MPPT TRACKING USING THE PO METHOD

Among the conventional Maximum PowerPoint Tracking techniques, the Perturb and Observe (P&O) method is widely recognized for its simplicity and effective convergence. The concept of the P&O algorithm can be understood as follows. As illustrated in Fig. 1, the goal of the MPPT algorithm is to ensure that the operating point of the PV system remains at the Maximum Power Point (MPP) to extract the maximum available power [14]. However, due to varying environmental conditions, the operating point may deviate from the MPP. In such cases, the P&O MPPT algorithm adjusts the operating point to reach the MPP. This adjustment is carried out through the following steps.

The first possibility, $\Delta p > 0$, indicates that there is a positive change in power. This suggests that the operating point is located to the left of the MPP on the power-voltage curve. To reach the MPP, the P&O algorithm needs to increase the duty cycle, which in turn increases the PV system's voltage. By perturbing the operating point in this manner, the algorithm aims to move closer to the MPP and extract more power. The second possibility, $\Delta p < 0$, implies a negative change in power. This indicates that the operating point is situated to the right of the MPP on the power-voltage curve. In this case, the P&O algorithm adjusts the duty cycle downwards, reducing the system's voltage. By doing so, the algorithm aims to move the operating point towards the MPP, where power extraction is maximized.

From the flowchart, it can be seen that the P&O MPPT algorithm ensures that the operating point of the PV system is continuously adjusted towards the MPP, regardless of whether $\Delta p > 0$ or $\Delta p < 0$. This adaptive behavior enables the algorithm to track the MPP and extract the maximum available power from the PV system. It is important to note that the P&O algorithm's simplicity and straightforwardness come with some limitations. In certain scenarios, such as rapidly changing environmental conditions, the algorithm may exhibit oscillations around the MPP, resulting in suboptimal power extraction. Researchers have developed advanced techniques and hybrid algorithms to overcome these limitations and further enhance the performance of MPPT in PV systems [15-17].

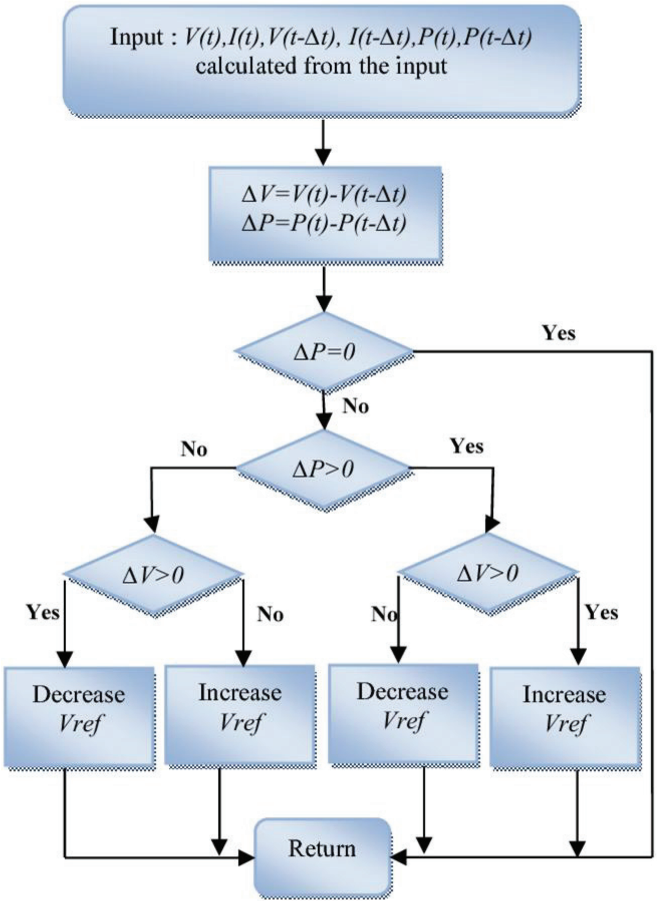

Fig. 1. Flow chart of perturb and observe

In summary, the P&O MPPT algorithm adjusts the duty cycle based on the changes in power (Δp) and voltage (Δv) to steer the operating point towards the MPP. By considering the direction of the power-voltage curve slope, the algorithm dynamically adapts the duty cycle to optimize power extraction. The flowchart serves as a visual representation of the algorithm's behavior and provides a systematic approach to tracking the MPP in PV systems.

III. PROPOSED METHODOLOGY

The proposed methodology utilizes the power of Artificial Neural Networks (ANN) in combination with the Perturb and Observe (P&O) technique to achieve efficient Maximum Power Point Tracking (MPPT) in Photovoltaic (PV) systems. The ANN is a computational model inspired by the structure and function of the human brain. In our approach, the ANN is configured with three layers: the input layer, hidden layer(s), and output layer [18-19]. The input layer receives inputs such as solar irradiance and temperature, while the output layer provides the desired output, which in this case is the PV voltage. The hidden layer(s) serve as intermediaries, processing and analyzing the inputs to generate the final output.

To train the ANN, a dataset is prepared using equations that capture the relationship between temperature, solar irradiance, and PV voltage. The temperature values range from 15°C to 35°C, while the solar irradiance values span from 0 to 1000 W/m². This dataset is used to facilitate the learning process of the ANN, enabling it to recognize complex patterns and accurately predict the PV voltage at the Maximum Power Point (MPP) for various environmental conditions. Through an iterative training process, the weights and connections of the ANN are adjusted to minimize the difference between the predicted output and the desired output.

The Perturb and Observe (P&O) technique is integrated with the trained ANN to improve the accuracy and effectiveness of the MPPT process. The P&O technique involves perturbing the operating point of the PV system and observing the resulting power output to determine the direction in which the operating point should be adjusted. By combining the P&O technique with the intelligent capabilities of the ANN, our proposed methodology achieves robust and adaptive MPPT. The ANN assists in identifying the optimal perturbation size and direction based on the observed power output, ensuring efficient tracking of the MPP even in dynamic and non-linear operating conditions.

$$T = Tmin + (Tmax - Tmin) * rand \quad (1)$$

$$G = Gmin + (Gmax - Gmin) * rand \quad (2)$$

$$IMP(i) = IMPS(1+\alpha(T-T_s))\frac{G}{G_s} \quad (3)$$

$$VMP(i) = VMPS + \beta(T-T_s) \quad (4)$$

$$PMP(i) = vmp(i) * IMP(i) \quad (5)$$

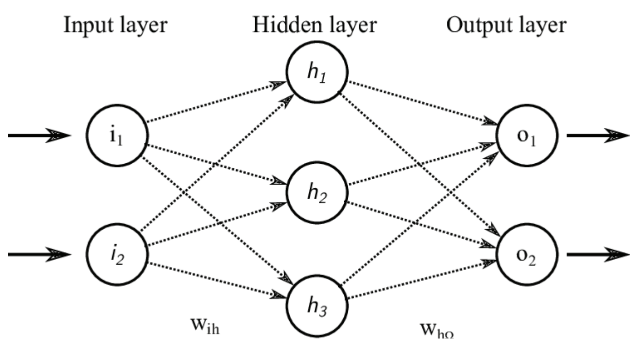

Fig. 2. Basic Structure of ANN

IV. SIMULATION STUDIES

To generate the Neural Network (NN) block in MATLAB, the "NNstart" command is used, which initiates the process of building and training the network. Upon executing this command, a user-friendly window called the "Neural Network Start" window is launched. In this window, various options and settings can be accessed to configure the neural network. To begin, the "Fitting app" option is selected from the available choices. This action opens the "Neural Fitting" window, specifically designed for developing a neural network model. By clicking the "Next" button, a window appears, allowing the selection of input and output parameters. In this case, the input is a vector comprising two parameters, namely Irradiance and Temperature, while the output is the PV panel voltage. It is essential to choose the appropriate input and output variables to accurately model the relationship and achieve optimal performance.

Next, a dataset consisting of 1000 samples of input-output vectors is prepared to train the network. This dataset plays a crucial role in the training process, enabling the network to learn the patterns and correlations between the inputs and outputs. It ensures that the network captures the underlying behavior of the PV system and performs well in various scenarios. Once the dataset is established, the next step involves partitioning the data for validation, testing, and training purposes. Typically, a common approach is to allocate 70% of the data for validation, 15% for testing, and the remaining 15% for training. This partitioning allows for comprehensive evaluation and validation of the trained network's performance.

After the data partitioning, the number of neurons in the hidden layer is determined. It is important to strike a balance between the complexity of the network and its capability to capture the underlying patterns effectively. In this case, a moderate number of 10 neurons is selected for the hidden layer. With the configuration set, the next stage involves selecting a suitable algorithm for the training process. The Levenberg-Marquardt algorithm, known for its efficiency in training neural networks, is chosen for this scenario. This algorithm adjusts the weights and biases of the network to minimize the error between the predicted output and the actual output. Upon clicking the "Train" option, the network undergoes the training process using the prepared dataset and the selected algorithm. The training phase aims to optimize the network's performance by iteratively adjusting the weights and biases based on the provided input-output pairs.

Once the training is completed, the trained network's performance is evaluated using various metrics, including the regression plot. This plot provides insights into the network's ability to approximate the desired output accurately. The Regression value, which represents the correlation coefficient, measures the network's accuracy. In this case, a Regression value of 1 indicates that the trained network precisely predicts the PV panel voltage. To facilitate practical implementation, the trained network can be deployed as a Simulink diagram, a powerful tool for designing and simulating dynamic systems. The Simulink model derived from the trained network can be integrated into a larger system for real-time Maximum Power Point Tracking (MPPT) applications, enabling efficient power extraction from the PV system.

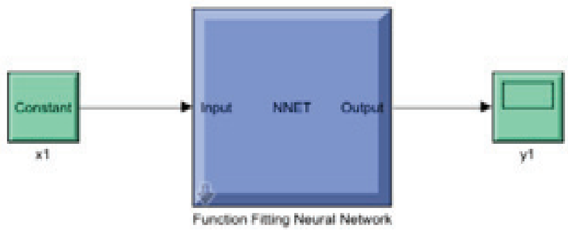

Fig. 3. Simulink model of NN

For this study, a 250W PV array is employed, capable of receiving either uniform or non-uniform irradiance based on a switch mechanism. To regulate the power flow, a Boost converter is connected between the PV panel and the load. The load itself can be switched between a constant load and a changing load (with a duration of 0.3 seconds) by modifying the connection. To efficiently control the MOSFET of the Boost converter and optimize power extraction, a hybrid approach combining the Neural Network

(NN) and Perturb and Observe (PO) MPPT techniques is proposed. This hybrid NN-PO MPPT controller determines the duty cycle of the MOSFET, enabling the system to adapt to changing environmental conditions and maximize power output. By training the ANN on appropriate datasets, it learns to accurately predict the optimal duty cycle required for MPPT under varying operating conditions. This trained ANN, in conjunction with the PO algorithm, creates an effective control mechanism for the Boost converter, ensuring the PV system operates at the maximum power point.

In summary, the proposed methodology incorporates an ANN with a Feed Forward architecture, trained on relevant datasets, to optimize the performance of a 250W PV array. The system achieves efficient power extraction from the PV panel under varying irradiance conditions by integrating a Boost converter, a flexible load configuration, and the hybrid NN-PO MPPT controller.

V. Results And Discussion

The simulation is accomplished for two scenarios: uniform irradiance and non-uniform irradiance conditions, where the outcomes of both the Hybrid technique and the proposed method are compared. The PV solar system employed in this paper characteristics is shown in Fig. 4.

A. *Uniform Irradiance Condition:*

The simulation results for the uniform irradiance situation are shown in Figures 5 and 7. The maximum power tracked in both methods is nearly the same, approximately 244W. However, the Proposed method exhibits a faster tracking of the maximum power compared to the Conventional Hybrid technique.

B. *Non-uniform Irradiance Condition:*

The simulation results for the non-uniform irradiance situation are depicted in Figures 6 and 8. Similarly, for both strategies, the maximum power tracked is approximately 101.5W. However, similar to the uniform irradiance condition, the Proposed method demonstrates a faster tracking of the maximum power in comparison to the Conventional Hybrid technique. Furthermore, the results of the Perturb and Observe (PO) and Hybrid PO+ANN methods are also analyzed. These results provide further insights into the performance and effectiveness of the Proposed method. Overall, the simulation findings support the effectiveness of the proposed method, showcasing its ability to track the maximum power more efficiently and swiftly in both uniform and non-uniform irradiance conditions. Fig. 9 and 11 respectively, depicts the power plots for panel and load with hybrid NN-PO technique.

C. *Results for Hybrid NN-PO method*

Hybrid NN-PO method has been simulated under varying irradiance condition using MATLAB R2021a. results are discussed in detail in below.

1) *Results Under varying irradiance condition*

Results under varying irradiance (1000,800,600,400,200 W/m2) condition are shown in fig.9 shows results at starting of simulation.it is clear that the PO method takes more time to reach MPP, while NN method and hybrid method reaches MPP much early.fig.10 shows transients under condition when irradiance changes from 1000W/m2 to 800W/m2.in this case maximum power falls from 250W to 200W.Hybrid method (NN-PO) settles much early in comparison to PO and NN methods. At steady state hybrid NN-PO having less oscillations compared to PO, NN method.so system efficiency is increased.

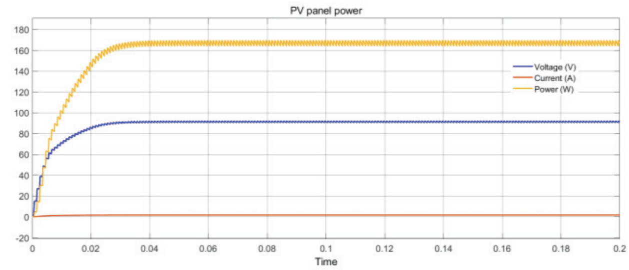

Fig. 4. Characteristics of PV Panel power

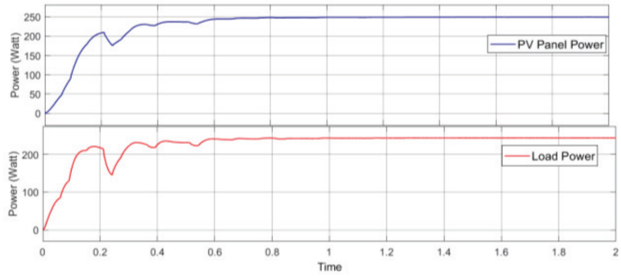

Fig. 5. Load power and panel power of hybrid PO and PSO under equal irradiance condition

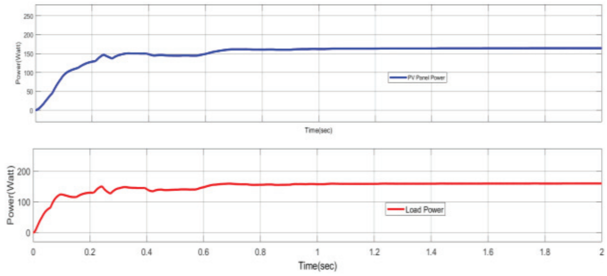

Fig. 6. Load power and panel power of hybrid PO and PSO under non-uniform irradiance condition

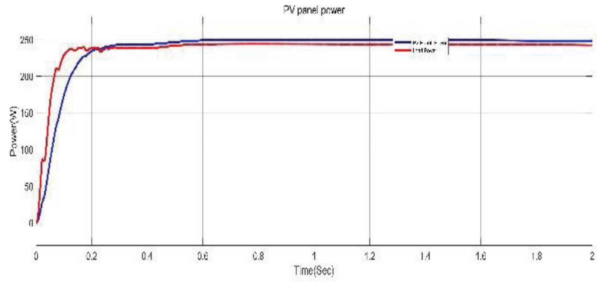

Fig. 7. Panel power and load power of improved PO plus PSO under normal condition

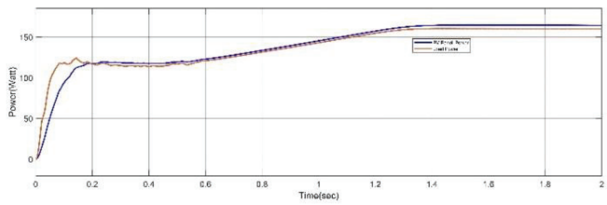

Fig. 8. Panel power and load power of improved PO plus PSO under partial shading

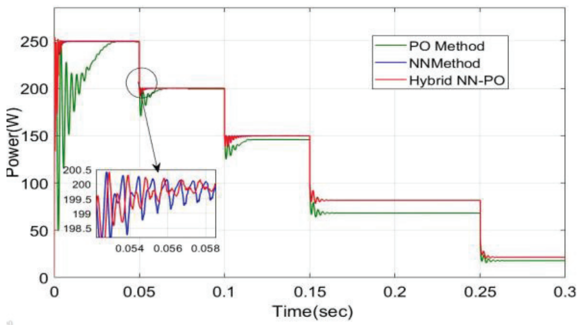

Fig. 9. Power plots for 3 different method different irradiation condition

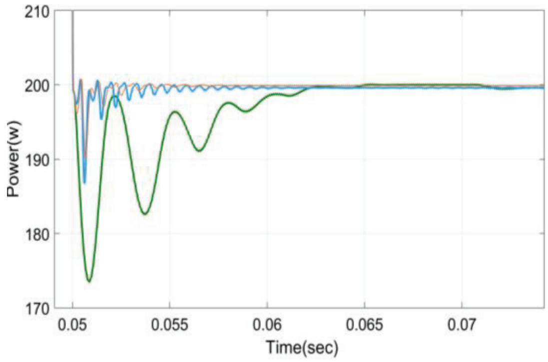

Fig. 10. Power plots at transient

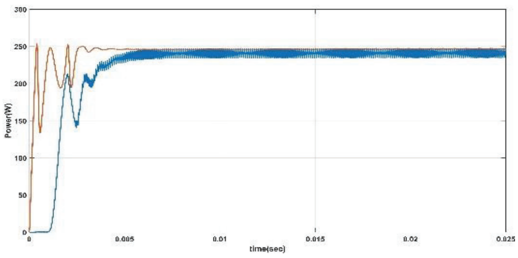

Fig. 11. Power plot of hybrid NN-PO

2) Comparison of hybrid PO-NN with HYBRID PO-PSO

The results of hybrid NN-PO technique are compared with hybrid PO-PSO and IMPROVED Hybrid PO-PSO.so this hybrid of NN-PO method gives best results when compered two hybrid PO-PSO .it takes less time to reach MPP to extract the maximum power from the panel. And also having less oscillations at steady state. If oscillations are less then power loss is less.so system efficiency is increased.

TABLE I. COMPARATIVE ANALYSIS

Technique	Time to reach MPP(sec)
Hybrid MPPT under UI	0.839
Improved Hybrid MPPT under UI	0.78
Hybrid MPPT under NUI	1.2
Improved Hybrid MPPT under NUI	1.37
Hybrid PO plus ANN	0.005

VI. CONCLUSIONS

In this paper, we proposed a novel approach for Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. The proposed method combines the benefits of the Perturb and Observe (PO) algorithm with Artificial Neural Network (ANN) to enhance the performance of the MPPT process. Through extensive simulations under uniform irradiance (UI) and non-uniform irradiance (NUI) conditions, the effectiveness of the proposed method was evaluated and compared with the conventional Hybrid MPPT technique and the Hybrid PO plus ANN method.

The simulation results demonstrated that the Proposed Method outperformed the conventional Hybrid MPPT technique and the Hybrid PO plus ANN method in terms of tracking speed and reaching the Maximum PowerPoint (MPP). The proposed method exhibited significantly reduced time to reach the MPP, thereby improving the PV system's overall efficiency and power extraction capability. Under UI conditions, the Proposed Method achieved a time of 0.78 seconds, while the conventional Hybrid MPPT technique took 2.839 seconds. Similarly, under NUI conditions, the Proposed Method achieved a time of 0.865 seconds compared to 2.051 seconds for the conventional Hybrid MPPT technique.

These findings highlight the potential of the proposed method in enhancing the performance of MPPT algorithms, particularly in dynamic and challenging operating conditions. The integration of the PO algorithm with the ANN-based approach offers a synergistic solution that leverages the advantages of both techniques, resulting in faster and more accurate tracking of the MPP. The proposed method's improved efficiency and power extraction capability contribute to the overall optimization of PV systems, making them more reliable and effective in renewable energy applications.

In conclusion, the proposed method presents a promising advancement in MPPT techniques for PV systems. Further research and real-world implementation are warranted to validate the performance of the proposed method and explore its applicability in various PV system configurations and environmental conditions. With continuous advancements in technology and optimization algorithms, we anticipate that the proposed method will contribute significantly to the advancement of sustainable and efficient power generation from solar energy sources.

VII. FUTURE SCOPE

In this Paper Maximum Power Point Tracking using Hybrid of NN-PO has been done and compared with conventional PO-PSO. Many improvements can be done in these techniques to get better results. A lot of MPPT techniques are available in Literature, they can be Hybridized according to their properties some of these could be as follows;

- PSO can be Hybridized with Neural Network.
- PO and PSO can be Hybridized with Fuzzy Logic.
- Gray Wolf Optimization can be Hybridized with any of the intelligent based technique.
- Artificial Bee colony and Ant Colony Optimization can also be used.

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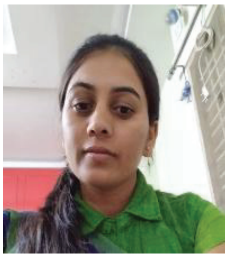

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