

An efficient ANN-based global maximum power point searching approach for solar PV system under partial shading conditions

Lakshminarayana Munirathnam¹, Yogeesh Amabalagere Chandrashekaraiah², Somu Pundalik Parande³, Vani Bengaluru Purushothama⁴, Ramya Mullur Varadhanayaka⁵, Bellary Kursheed⁶

¹Department of Medical Electronics Engineering, M.S. Ramaiah Institute of Technology, Bengaluru, India

²Department of Computer Science and Engineering, Government Engineering College (Affiliated to Visvesvaraya Technological University), Chamarajanagar, India

³Department of Electronics and Communication Engineering, Basaveshwara Engineering College, Bagalkot, India

⁴Department of Computer Science and Engineering (Data Science), Sai Vidya Institute of Technology, Visvesvaraya Technological University, Bengaluru, India

⁵Department of Robotics and Automation, JSS Academy of Technical Education, Bengaluru, India

⁶Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Don Bosco Institute of Technology, Bengaluru, India

Article Info

Article history:

Received Oct 10, 2025

Revised Aug 27, 2026

Accepted Sep 4, 2026

Keywords:

Artificial neural networks
Global maximum power point
Maximum power point tracking
Partial shading conditions
Solar photovoltaic

ABSTRACT

For solar photovoltaic (PV) systems operating in partial shading conditions (PSCs), this research suggests a simplified maximum power point tracking (MPPT) controller based on artificial neural networks (ANNs). By adding multiple local peaks (LPs) to the power-voltage (P-V) curve, PSCs make it impossible for traditional techniques to follow the global maximum power point (GMPP), which results in substantial energy loss and decreased system reliability. In order to overcome this, a DC-DC boost converter's (BC's) duty cycle is adaptively controlled by the suggested ANN-based controller for precise GMPP tracking. Three shading scenarios are used to validate the approach on a 3×2 PV array. According to simulation results, tracking efficiency is higher than 99.4% and overall system efficiency is higher than 99.3%. The ANN greatly reduces oscillations around the GMPP by achieving quick convergence (<16 ms) with little power loss (<4 W). These findings demonstrate that the suggested method is a dependable option for real-time PV applications under dynamic environmental settings, outperforming traditional MPPT techniques in terms of speed, accuracy, and stability.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Lakshminarayana Munirathnam

Department of Medical Electronics Engineering, M.S. Ramaiah Institute of Technology

Bengaluru, Karnataka, India

Email: lakshminarayana@msrit.edu

1. INTRODUCTION

The most popular power production choice today is renewable energy because of its minimal carbon footprint, excellent efficiency, scalability, and lower production expenses than traditional energy systems. They fall into four primary categories: solar, wind, tidal, and fuel cells [1]. Although wind energy is extensively utilized, its usefulness is limited by its unpredictability and intermittency [2]. As a result, solar or photovoltaic (PV) systems are now being studied more as a reliable substitute. Applications including street illumination, water distribution, solar vehicles, and remote wireless networks with restricted grid access are all seeing an increase in the utilization of PV systems [3], [4]. However, because of equipment expenditures, PV-generated power is still more costly than grid power. Enhancing solar power efficiency without requiring

costly hardware updates is possible through enhancing the maximum power point tracking (MPPT) approach [5], [6]. Partial shading conditions (PSCs) cause the power–voltage (P–V) curve to show several local peaks (LPs) and one global peak (GP) because temperature and irradiance have a significant impact on PV arrays. For dependable functioning, it is consequently crucial to track the global maximum power point (GMPP) accurately [7], [8].

Numerous MPPT techniques have been put forth to improve PV systems' effectiveness under PSCs [9], [10]. The most extensively researched and used MPPT approaches under uniform irradiance conditions (UICs) are still the conventional ones, such as incremental conductance (IC) [11] and perturb and observe (P&O) [12]. However, when PSCs are applied to the PV system, these traditional techniques often fail to detect the GMPP. To overcome this restriction, several sophisticated MPPT techniques have been developed to precisely track the GMPP in these challenging conditions [13]. For instance, the fractional-order approach and robust fuzzy logic (FL) control are used in the MPPT strategy suggested in [14] to increase tracking efficiency in the face of changing weather. However, FL-based approaches have inherent drawbacks: choosing a suitable fractional-order factor necessitates a careful trade-off between tracking precision and response speed, and their rule tables rely significantly on the designer's experience.

This section covers a few contemporary MPPT techniques under PSCs, using a variety of methods, along with their advantages and disadvantages. The effectiveness, tracking speed, settling time, steady-state behaviour, and oscillations of a variable step size artificial neural network (ANN)-based MPPT method were compared to traditional methods by Kiran *et al.* [15] using a boost converter (BC) to control PV voltage. For PV systems under PSCs, Demirci *et al.* [16] suggested an improved ANN-based MPPT strategy that uses analytical and metaheuristic training techniques to achieve faster convergence and better accuracy. In order to replace computationally demanding MPC, Bana *et al.* [17] developed an ANN-based controller that greatly reduces complexity through streamlined linear formulations. For a 100-kW grid-tied PV system, Younas *et al.* [18] created a deep learning-based stacking long short-term memory (LSTM) MPPT controller that outperformed P&O and FF-DNN techniques. An LSTM-based MPPT framework for intelligent BC control in solar-powered EV charging applications was also introduced by Khan *et al.* [19]. To increase accuracy and resilience, Kesavan *et al.* [20] offered a simplified shadow distribution method that lessens the computational load for $n \times n$ PV arrays. Xia *et al.* [21] developed the anti-fuzzy optimization (AFO) approach, which dynamically adjusts to shading conditions by combining FL and ant colony optimization (ACO). Additionally, intelligent soft computing methods have become more popular. Compared to IC, the adaptive neuro-fuzzy inference system (ANFIS)-based MPPT controller proposed by Türkay and Yüksek [22] has a faster response and fewer oscillations. Hasheminasab *et al.* [23] enhanced active and reactive power exchange in inverter-based systems by extending ANFIS to a virtual impedance controller. In order to achieve precise MPP tracking, hybrid techniques have also surfaced, such as Gandhi and Kumar [24], which integrated P&O, FLC, and PSO. FL, generative adversarial networks (GANs)-based synthetic data generation, and transformer topologies were all combined by Elakkiya *et al.* [25] to create a hybrid MPPT system that was resilient and scalable. A neuro-fuzzy fractional-order sliding mode controller (SMC) was developed by Ullah *et al.* [26]. It was verified by experiments and Lyapunov stability, showing notable gains in accuracy and energy extraction in the presence of surrounding instabilities.

Shaikh *et al.* [27] demonstrate greater efficiency than filter-based and PI-controlled systems by suggesting a modified sliding mode control (MSMC) for the smooth integration of PV-derived DC power into the AC grid via an inverter. A GAN-based inverter with a hybrid PLL-SMC is introduced by Soomar and Musznicki [28], improving PV grid integration with 5% total harmonic distortion (THD) and 99.1% MPPT efficiency. A thorough analysis of MPPT strategies is given by Guanhua *et al.* [29], who classify them into classical, adaptive, and hybrid approaches and emphasize trade-offs between computing complexity, simplicity, and accuracy under various environmental situations.

Problem statement: accurate GMPP tracking is a difficult issue because PSCs produce many local maxima in the P–V features that distinguish solar PV systems. Due to their propensity to become caught in LPs, traditional MPPT strategies like P&O and IC fail under PSCs, leading to decreased energy harvesting and system inefficiencies. While sophisticated techniques based on ANN and ANFIS have been put forth, many of these approaches have issues with implementation in real-time systems, sluggish convergence, and high computing complexity. Consequently, a straightforward, quick, and computationally effective MPPT system that can reliably track GMPP under a variety of shading situations is required. In order to close this gap, this work suggests a lightweight ANN-based MPPT controller that guarantees quick convergence, less oscillations, and excellent accuracy. The suggested method outperforms traditional and hybrid MPPT techniques with efficiency surpassing 99% under PSCs while remaining simple to apply for real-world PV applications.

Contribution: the efficiency of an MPPT technique based on ANNs under various environmental conditions is examined in this study using software simulations across three PSCs. In addition to increasing tracking speed, accuracy, and system efficiency, the suggested ANN technique reduces power loss, tracking

loss, and oscillation around the GMPP by minimizing early oscillations during the tracking process. The ANN's straightforward GMPP search approach guarantees reliable operation even in the presence of PSCs, increasing the amount of energy extracted from the PV system. This work's contributions can be summed up as follows: this work suggests a lightweight and simplified ANN-based MPPT architecture that uses a compact (2–3–1) feedforward structure integrated with a deterministic GMPP searching mechanism in contrast to current ANN and deep learning techniques. This reduces computational complexity while maintaining high accuracy. The suggested method allows for quick convergence, few oscillations, and low implementation overhead, which makes it appropriate for real-time applications, in contrast to earlier approaches that depend on intricate training models or big datasets. The hybridization of a threshold-based GMPP search with ANN-driven duty cycle management, which guarantees dependable tracking under PSCs with decreased tracking and power losses, is the main engineering contribution. The approach offers a useful and scalable substitute for traditional and intelligent MPPT approaches, demonstrating >99% efficiency, enhanced tracking speed, and stable operation across various shading circumstances. The following is an overview of the paper. Section 2 discusses the MPPT technique for PV systems that use an ANN controller. Simulation experiments and performance assessment using PSCs are covered in section 3. The overall conclusions are summarized in section 4.

2. METHOD

The solar PV module produces P-V and voltage-current (V-I) attributes in a variety of environmental situations, such as temperature and irradiance variations, especially when there are PSCs. It is difficult to determine the MPP from the P-V curve under these circumstances since there may be several LPs. An ANN-based MPPT control technique is used to track the GMPP and optimize the PV array's power to solve this problem. The suggested approach increases the effectiveness and dependability of MPP tracking by calculating the duty cycle (D) via the ANN controller and applying it to the BC via a pulse width modulation (PWM) generator. A 3×2 solar PV array with series-parallel (SP) connections makes up the system architecture; each module can generate 120 W. The solar PV array, an ANN-based MPPT controller, a PWM generator, a BC with load connection, and the GMPP searching strategy are the main elements of the model. The PV array uses temperature and irradiance inputs to determine output voltage (V), current (I), and power (P) values.

The GMPP search mechanism receives these parameters and uses the ANN-based MPPT controller to calculate the ideal duty cycle (D). The PWM generator, which produces gate pulses to drive the insulated-gate bipolar transistor (IGBT) in the BC, is then given the duty cycle while running at a switching frequency of 20 kHz. The BC regulates the output by varying the duty cycle, serving as an interface between the PV array and the load. Stable and effective transmission of power to the load resistor is ensured by the converter, which raises the input PV voltage to the required DC output level. In addition to improving GMPP monitoring performance under PSCs, its architecture guarantees lower oscillations, increased system efficiency, and more PV system energy extraction. The MPPT framework based on an ANN controller for the suggested solar PV system is shown in Figure 1.

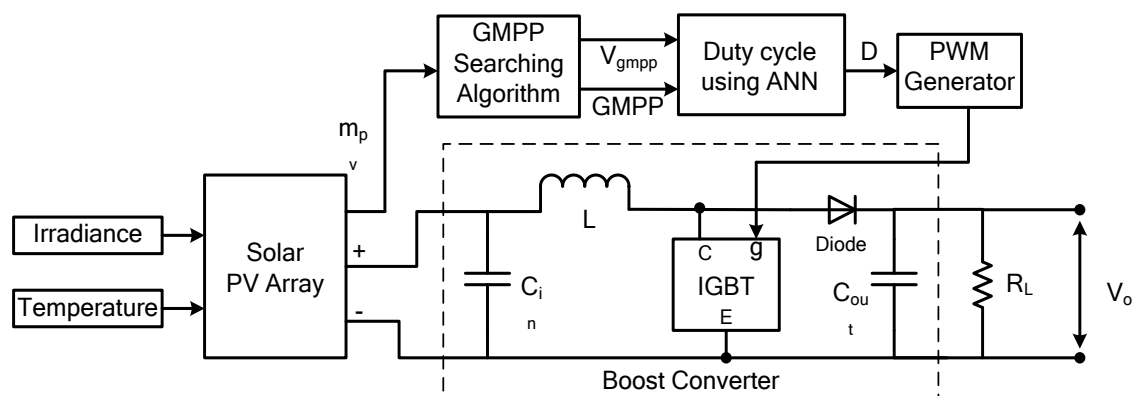


Figure 1. The proposed ANN controller-based MPPT method for the solar PV system

2.1. Global maximum power point searching algorithm

A method of tracking the GMPP for a standalone solar PV system is put into practice. It combines an ANN controller with searching. Finding the GMPP and the associated voltage V_{gmpp} is the main objective of the search algorithm. After that, the ANN is activated to supply the correct D. Algorithm 1 illustrates the GMPP searching approach's flow. PV power (P_{pv}), PV voltage (V_{pv}), and PV current (I_{pv}) are generated by the solar PV array. Determine the ΔP and the difference between the PV powers $P_{pv}(s)$ and the previous $P_{pv}(s-1)$ first. The procedure for searching is initiated each time the irradiance changes. The change in irradiance is detected if the P_{pv} fluctuation ΔP surpasses a suitable threshold (TH) that customers have selected depending on the PV array configuration. Because simulation results show that the power change is greater than 0.95 W every time the irradiance changes, the reset condition is set to $\Delta P \geq 0.95$.

Only when the $\Delta P \geq 0.95$ will the $GMPP(s-1)$ and $V_{gmpp}(s-1)$ be reset and returned to the initial phase. The searching algorithm extracts the greatest power in terms of $GMPP(s)$ and its related voltage $V_{gmpp}(s)$ when the power $P_{pv}(s)$ is compared to the prior power $P_{pv}(s-1)$ and $GMPP(s-1)$ is zero. GMPP will be tracked if the power $P_{pv}(s)$ exceeds its $GMPP(s-1)$; if not, the earlier $GMPP(s-1)$ and voltage $V_{gmpp}(s-1)$ are regarded as the final GMPP (s) and voltage $V_{gmpp}(s)$. Until the $V_{gmpp}(s)$ and $GMPP(s)$ are tracked, the procedure is repeated.

Algorithm 1. GMPP searching algorithm

Input: $V_{pv}(s), I_{pv}(s)$;

Output: $GMPP(s), V_{gmpp}(s)$;

Start

1. Calculate $P_{pv}(s)$ and ΔP ;
 2. $P_{pv}(s) = V_{pv}(s) * I_{pv}(s)$;
 3. $\Delta P = P_{pv}(s) - P_{pv}(s-1)$;
 4. **If** ($\Delta P \geq TH$)
 5. Initialize: $GMPP(s-1) = 0$; $V_{gmpp}(s-1) = 0$;
 6. **End**
 7. **If** ($P_{pv}(s) \geq P_{pv}(s-1) \ \&\& \ GMPP(s-1) = 0$)
 8. $GMPP(s) = P_{pv}(s)$;
 9. $V_{gmpp}(s) = V_{pv}(s)$;
 10. **Else**
 11. **If** ($P_{pv}(s) > GMPP(s-1)$)
 12. $GMPP(s) = P_{pv}(s)$;
 13. $V_{gmpp}(s) = V_{pv}(s)$;
 14. **Else**
 15. $GMPP(s) = GMPP(s-1)$;
 16. $V_{gmpp}(s) = V_{gmpp}(s-1)$;
 17. **End**
 18. **End**
 19. **Update**: $GMPP(s)$ and $V_{gmpp}(s)$;
- End**

2.2. Artificial neural network-based duty cycle generation

An ANN is a numerical or mathematical framework that is modelled after the structure and/or functions of biological neural networks (BNNs). It is recognized as a technology that takes a unique approach to difficult problems. The advantages of the ANN approach are greater than those of the conventional methods. The disadvantage of the conventional method is that it sometimes fails to track MPP and reacts slowly to PSCs. The ANN operation is illustrated in Figure 2. Figure 2(a) illustrates the three-layer (2-3-1) feed-forward NN that was developed for the present work. The two neurons that comprise the input layer are the produced GMPP and V_{gmpp} of the searching technique. The second layer consists of three neurons with sigmoid activation functions, which are known as the hidden layer. One neuron with a linear activation function provides the D in this output layer. To train NNs, MATLAB's nntool is utilised. 100 epochs and 3,000 samples are taken into consideration for NN training. The NN training process is shown in Figure 2(b). The algorithm developed by Levenberg and Marquardt uses training to acquire the NN. The V_{gmpp} and GMPP have two functions. In addition to being employed as input–target pairs to update weights during the

Levenberg–Marquardt (LM) training phase, they serve as inputs to the ANN network for duty cycle prediction. As a result, the trained network utilizes them for inference and LM uses them for learning.

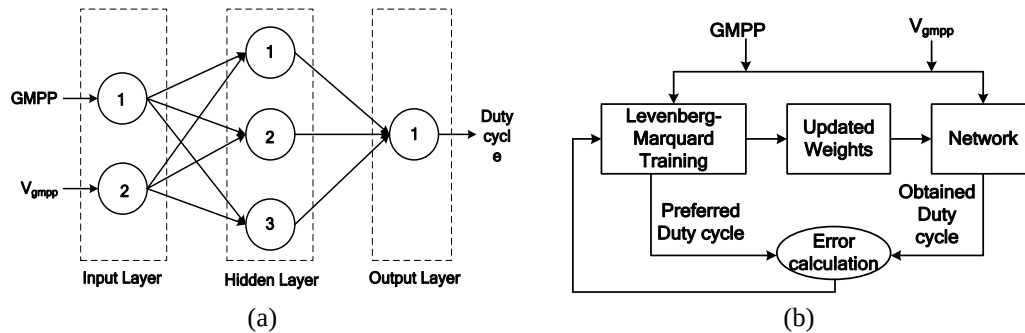


Figure 2. ANN operation, including; (a) ANN structure and (b) NN training process

The procedure of changing the NN's weight is called training. To increase a NN's efficiency, its weights are altered throughout training. Throughout training, the hyperlink weights are changed until the input-output arrangements that suit the data the best with the fewest errors are found. The efficiency in our case is measured by mean squared error (MSE). To lower the MSE (up to 10^{-8}), the synaptic weights are altered. However, the training process requires a set of examples that show appropriate network behaviour inputs and target outputs. The current study trains the ANN for a specific kind of PV module using a dataset (GMPP, V_{gmpp} , D) that covers a range of conditions. The ANN was trained using 3,000 samples generated under irradiance levels of 300–1,000 W/m² and temperature of 25 °C. Training used the LM algorithm with a learning rate of 0.01, batch size of 32, and 100 epochs. Performance was validated using 70% training, 15% validation, and 15% testing splits.

Since the ANN learns module-specific nonlinear mappings, retraining is typically necessary if the PV module properties (e.g., I-V curve and ratings) change dramatically. This can be lessened, though, by training with a generalized dataset that includes several PV modules, increasing model adaptability, and decreasing the frequency of retraining. The chosen range reflects real-world operational circumstances where GMPP tracking is essential and PV systems produce substantial electricity. These areas give marginal power even if shading may limit irradiance to 100–200 W/m². Nevertheless, the ANN's nonlinear learning capabilities allows it to generalize to lower values. High prediction accuracy was demonstrated by the ANN's minimal MSE of 10^{-8} . Using the LM approach, the training converged in less than 100 epochs.

3. RESULTS AND DISCUSSION

MATLAB/Simulink is used to simulate and study the suggested ANN controller-based MPPT technique. This study takes into account the Waaree Energies WU-120 solar PV module, which is anticipated to generate 120.7 W of power. For the BC's MPPT technique, the sampling time is set at 0.01 s since MPP observations need to be made after the system has reached the steady-state condition. To prevent failure, this number was selected to account for the transient response of the MPPT inputs, such as the GMPP and V_{gmpp} . The partial shading patterns (SP-1–SP-3), simulation intervals, and matching maximum GMPP power results are shown in Table 1. A 3×2 PV array was subjected to three different irradiance combinations to simulate actual PSC situations. The maximum power outputs for SP-1, SP-2, and SP-3 were 271.4 W, 480.2 W, and 316 W, respectively, following the successful identification and tracking of the GMPP for each case by the ANN-based controller. The substantial output power fluctuation demonstrates that PV performance is reliant on irradiance uniformity and the ANN controller's flexibility in the face of quickly shifting conditions. Simulation observations were used to empirically define the threshold value (TH=0.95), where any change in irradiance consistently resulted in a power variation greater than this amount, allowing for the accurate identification of PSC transitions. The TH is system-dependent and requires being flexibly adjusted or normalized (e.g., as a % of rated power) to generalize across various PV array sizes and ratings, even if it works well for the specified 3×2 PV arrangement.

The simulation results of the solar PV system under PSCs are illustrated in Figure 3. The PV results and BC output results are illustrated in Figures 3(a) and (b), respectively. The maximum PV power of 270.42 W, 476.85 W, and 314.33 W is extracted using an ANN controller for SP-1, SP-2, and SP-3,

respectively. Similarly, the solar PV system obtains the BC output power of 268.77 W, 472.84 W, and 312.45 W for SP-1, SP-2, and SP-3, respectively.

Table 1. Partial shading patterns under PSCs and peak GMPP power

Pattern no.	Partial shading pattern	Simulation time (sec)	Max. GMPP power (W)
SP-1	[400 700 1000, 400 700 1000]	0 to 0.1	271.4
SP-2	[500 900 500, 500 900 500]	0.1 to 0.2	480.2
SP-3	[600 900 700, 600 900 400]	0.2 to 0.3	316

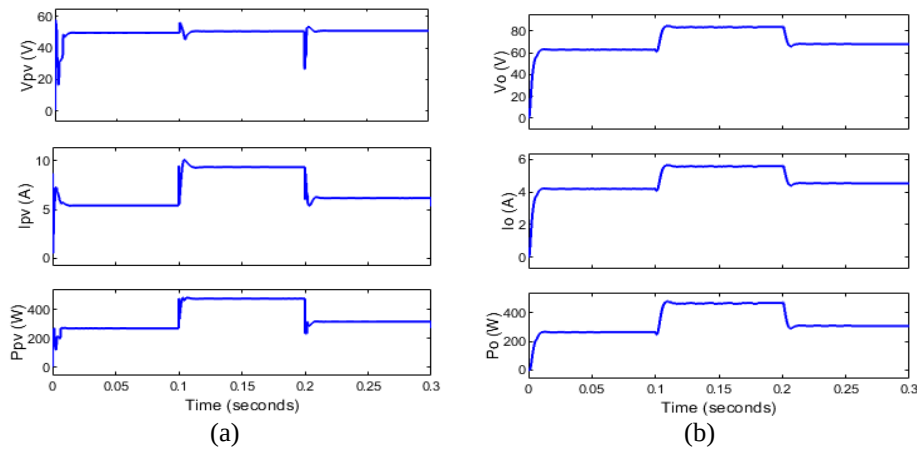


Figure 3. Simulation results of solar PV system under PSCs; (a) PV results and (b) BC output results

The PV array, converter output, and GMPP outcomes under PSCs are shown in detail in Table 2. For SP-1, the output power was 268.77 W, with a GMPP of 271.4 W at 48.45 V and 5.6 A, while the PV array produced 49.8 V and 5.43 A, generating 270.42 W of power. The PV current increased to 9.4 A under SP-2, which had more balanced irradiance. This resulted in a significant increase in PV power to 476.85 W, and the ANN precisely monitored the GMPP at 49.1 V and 9.78 A (480.2 W). The GMPP steadied at 50.48 V, 6.26 A, and 316 W in SP-3, whereas the PV power marginally decreased to 314.33 W, as a result of the uneven irradiance. These findings demonstrate that, even in the presence of several LPs on the PV power–voltage curve, the ANN controller reliably maintains accurate GMPP identification.

The simulation results under PSCs are illustrated in Figure 4. The GMPP versus PV power comparison and duty cycle results are illustrated in Figures 4(a) and (b), respectively. The PSCs tracked GMPP power of 271.4 W at SP-1, 480.2 W at SP-2, and 316 W at SP-3. The system obtains the duty cycle of 0.228, 0.415, and 0.267 using the ANN approach at SP-1, SP-2, and SP-3, respectively.

Table 2. Simulation results of V, I, and P of PV, output and GMPP parameters under PSCs

Parameters	SP-1	SP-2	SP-3
PV voltage (V)	49.8	50.68	51.02
PV current (I)	5.43	9.4	6.16
PV power (W)	270.42	476.85	314.33
Output voltage (V)	63.04	83.9	68.3
Output current (I)	4.264	5.64	4.57
Output power (W)	268.77	472.84	312.45
GMPP voltage (V)	48.45	49.1	50.48
GMPP current (I)	5.6	9.78	6.26
GMPP power (W)	271.4	480.2	316

The primary performance metrics of the ANN-based MPPT controller are evaluated in Table 3 under the same shading circumstances (SP-1–SP-3). The performance analysis of the solar PV system under PSCs is illustrated in Figure 5. The tracking and power losses are shown in Figure 5(a). The tracking and system efficiency of the work is shown in Figure 5(b). The tracking loss is the difference between GMPP power and PV power, whereas the power loss is the difference between PV and output power. The findings demonstrate that the ANN controller tracks the GMPP effectively in every situation with a high degree of precision and a short response time. The duty cycle response time exhibits rapid adaptability, ranging from

2 ms to 6.8 ms, while the tracking time stays below 16 ms. The system efficiency surpasses 99% for every pattern, and the tracking efficiency continuously stays over 99.3%, indicating very little energy waste during tracking. The power loss falls between 1.65 W to 4.01 W, which is remarkably low given the way dynamically the system operates. Due to greater irradiance fluctuation, the tracking loss is notably lowest (0.98 W) for SP-1 and highest (3.35 W) for SP-2. Effective power extraction is achieved even under complex PSCs because of the ANN controller's precise duty cycle adjustment, which ranges from 0.228 to 0.415, to maintain ideal voltage and current levels.

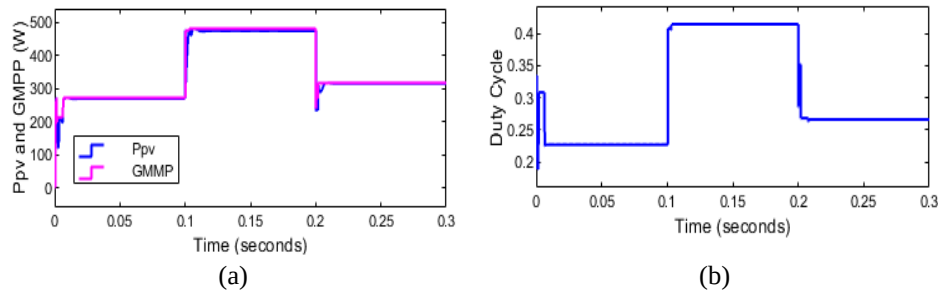


Figure 4. Simulation results under PSCs; (a) GMPP versus PV power outputs and (b) duty cycle

Table 3. Performance results of solar PV system under PSCs using ANN controller

Parameters	SP-1	SP-2	SP-3
Duty cycle	0.228	0.415	0.267
Tracking time (ms)	14	16	8
Duty cycle response time (ms)	6.8	3.1	2
Tracking loss (W)	0.98	3.35	1.67
Power loss (W)	1.65	4.01	1.88
Tracking efficiency (%)	99.63	99.31	99.47
System efficiency (%)	99.38	99.15	99.41

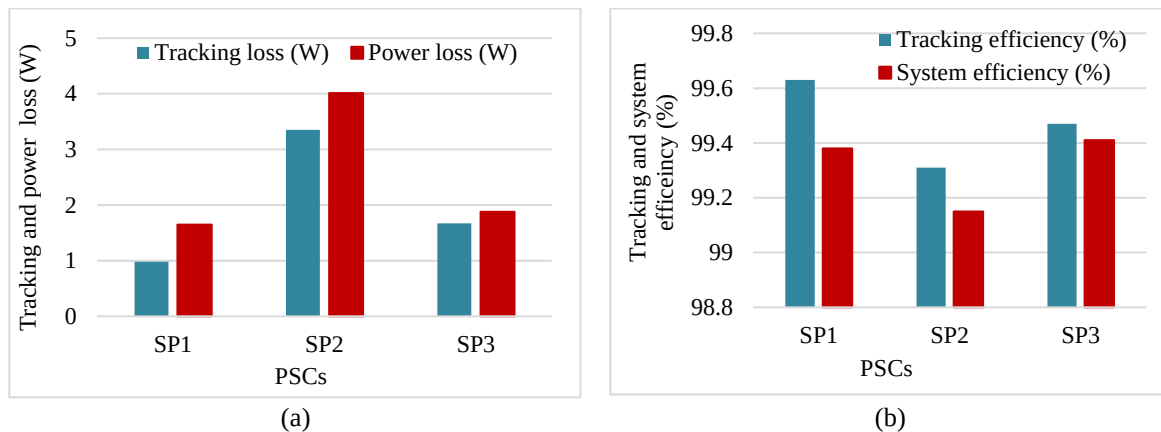


Figure 5. Performance analysis of solar PV system under PSCs; (a) tracking and power losses and (b) tracking and system efficiency

A thorough performance comparison of the suggested ANN-based MPPT strategy against several of the current approaches from the existing literature is shown in Table 4. Two key metrics for assessing MPPT controllers are used in the comparison: average tracking time, expressed in seconds (s), which shows the quickly the system finds the MPP, and average tracking efficiency, expressed as a percentage (%), which shows the extent to which the controller maintains functioning at that maximum point. Three previous studies are compared in the table: Xia *et al.* [21], which used FL and several bio-inspired optimization strategies like PSO, AFO, and ACO; Gandhi and Kumar [24], which looked into different improved versions of the PSO procedure; and a very recent study from Elakkiya *et al.* [25], which used cutting-edge methods like a specialized FL system (FLAGATST), LSTM networks, and radial basis function networks (RBFN). The outcomes of the current work, which demonstrate the effectiveness of the suggested ANN controller, are shown in the last row.

The table's data shows a distinct pattern in the development of MPPT methods. Earlier methods, such as the optimization techniques in [21], [24], frequently had to choose between accuracy and speed. For example, the IPSO controller in [24] had a somewhat sluggish tracking time of more than 1.19 seconds, although achieving a high efficiency of 99.171%. Since then, the focus has switched to machine learning and deep learning techniques, as demonstrated by [25], which maintained efficiency above 98.8% while drastically cutting tracking times to about 0.02 seconds. The proposed system offers better tracking time and efficiency over recent ANN [16], [17] and DL-LSTM-based approaches [18], [19]. The suggested ANN approach needs to be assessed in relation to this contemporary standard. This work outperformed all other controllers listed in both key performance measures, with an average tracking time of 0.01266 seconds and an average tracking efficiency of 99.47%. The aforementioned table offers strong proof that the suggested ANN controller is a noteworthy development in MPPT technology. It solidifies ANN as a very reliable and efficient method for improving the performance of solar PV systems, especially in the difficult circumstances of partial shadowing, by establishing a new state-of-the-art in tracking speed and operating efficiency.

Table 4. Performance comparison of the proposed work with existing works using different controllers

Ref.	Controller	Avg. tracking time (s)	Avg. tracking efficiency (%)
Xia <i>et al.</i> (2024) [21]	FL	0.42	98.9
	PSO	0.91	98.2
	AFO	0.88	98.6
	ACO	0.94	93.4
Gandhi and Kumar (2025) [24]	PSO	1.188	98.394
	IPSO	1.194	99.171
	PSO-PO	1.195	99.128
	FLAGATST	0.0203	98.894
Ullah <i>et al.</i> (2025) [26]	LSTM	0.0214	98.273
	RBFN	0.0217	97.888
	ANN	0.18	98.37
Demirci <i>et al.</i> (2025) [16]	ANN	0.096	97.38
Bana <i>et al.</i> (2024) [17]	ANN	0.02	99.01
Younas <i>et al.</i> (2024) [18]	DL-LSTM	0.038	99.33
Khan <i>et al.</i> (2026) [19]	DL-LSTM	0.038	99.33
This work	ANN	0.01266	99.47

The ANN eliminates iterative search delays and achieves faster tracking by learning the nonlinear P–V characteristics of the PV system and directly mapping inputs to the optimal duty cycle; as a result, accurate GMPP identification minimizes steady-state oscillations and lowers tracking-induced power loss. Rapid convergence even under PSCs is made possible by this data-driven behavior, which enhances dynamic reaction and total energy extraction. In terms of implications, the ANN is computationally more effective during inference than metaheuristic approaches but slightly heavier than FL due to training overhead; it can scale to bigger PV arrays if trained with different datasets, albeit complexity and retraining needs rise. Error analysis, however, shows that ANN performance may deteriorate under invisible shading patterns or strong transients, resulting in sporadic mis-tracking, underscoring the need for adaptive or hybrid improvements.

4. CONCLUSION

This study shows that in solar PV systems with partial shadowing, the suggested ANN-based MPPT controller greatly improves power extraction. The technique consistently monitors the GMPP by successfully resolving the many LP problem in the P–V characteristics, reducing energy loss and enhancing system dependability. With tracking efficiencies above 99.4%, system efficiency above 99.3%, and quick dynamic reaction within 8–14 ms, simulation results across three shading patterns verify steady and precise functioning. The ANN methodology offers lower power loss, quicker convergence, and less steady-state oscillations than traditional MPPT methods. The system's resilience to changing irradiance profiles is confirmed by the obtained GMPP values of 271.4 W, 480.2 W, and 316 W under SP-1, SP-2, and SP-3 circumstances, respectively. The suggested approach's computational efficiency and straightforward implementation structure make it a promising candidate for adoption in real-time embedded MPPT controllers. However, the current study is restricted to simulation-based validation and a single 3×2 PV configuration; future research should examine performance on multi-string PV systems and under extremely transient and quickly changing climatic circumstances. The work can be extended to various temperature setting apart from 25 °C to realize the performance metrics. ANN demonstrated superior performance in simulations compared to conventional methods; however, hardware validation is needed to confirm scalability and real-world applicability.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Lakshminarayana	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓			✓
Munirathnam														
Yogeesh Amabalagere	✓	✓		✓	✓	✓	✓			✓	✓			✓
Chandrashekaraiah														
Somu Pundalik	✓	✓		✓	✓	✓		✓		✓		✓		
Parande														
Vani Bengaluru	✓		✓	✓	✓	✓			✓	✓	✓			
Purushothama														
Ramya Mullur		✓		✓	✓	✓	✓		✓	✓		✓	✓	
Varadhanayaka														
Bellary Kursheed	✓	✓	✓		✓	✓		✓		✓	✓			✓

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [LM], upon reasonable request.

REFERENCES

- [1] N. Afsharzade, A. Papzan, M. Ashjaee, S. Delangizan, S. Van Passel, and H. Azadi, "Renewable energy development in rural areas of Iran," *Renew. Sustain. Energy Rev.*, vol. 65, pp. 743–755, Nov. 2016, doi: 10.1016/j.rser.2016.07.042.
- [2] J. Shair, X. Xie, L. Wang, W. Liu, J. He, and H. Liu, "Overview of emerging subsynchronous oscillations in practical wind power systems," *Renew. Sustain. Energy Rev.*, vol. 99, pp. 159–168, Jan. 2019, doi: 10.1016/j.rser.2018.09.047.
- [3] I. F. Silva, P. dos S. Vicente, F. L. Tofoli, and E. M. Vicente, "Plotting Characteristic Curves of Photovoltaic Modules: A Simple and Portable Approach," *IEEE Ind. Appl. Mag.*, vol. 27, no. 3, pp. 63–72, May 2021, doi: 10.1109/MIAS.2020.3024494.
- [4] C. Keerthisinghe et al., "PV-Battery Systems for Critical Loads During Emergencies: A Case Study from Puerto Rico After Hurricane Maria," *IEEE Power Energy Mag.*, vol. 17, no. 1, pp. 82–92, Jan. 2019, doi: 10.1109/MPE.2018.2877896.
- [5] Y. Yang, E. Koutroulis, A. Sangwongwanich, and F. Blaabjerg, "Pursuing Photovoltaic Cost-Effectiveness: Absolute Active Power Control Offers Hope in Single-Phase PV Systems," *IEEE Ind. Appl. Mag.*, vol. 23, no. 5, pp. 40–49, Sep. 2017, doi: 10.1109/MIAS.2016.2600722.
- [6] M. A. Farahat, M. A. Enany, and A. Nasr, "Assessment of maximum power point tracking techniques for photovoltaic system applications," *J. Renew. Sustain. Energy*, vol. 7, no. 4, Jul. 2015, doi: 10.1063/1.4928680.
- [7] E. Dallago, A. Liberale, D. Miotti, and G. Venchi, "Direct MPPT Algorithm for PV Sources With Only Voltage Measurements," *IEEE Trans. Power Electron.*, vol. 30, no. 12, pp. 6742–6750, Dec. 2015, doi: 10.1109/TPEL.2015.2389194.
- [8] A. Ramyar, H. Iman-Eini, and S. Farhangi, "Global Maximum Power Point Tracking Method for Photovoltaic Arrays Under Partial Shading Conditions," *IEEE Trans. Ind. Electron.*, vol. 64, no. 4, pp. 2855–2864, Apr. 2017, doi: 10.1109/TIE.2016.2632679.
- [9] M. A. G. de Brito, L. Galotto, L. P. Sampaio, G. de A. e Melo, and C. A. Canesin, "Evaluation of the Main MPPT Techniques for Photovoltaic Applications," *IEEE Trans. Ind. Electron.*, vol. 60, no. 3, pp. 1156–1167, Mar. 2013, doi: 10.1109/TIE.2012.2198036.
- [10] N. Kumar, I. Hussain, B. Singh, and B. K. Panigrahi, "MPPT in Dynamic Condition of Partially Shaded PV System by Using WODE Technique," *IEEE Trans. Sustain. Energy*, vol. 8, no. 3, pp. 1204–1214, Jul. 2017, doi: 10.1109/TSTE.2017.2669525.
- [11] F. Liu, S. Duan, F. Liu, B. Liu, and Y. Kang, "A Variable Step Size INC MPPT Method for PV Systems," *IEEE Trans. Ind. Electron.*, vol. 55, no. 7, pp. 2622–2628, Jul. 2008, doi: 10.1109/TIE.2008.920550.
- [12] S. K. Kollimalla and M. K. Mishra, "Variable Perturbation Size Adaptive P&O MPPT Algorithm for Sudden Changes in

- Irradiance," *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 718–728, Jul. 2014, doi: 10.1109/TSTE.2014.2300162.
- [13] B.-R. Peng, K.-C. Ho, and Y.-H. Liu, "A Novel and Fast MPPT Method Suitable for Both Fast Changing and Partially Shaded Conditions," *IEEE Trans. Ind. Electron.*, vol. 65, no. 4, pp. 3240–3251, Apr. 2018, doi: 10.1109/TIE.2017.2736484.
- [14] S. Tang, Y. Sun, Y. Chen, Y. Zhao, Y. Yang, and W. Szeto, "An Enhanced MPPT Method Combining Fractional-Order and Fuzzy Logic Control," *IEEE J. Photovoltaics*, vol. 7, no. 2, pp. 640–650, Mar. 2017, doi: 10.1109/JPHOTOV.2017.2649600.
- [15] S. R. Kiran, C. H. H. Basha, V. P. Singh, C. Dhananjayulu, B. R. Prusty, and B. Khan, "Reduced Simulative Performance Analysis of Variable Step Size ANN Based MPPT Techniques for Partially Shaded Solar PV Systems," *IEEE Access*, vol. 10, pp. 48875–48889, 2022, doi: 10.1109/ACCESS.2022.3172322.
- [16] A. Demirci, I. Dagal, S. M. Tercan, H. Gundogdu, M. Terkes, and U. Cali, "Enhanced ANN-Based MPPT for Photovoltaic Systems: Integrating Metaheuristic and Analytical Algorithms for Optimal Performance Under Partial Shading," *IEEE Access*, vol. 13, pp. 92783–92799, 2025, doi: 10.1109/ACCESS.2025.3572554.
- [17] P. R. Bana, S. D'Arco, and M. Amin, "ANN-Based Robust Current Controller for Single-Stage Grid-Connected PV With Embedded Improved MPPT Scheme," *IEEE Access*, vol. 12, pp. 100251–100262, 2024, doi: 10.1109/ACCESS.2024.3429347.
- [18] U. Younas, A. A. Kulaksiz, and Z. Ali, "Deep Learning Stack LSTM Based MPPT Control of Dual Stage 100 kWp Grid-Tied Solar PV System," *IEEE Access*, vol. 12, pp. 77555–77574, 2024, doi: 10.1109/ACCESS.2024.3407605.
- [19] F. Khan, H. O. Bansal, and D. Singh, "Development and Real-Time Validation of Deep Learning-Based LSTM-Tuned MPPT Control for a 5 kW Solar-Powered EV Charging System," *IET Power Electron.*, vol. 19, no. 1, Jan. 2026, doi: 10.1049/pel2.70156.
- [20] P. K. Kesavan, A. Karthikeyan, M. Kumar, and S. Mandal, "A Simple Primary Key Algorithm Based Shade Dispersion Method for Maximizing PV Power Generation Under Partial Shading Conditions," *Chinese J. Electr. Eng.*, vol. 10, no. 2, pp. 93–102, Jun. 2024, doi: 10.23919/CJEE.2024.000067.
- [21] K. Xia, Y. Li, and B. Zhu, "Improved Photovoltaic MPPT Algorithm Based on Ant Colony Optimization and Fuzzy Logic Under Conditions of Partial Shading," *IEEE Access*, vol. 12, pp. 44817–44825, 2024, doi: 10.1109/ACCESS.2024.3381345.
- [22] Y. Türkay and A. G. Yükek, "Investigating the Potential of an ANFIS-Based Maximum Power Point Tracking Controller for Solar Photovoltaic Systems," *IEEE Access*, vol. 13, pp. 41768–41784, 2025, doi: 10.1109/ACCESS.2025.3547954.
- [23] S. Hasheminasab, M. Alzayed, and H. Chaoui, "An Adaptive Neuro-Fuzzy Controller to Enhance Power Sharing in Distributed Energy Resources Applications," *IEEE Access*, vol. 13, pp. 94667–94680, 2025, doi: 10.1109/ACCESS.2025.3575039.
- [24] P. Gandhi and S. Kumar, "Instrumentation guided power quality enhancement in renewable energy/battery integrated microgrids by 3DOF-PID controllers," *J. Instrum.*, vol. 20, no. 10, p. P10023, 2025, doi: 10.1088/1748-0221/20/10/p10023.
- [25] E. Elakkiya, S. A. Raj, and S. Priya, "FLAGaTST: Fuzzy Logic Transformed Adversarial GAN and Time Series Transformer for Robust MPPT Under Partial Shading Conditions," *IEEE Access*, vol. 13, pp. 164409–164425, 2025, doi: 10.1109/ACCESS.2025.3611707.
- [26] S. Ullah *et al.*, "A Uniform Robust Exact Differentiator Based Neuro-Fuzzy Fractional Order Sliding Mode Control for Optimal Standalone Solar Photovoltaic System," *IEEE Access*, vol. 13, pp. 4411–4423, 2025, doi: 10.1109/ACCESS.2024.3524887.
- [27] S. Shaikh *et al.*, "Modified sliding mode control for seamless integration of P.V. energy in A.C. grid," *Energy Reports*, vol. 12, pp. 673–686, Dec. 2024, doi: 10.1016/j.egy.2024.06.062.
- [28] A. M. Soomar and P. Musznicki, "Developing gallium nitride-based inverters for high-performance photovoltaic integration in alternating current grids," *Int. J. Electr. Comput. Eng.*, vol. 15, no. 3, p. 2583, Jun. 2025, doi: 10.11591/ijece.v15i3.pp2583-2598.
- [29] L. Guanghua, A. M. Soomar, S. H. H. Shah, S. Shaikh, and P. Musznicki, "Maximum power point tracking strategies for solar PV systems: A review of current methods and future innovations," *Results Eng.*, vol. 28, p. 107227, Dec. 2025, doi: 10.1016/j.rineng.2025.107227.

BIOGRAPHIES OF AUTHORS



Lakshminarayana Munirathnam    is currently serving as an assistant professor at M.S. Ramaiah Institute of Technology. He completed his Bachelor of Engineering (B.E.), Master of Technology (M.Tech.), and Ph.D. from Visvesvaraya Technological University (VTU), Belagavi. With a career spanning 19+ years, he has a wealth of experience in his field. He has published many conference and journal articles. He is the member of professional bodies IEEE, MISTE, and IAENG. His current research interests include the areas of multimedia communication, image and video processing, and DSP applications in embedded system design. He can be contacted at email: lakshminarayana@msrit.edu.



Yogeesh Amabalagere Chandrashekaraiah    has completed his B.E., M.Tech., and Ph.D. from Visvesvaraya Technological University, Belagavi, Karnataka, India. He is currently working as an associate professor in CS&E at Government Engineering College, Chamarajanagar, Karnataka, India. His areas of interest are wireless sensor network, IoT, and machine learning. He can be contacted at email: yogeesh13@gmail.com.



Somu Pundalik Parande    is an assistant professor in the Department of Electronics and Communication Engineering, Basaveshwara Engineering College, Bagalkot. He has completed his B.E. from Karnataka University, Dharwad, India, and M.Tech. from Mumbai University, India. He completed Ph.D. from Visvesvaraya Technological University (VTU), Belagavi, Karnataka, India, in 2022. His research area is wireless sensor network. He has 19 years of teaching experience. He can be contacted at email: somuparande63@gmail.com.



Vani Bengaluru Purushothama    is an experienced engineering educator and researcher with over 17 years of academic service, currently serving as an associate professor at Sai Vidya Institute of Technology. She earned her Ph.D. from VTU with a dissertation on “Novel Framework of Cognitive Radio Network for efficient network resource management in 5G Communication”. Her research area includes wireless communications, cognitive radio networks, machine learning, and IoT. She has published over 19 papers in journals and international conferences. In addition to teaching and research, she is faculty advisor to the IEEE Robotics and Automation Society and convenor of the SARA Women Cell, demonstrating a strong blend of technical expertise and academic leadership. She can be contacted at email: vaniganesh2003@gmail.com.



Ramya Mullur Varadhanayaka    is an accomplished academican with over a decade of experience in engineering education and research. She holds a Ph.D. in Electrical Science and specializes in remote laboratories, IoT, industrial automation, robotics, and virtual reality applications in education. As a patent holder and author of numerous Scopus-indexed publications, she actively contributes to cutting-edge research and innovation. She is an IEEE Senior Member and advisor for the IEEE RAS Student Branch, having coordinated several national workshops, FDPs, and funded student projects. Her commitment to technical excellence and experiential learning continues to inspire students and educators alike. She can be contacted at email: ramyamv@jssateb.ac.in.



Bellary Kursheed    is currently serving as an associate professor in the Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning) at Don Bosco Institute of Technology, Bangalore. She earned her Ph.D. in Electronics and Communication Engineering from Visvesvaraya Technological University, Belagavi. She received her M.Tech. degree in the field of Computer Networks from Visvesvaraya Technological University, Belagavi. She has 21 years of experienced as an academican. She has contributed to the academic community by publishing many national and international journals or conferences. She received 3 Lakhs funds from Government of Karnataka Vision Group on Science and Technology for the project “RFID based vehicle antitheft and automatic toll collection system” and received fund from KSTA and KSCST three times. Her areas of interests include wireless communication, multimedia communication, cognitive radio, and micro controllers. She can be contacted at email: bkursheedofficial@gmail.com.