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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 460-465 | e-ISSN: 2347-470X

Comparative Analysis of Particle Swarm Optimization and Artificial Neural Network Based MPPT with Variable Irradiance and Load

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ABSTRACT- The escalating demands and increasing awareness for the environment, resulted in deployment of Photovoltaic (PV) system as a viable option. PV system are widely installed for numerous applications. However, the challenges in tracking the maximum power with intermittent atmospheric condition and varying load is significant. Maximum Power Point Tracking (MPPT) algorithms are employed and based on their convergence speed, control of external variations and oscillation, the output power efficiency, and other significant factors viz. the algorithm complexity and implementation cost, novel MPPT approach are preferable than the conventional approach. This paper presents an artificial intelligence-based optimization controller for MPPT in a PV system under varying load and irradiance conditions. Comparative analysis of Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) based MPPT is simulated and analysed. The PV system consisting of PV array and boost converter with MPPT controller feeds the DC load. The power conversion and panel efficiency are the significant factors to determine the effectiveness of tracking maximum power point. The simulation results show the performance of these controllers on the PV panel output power and the load side output power under changing loads and irradiance. In addition, the comparison of PV panel efficiency of ANN and PSO based MPPT techniques w.r.t changing loads is carried out. Based on the above analysis, PSO based MPPT algorithm marginally outperforms the ANN based MPPT algorithm. Further, the implementation of hybrid MPPT (ANN&PSO) for higher accuracy and tracking capability can be carried out as future work.

Keywords: Maximum Power Point Tracking (MPPT); Artificial Neural Network (ANN); Particle Swarm Optimization (PSO); Photovoltaic (PV) System.

ARTICLE INFORMATION

Author(s): Spandan Srivastava, Charu Lata, Prateek Lohan and Rinchin W. Mosobi
Received: 28/04/2022; **Accepted**: 20/07/2022; **Published**: 10/08/2022;
e-ISSN: 2347-470X;
Paper Id: IJEER100309;
Citation: 10.37391/IJEER.100309
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-10/ijeer-100309.html

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This article belongs to the Special Issue on **Recent Advancements in the Electrical & Electronics Engineering**

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1. INTRODUCTION

Energy employment and environmental issues resulting from global warming and pollution have paved the way for renewable energy sources. Photovoltaic (PV) system being unlimited, clean, and a free source of solar energy find various application. As a result, photovoltaic (PV) energy is the current trend in the electric power industry, and is widely installed globally. However, it suffers from two major issues: low energy conversion efficiency and a nonlinear change in the operating point on the I-V and P-V curves, known as the Maximum Power Point (MPP) [1]. As a result, Maximum Power Point Tracking (MPPT) approach with perturb and observe algorithm [2], artificial neural network (ANN) [3], Particle Swarm Optimization (PSO) [4,5], fuzzy logic control [6], and others are majorly used techniques to track MPP. The differences among these algorithms can be known by their convergence speed, convergence speed, control of external variations and oscillation, maximum output power efficiency, algorithm complexity and implementation cost.

In this paper, a comparative analysis of MPPT technique with ANN and PSO is performed under variable solar irradiance and load conditions. The PV system comprising of solar array and boost converter with MPPT controller feeds the DC load. The modelling and simulation are carried on MATLAB platform and the results indicates the effectiveness of this MPPT algorithm in terms of PV Panel efficiency.

2. PHOTOVOLTAIC MODELING

2.1 Basis of Photovoltaic Modeling

The ideal PV cell circuit is shown in Fig 1 which is further detailed in [1, 2] The ideal PV cell is mathematically represented by the following basic equation (1) and (2) and further explanation is detailed in [1, 2]:

$$I = I_{pv,cell} - I_{0,cell}\left[exp\left(\frac{qV}{akT}\right) - 1\right] \quad (1)$$

$$I_d = I_{0,cell}\left[exp\left(\frac{qV}{akT}\right) - 1\right] \quad (2)$$

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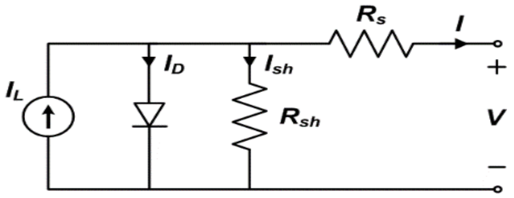

Figure 1: Equivalent PV circuit

2.2 Modeling of PV Array

Since practical arrays are made of several linked PV cells, their characteristics at the PV terminal demands addition of extra parameters to the fundamental as in (3) and (4)

$$I = I_{PV} - I_0\left[exp\left(\frac{V + R_S I}{V_t a}\right) - 1\right] \tag{3}$$

$$I_{PV} = \left(I_{PV,n} + K_I \Delta T\right)\frac{G}{G_n} \tag{4}$$

The overall stepwise mathematical modeling of PV array is further explained in [1,2,7]

3. MPPT ALGORITHMS

MPPT converters employs an algorithm to constantly identify the maximum instantaneous power of the PV array [8]. Since the input and output variables of the array (solar irradiation and load) are intermittent throughout, an MPPT algorithm is needed to extract and transmit the maximum instantaneous power to the load. PV array with DC-DC converter and MPPT control circuit [9] is shown in Fig. 2. MPPT [8-9] techniques are broadly classified into conventional and novel MPPT methods.

- Conventional Methods - Direct (offline) and Indirect (online) Methods
- Novel (soft computing) Methods – Artificial intelligence (ANN), biologically inspired (PSO) etc.

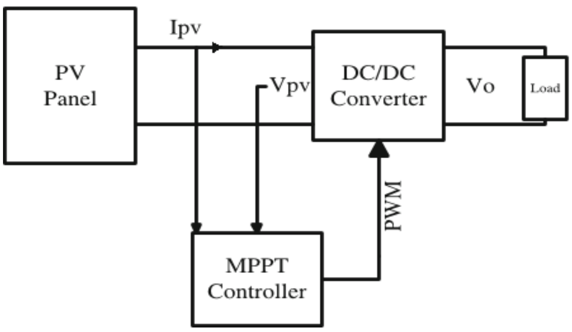

Figure 2: MPPT connected PV array feeding DC-DC converter [10]

By repeatedly perturbing the operational point of the PV array, the MPP is determined using direct procedures, also known as genuine searching methods. In this area, the Perturb and Observe, Hill Climbing [11] and Incremental Conductance methods are frequently utilized. Various novel (soft computing) optimization algorithms were employed to obtain the MPP including artificial intelligence and biologically inspired.

Artificial Intelligence and indirect approaches improve the dynamic performance of MPP tracking. Artificial Intelligence algorithms that focus on the nonlinear features of PV arrays provide a rapid, but computationally challenging solution to the MPPT problem. The indirect methods derive the array's MPP from its output properties. The MPP can be determined using the simple and effective fractional open-circuit voltage and short-circuit current approaches.

3.1 Artificial Neural Network (ANN)

ANN applications would require no particular facts regarding the device and mathematical modelling. In this manner it copes with more complicated issues by mapping the input-output of the device. ANN is the intelligence-primarily based superior MPPT technique, because of its inherent nature of the mastering method and organic nature of neurons. A three – layer neural network is used for MPPT, as shown in *Figure 3* [12-13]. Temperature (T) and Irradiance (G) are the input variables and the voltage of MPP (Vmpp) is the output variable.

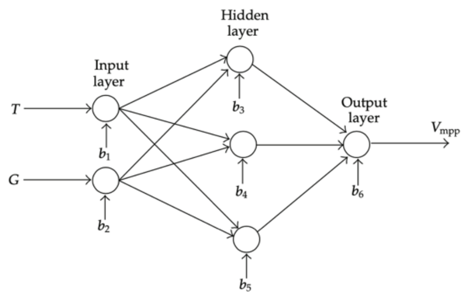

Figure 3: Neural Network Structure

The Levenberg-Marquardt backpropagation algorithm has been used to train the Neural Network. Trial and error technique is used to find the number of hidden layers. The inputs are 1000x2 matrix representing static data consisting of 1000 samples of 2 elements Temperature T and Irradiance G. The targets are 1000x1 matrix representing static data consisting of 1000 samples of 1 element V_{mpp}. In addition, current of MPP (I_{mpp}) can be determined by way of using the I-V curve of the modelled PV, and the maximum power P_{max} is calculated by multiplying V_{mpp} and I_{mpp}. At every instant of control, chopper with specified value of V_{mpp}, I_{mpp}, I_{out} and V_{out}, the duty cycle is derived as:

$$D = 1 - \sqrt{\frac{V_{mpp}}{I_{mpp}} \times \frac{I_{out}}{V_{out}}} \tag{5}$$

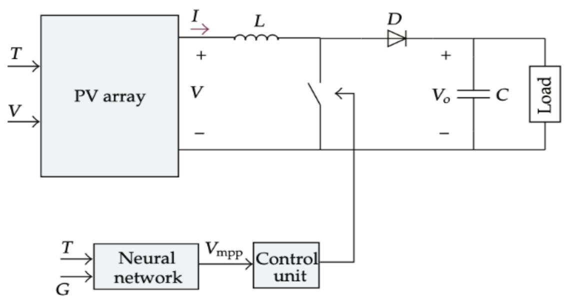

Figure 4: PV array with DC-DC converter and its control unit

3.2 Particle Swarm Optimization (PSO)

The PSO algorithm's movement is inspired by the behavior of flocking birds, which is based on the PSO optimizer's individual and neighboring experiences throughout each particle step. The PSO algorithm procedure is separated into four phases. The optimizer initiates the search with a random particle value in the first case. This particle value is chosen depending on the degree of solution space potential for numerous different optimizations. It compares the previous and next best fitness values (Pbi) and (Pli), respectively, in the second step to look for optimum solutions in the same space [13]. The global best positions (Gbi) are compared in the third stage to select the global fitness value. These positions are mathematically adapted and recorded for the subsequent phase, as stated in (6) and (7).

$$V_i^{k+1} = \omega \times V_i^k + r_1 \times c_1 \times \left(P_{bi} - X_i^k\right) + r_2 \times c_2 \times \left(G_{bi} - X_i^k\right) \quad (6)$$

$$X_i^{k+1} = X_i^k + V_i^k \quad (7)$$

where X_i represents each particle's current position, Vi represents the search space's speed, i represents the optimization vector, k represents the number of iterations, ω is the speed's inertia weight factor, c_1 is the single particle's cognitive coefficient, c_2 is the total particle's social coefficient, and r_1, r_2 are the search space's random velocity in the range of 0 to maximum value. The best particle in terms of fitness evaluation is selected and saved in the fourth step to improve the particle movement steps in each iteration. Those steps keep going until a stopping condition is reached or the number of iterations based on the system's necessary accuracy and control processing time, the stopping condition and iterations number are proposed. The algorithm is depicted in *Figures 5&6.*

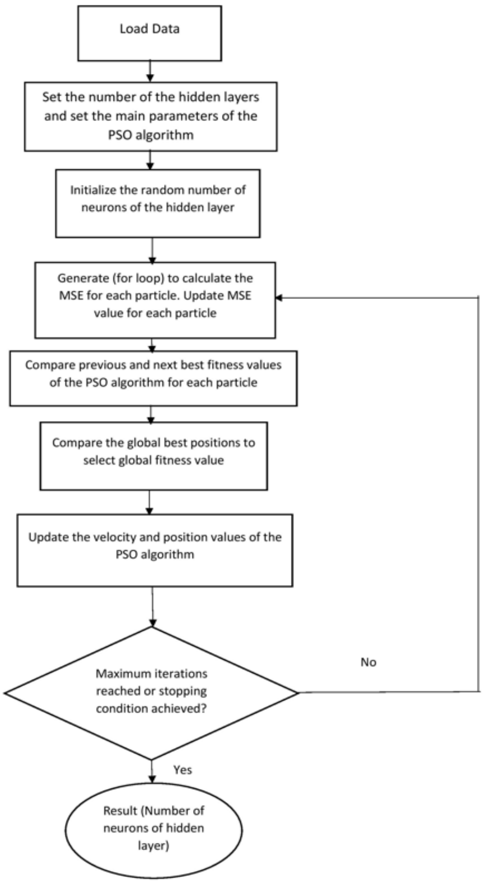

Figure 5: Algorithm to find the Hidden Layers of the PSO

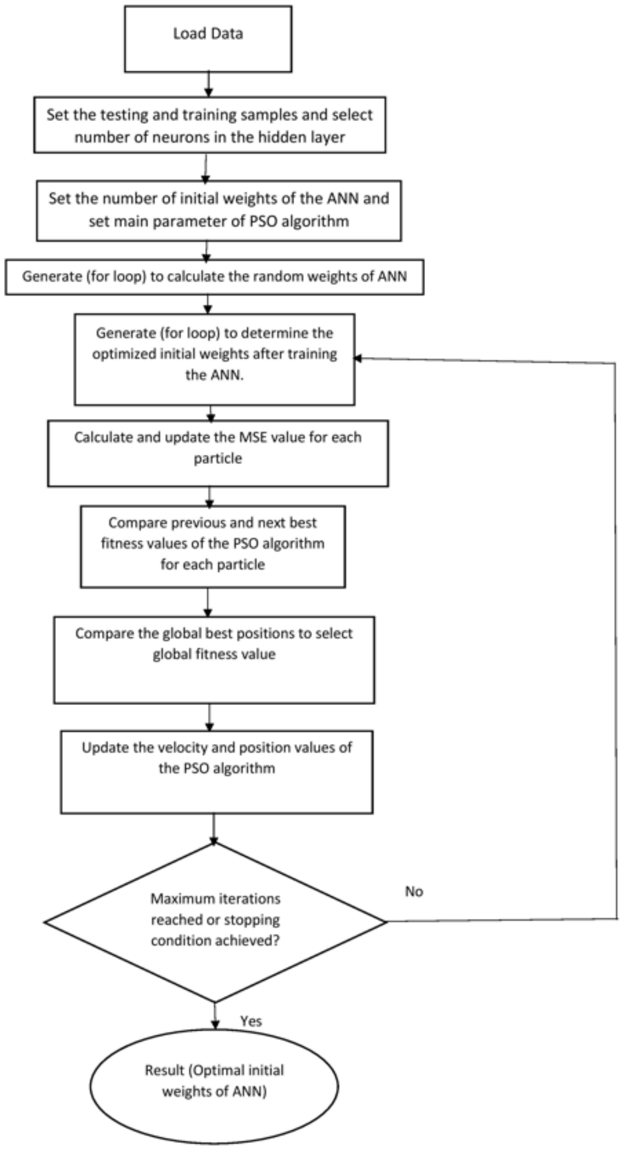

Figure 6: Algorithm to find the Initial Weights of the PSO

4. SIMULATION RESULT AND ANALYSIS

To analyse the implementation of the ANN and PSO MPPT algorithms in the PV system, a comparison under varying load and solar irradiance is performed. The power conversion and panel efficiency are the significant factor to determine the effectiveness of tracking maximum power point. The power output of PV panel and the load side power output, along with PV panel efficiency are determined in each case. *Table-I* lists the parameters of PV array. Fig. 9 depicts the I-V characteristics of PV array under varying irradiance i.e,1000 W/m^2, 800 W/m^2, 600 W/m^2, 400 W/m^2 and 200 W/m^2 at an interval of 0.2 sec with load remaining constant at 40 ohms. With increased irradiance, the PV current changes drastically with slight variation in PV voltage. Fig.10 depicts the P-V curve with variable irradiance and constant load at 40 ohms. The MATLAB Simulink of the PV system with ANN and PSO based MPPT are shown in *Figures 7&8* respectively.

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Table 1: Solar Array Parameters

Parameter	Duration (Sec)
Current of MPP, I_{mpp}	8.15 A
Voltage of MPP, V_{mpp}	30.7 V
Maximum power, P_{max}	250.205 W
Short circuit current, I_{sc}	8.66 A
Open circuit voltage, V_{oc}	37.3 V
Equivalent series resistance, R_p	224.1886 Ω
Equivalent parallel resistance, R_s	0.23724

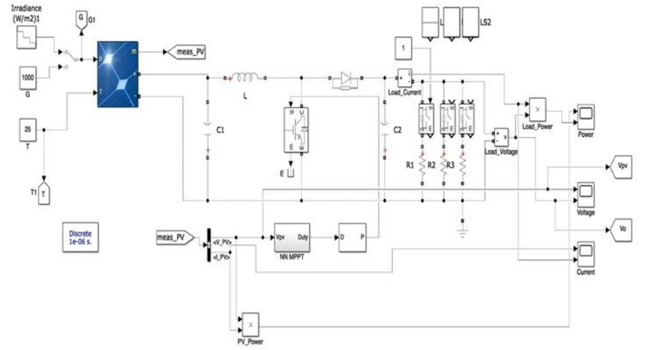

Figure 7: Simulation of MPPT using Neural Network

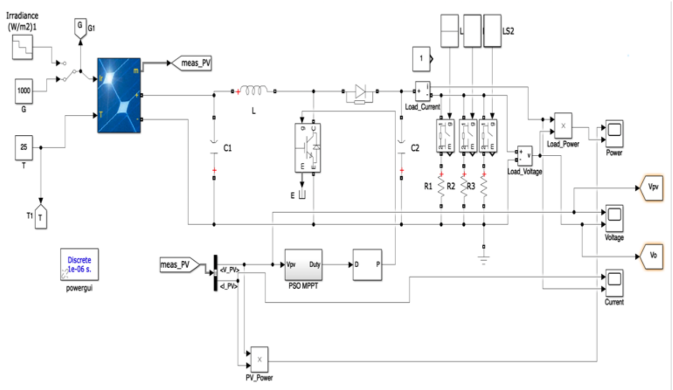

Figure 8: Simulation of MPPT using Particle Swarm Optimization

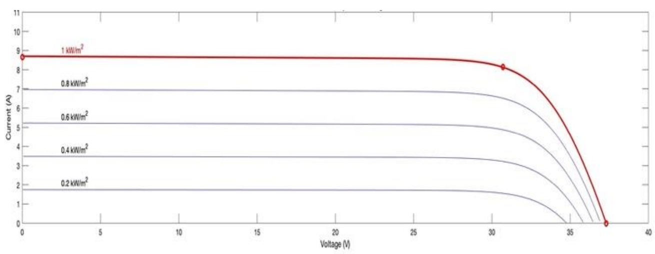

Figure 9: I-V characteristics of Solar Array

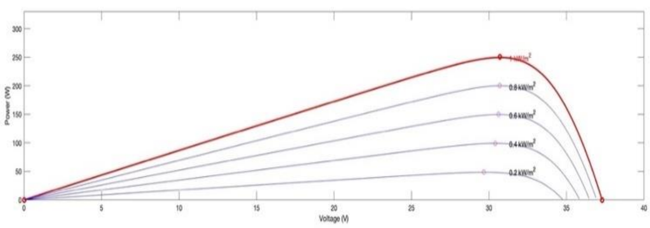

Figure 10: P-V characteristics of Solar Array

4.1 Artificial Neural Network

The performance under different loads with ANN has been illustrated in *Table 1* and the plots for power output, voltage and current in the load side is shown in *Figures 11-13*. The load is changed from 20 Ω to 30 Ω to 40 Ω at 0.3 second intervals, with the irradiance remaining constant at 1000 W/m^2. Similarly, *Table 3* illustrated the results for varying irradiances and constant load. *Figures 14-16* shows the variation of power output, voltage and current in the load side with irradiance changing from 1000 W/m^2 to 800 W/m^2 to 600 W/m^2 to 400 W/m^2 to 200 W/m^2 at an interval of 0.2 sec.

Table 2: Performance at different loads for ANN

Load (Ω)	Power Output of PV Panel (W)	Power obtained at load side (W)	Efficiency of PV Panel
20	245.7	245.7	98.19
30	246.2	245.3	98.03
40	246.6	244.9	97.87

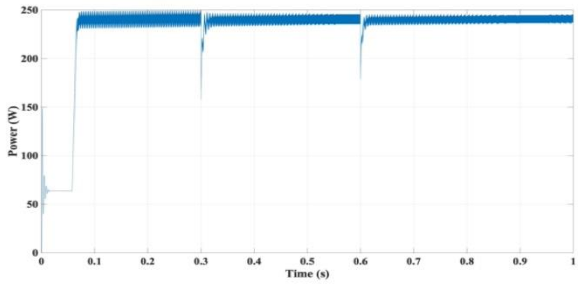

Figure 11: Load Side Power with Varying Loads

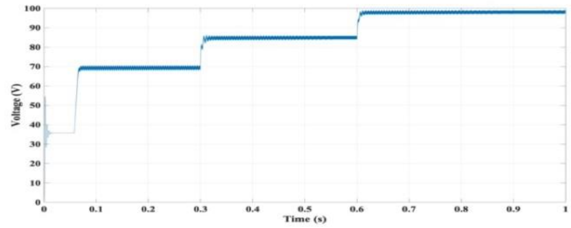

Figure 12: Load Side Voltage with Varying Loads

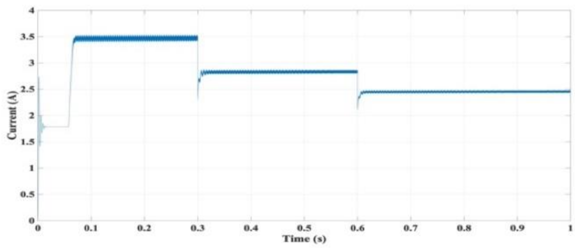

Figure 13: Load Side Current with Varying Loads

Table 3. Performance at different irradiances for ANN

Irradiance (W/m^2)	Power Output of PV Panel (W)	Power Output of Load Side (W)	Rated Power (W)	Efficiency of PV Panel
1000	246.2	242.3	250.2	96.84
800	196.1	193.9	199.9	96.99
600	146.8	144.5	149.6	96.59
400	96.93	94.68	98.97	95.66
200	46.22	45.06	48.37	93.15

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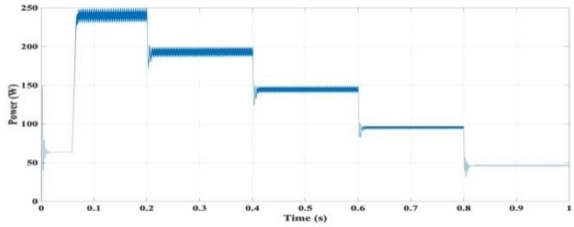

Figure 14: Load Side Power with Varying Irradiance

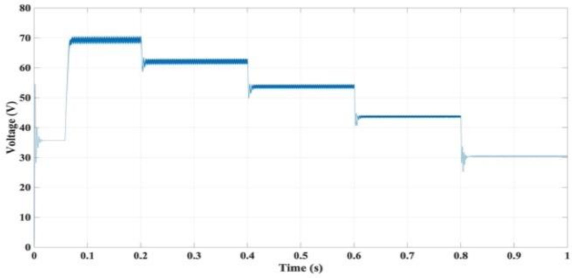

Figure 15: Load Side Voltage with Varying Irradiance

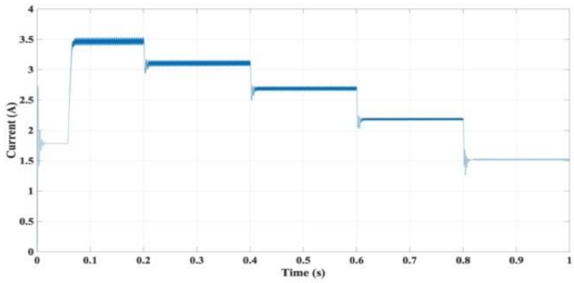

Figure 16: Load Side Current with Varying Irradiance

4.2 Particle Swarm Optimization (PSO)

The performance analysis of PSO under variable resistive loads has been shown in *Table IV* and the graphs for output power, voltage and current of load side with variable loads is displayed in *Figures 17-19*. Similarly, the results for varying irradiance are being illustrated in *Table V* and their respective plots in *Figures 20-22*.

Table 4. Performance at different loads for PSO

Load (Ω)	Power Output of PV Panel (W)	Power obtained at load side (W)	Efficiency of PV Panel
20	246.2	246.9	98.67
30	246.4	246.2	98.39
40	246.2	245.6	98.15

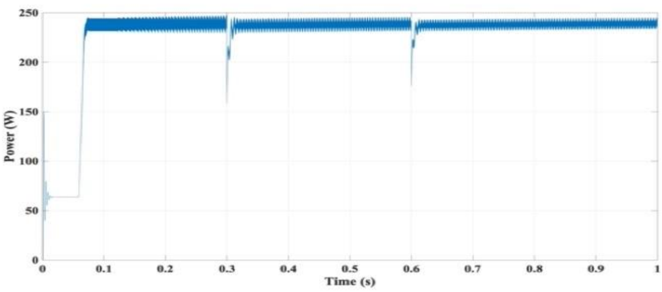

Figure 17: Load Side Power with Varying Loads

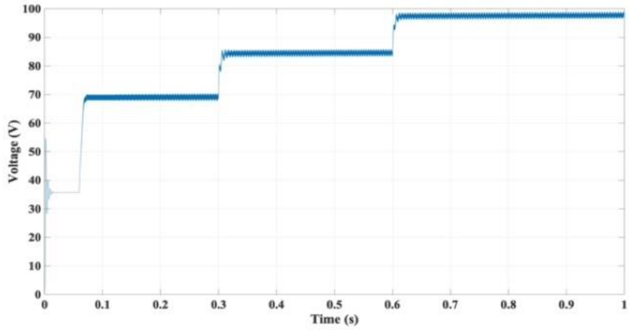

Figure 18: Load Side Voltage with Varying Loads

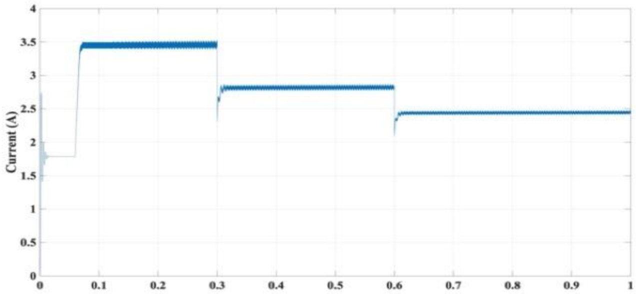

Figure 19: Load Side Current with Varying Loads

Table 5: Performance at different Irradiances for PSO

Irradiance (W/m^2)	Power Output of PV Panel (W)	Power Output of Load Side (W)	Rated Power (W)	Efficiency of PV Panel
1000	244	243.2	250.2	97.20
800	196.3	194.6	199.9	97.34
600	144.9	144.7	149.6	96.72
400	97.25	94.82	98.97	95.79
200	47.66	46.19	48.37	95.49

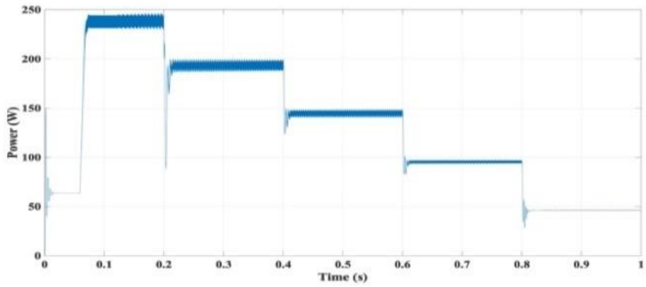

Figure 20: Load Side Power with Varying Irradiance

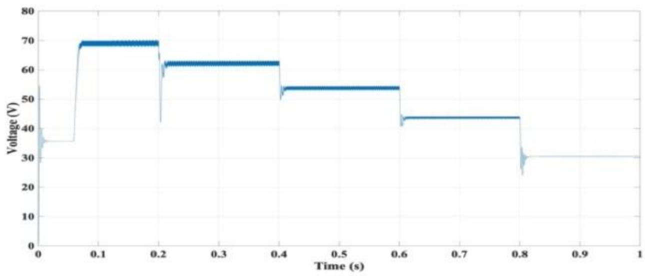

Figure 21: Load Side Voltage with Varying Irradiance

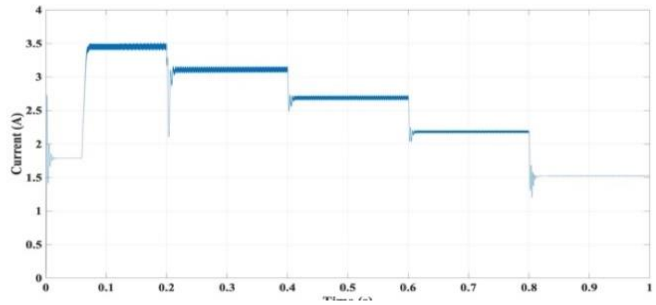

Figure 22: Plot of Load Side Current with Varying Irradiance

The panel efficiency w.r.t changing loads is plotted for both the techniques as shown in *Figure 23* and with varying irradiance as shown in *Figure 24*. As seen from the graphs, PSO based MPPT technique gives better performance compared to ANN algorithm.

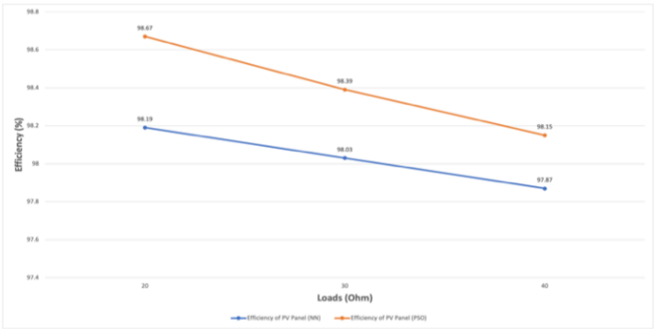

Figure 23: Comparison of Panel Efficiency for ANN and PSO for Varying Loads

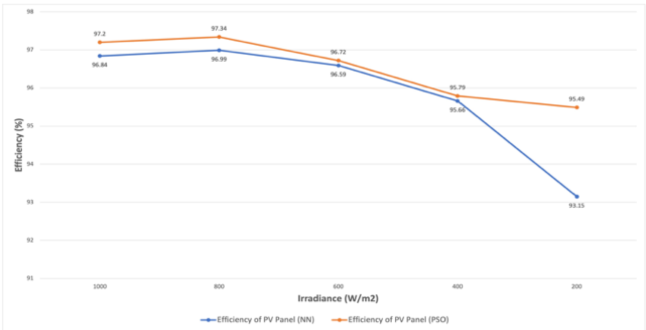

Figure 24: Comparison of Panel Efficiency for ANN and PSO for Varying Irradiance

5. CONCLUSION

In this paper, a comparative analysis on the implementation of ANN and PSO MPPT algorithms in the PV system is presented, under the condition of varying load and solar irradiance. The test system includes a PV array with boost converter and its control connected to a resistive load and modelled in MATLAB Simulink. With the results on power conversion and panel efficiency of the PV system for ANN and PSO based MPPT, PSO based MPPT technique marginally outperforms the ANN based MPPT technique. At an irradiance of $1000 W/m^2$, the panel efficiency with PSO based MPPT is 97.20%, while ANN based MPPT gave an efficiency of 96.84% and so on for different irradiance value. Similarly with variable load the maximum panel efficiency for PSO MPPT is 98.67% and for ANN MPPT is 98.19%.

Thus, PSO technique has proved to be a more efficient and effective to track the maximum power point of the PV system as compared to the ANN method. Future aspects of the proposed work include the implementation of hybrid MPPT (ANN+PSO) for higher accuracy and tracking capability.

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