Performance Analysis of MPPT Algorithms Designed for Photovoltaic System



Shobha K P, Usha A, Prasanna Kumar H

Abstract: The capacity to reap the highest output power in various environmental conditions is one of the most critical tasks in the application of photovoltaic (PV) systems. Although many cutting-edge methods have been developed to accomplish this, the majority of these methods have significant drawbacks, such as poor tracking capabilities and a heavy computational load. Therefore, this work aims to present a control algorithm that considers the relationship between the solar array output power and the PWM duty cycle of the MPPT boost converter's controller. The proposed customized CNN is implemented in MATLAB/SIMULINK and compared with well known for its performance. The findings demonstrate an increase in the PV system's ability to generate power in all weather conditions, as well as a reduction in the effects of rapid changes in solar irradiation on output power.

Keywords: Photovoltaic, Maximum Power Point Tracking, Perturb and Observe Method, Customized CNN

I. INTRODUCTION

Diverse alternative renewable energies, such as wind energy, hydroelectric energy, geothermal energy, tidal energy, biological energy, and solar energy, are gaining widespread attention and exploitation as research on sustainable energy expands. Partial shading conditions [1] have grown to be an unavoidable issue for PV systems as the scale of the installation of PV equipment in urban regions has increased. In particular, photovoltaic modules and photovoltaic networks are composed of multiple photovoltaic cells. However, due to partial shading conditions, the sun's illumination on PV modules or PV arrays is uneven during the generation of PV power. This could change the output characteristics of PV cells [2]. The conversion efficiency of PV cells tends to decrease under partial shading conditions, which negatively affects the regular functioning of the PV energy production system. Therefore, a critical task is the regulation and optimization of PV systems under partial shading conditions [3], which has been a hot research topic in

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the field of PV power in recent years. Generally, the primary purpose of maximum point tracking power (MPPT) is to achieve the ideal output power in various situations. This aims to address the issue caused by partial shading conditions in PV systems.

Due to their low efficiency and relatively high capital cost per watt, PV energy systems are underutilised. Therefore, there is still a considerable distance to be covered in improving the reliability and efficiency of photovoltaic systems. The first step is to determine how to enhance the efficiency of photovoltaic modules through modelling and simulation. Various strategies can be designed and developed to optimize system performance after a PV module has been extensively modelled and simulated [4].

Several methods for monitoring maximum power in PV applications [5,6,7] have been documented. However, the majority of current approaches have shortcomings, including low efficiency, low precision, and slow response. Fundamentally, there are three broad categories within which MPPT algorithms can be classified: traditional techniques, control methods based on contemporary control theory, and metaheuristic techniques. Constant Voltage Tracking (CVT), Open Circuit Voltage Tracking (OVT), Short Circuit Current Tracking (SCT), Parasitic Capacitance (CP), and others are the main classical MPPT techniques. Constant voltage tracking CVT cannot accurately monitor the maximum power point (MPP) in areas with significant daily temperature or radiation variations. In principle, OVT open-circuit voltage monitoring is similar to the fixed voltage monitoring method; however, the difference lies in that the fixed voltage monitoring method maintains a constant voltage, whereas OVT monitors the evolution of voltage. In short-circuit current, the tracking mechanism monitors the variation of current. The standard MPPT-based method of modern control theory includes the Deep Learning control algorithm.

This is a widely used Artificial Intelligence (AI) algorithm [8, 9,10], which has significant benefits of fast tracking rates, high dynamic performance and steady state operation. Meta-heuristic algorithm is one desirable tool when solving complex optimization problems at present, which has been successfully applied in the MPPT of PV systems, for example, particle swarm optimization [11] (PSO) [12], differential evolution (DE), teaching-learning-based optimization (TLBO), and so forth. The PSO method suggested in the literature disperses initial particle positions at potential peak voltages.

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Based on the distinctive properties of the power curve with several peaks, this method will not fall into local optimal solutions. Regarding particle swarm optimisation, the Deep Learning algorithm for MPPT in partially shaded PV systems exhibits faster and more stable tracking. Although the desired effect is achieved, it still has a few disadvantages, such as a heavy calculation burden.

Therefore, the goal of this work is to develop more precise and reliable methods for generating the desired power that a PV system is capable of producing under various weather conditions. The shortcomings of the current approaches will be addressed by adopting a customised CNN-based MPPT technique. This technology has excellent modelling and inference capabilities. Since location data can be stored for use in deep learning functions, its primary benefit is faster real-time optimisation. To achieve high-quality MPPT performance for PV systems under partial shading conditions, this work develops an MPPT method based on a Customised CNN algorithm. Its main contribution can be summed up as follows.

- 1. Adaptive learning: It involves learning to perform tasks using the data set provided for training.
- 2. Fault tolerance via Redundant Information Coding: Faults can be semi-destructive to the neural network, ultimately degrading network performance. However, retraining data can provide fault tolerance to a large extent.
- 3. Real-Time Operation: The computations required for Customised CNN can be performed in real-time, but they necessitate specialised hardware that needs to be explicitly designed for this purpose.
- 4. Self-Organisation: A customised CNN forms its structure or representation that suits itself while processing information received from the training dataset.

II. METHODOLOGY

A. PV Cell Equivalent Circuit



Figure 1: PV cell equivalent circuit

The electrical properties of a PV module or cell are nonlinear and strongly influenced by temperature and solar irradiation. A photocurrent source connected in parallel to a diode, a shunt resistance (Rsh), and a series resistance (Rs) can be used to simulate a PV cell electrically. The model of <u>Figure 1</u> can be mathematically described by

$$i_{pv} = i_{l} - i_{o} \left[e^{\frac{q(v_{pv} + i_{pv}R_{s})}{nkT}} - 1 \right] - \frac{v_{pv} + i_{pv}R_{s}}{R_{sh}}$$
(1)

Where v_{PV} is the output voltage of the PV cell, V i_{PV} is a photo-generated current source. A

Retrieval Number:100.1/ijeat.D40840412423 DOI: <u>10.35940/ijeat.D4084.0412423</u> Journal Website: <u>www.ijeat.org</u> i₀ is the leakage current of the diode, A

q is the charge of an electron and numerically given as $1.6 \times 102^{-19} C.$

A is the ideality factor of the diode, which ranges between 1 and 1.8.

k is the Boltzman constant and is equivalent to $1.38 \times 102^{-23} \mbox{ J/K},$

T is the temperature (°C) on the panel surface.

 R_{s} and Rp are the series and parallel resistance values in ohms.

B. Analysis of DC-DC Converter

The output voltage of a boost converter is higher than the incoming voltage. In boost converters, switching is done using MOSFETs or IGBTs. The circuit schematic is shown in Figure 2. The current flowing through the inductor rises when switch Q1 is closed. The output capacitor is charged to a greater voltage than the input capacitor when the switch opens due to the series combination of the voltage across the inductor and the input voltage. The duty ratio of the switching signal determines the output voltage. The output voltage increases as the switch remains locked for an extended period of time.



Figure 2: Boost Converter circuit schematic.



Figure 3: Boost Converter working modes

When the switch is closed during the ON phase, the inductor current increases linearly, and the voltage across the inductor is

$$v_{in} = L \frac{\mathrm{di}}{\mathrm{dt}} \tag{2}$$

Assuming that the inductor current rises linearly from I_1 to I_2 in time t_1

$$v_{in} = L \frac{(I_2 - I_1)}{t_1}$$
$$t_1 = \frac{L\Delta I}{v_{in}}$$

The difference between the source voltage and the output voltage will be the voltage across the inductor when the switch is open.

$$V_L = v_{in} - v_o \tag{3}$$

The disparity between the source voltage and the output voltage will be the voltage across the inductor when the switch is open.

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$$L\frac{di}{dt} = v_{in} - v_o \tag{4}$$

$$L\frac{(I_{2}-I_{1})}{t_{2}} = v_{in} - v_{o}$$
 (5)

$$t_2 = \frac{\mathrm{L}\Delta \mathrm{I}}{v_o - v_{in}} \tag{6}$$

Where $\Delta I = I_2 - I_1$ is the peak ripple current of inductor L.

$$\Delta I = \frac{t_1 v_{in}}{L} = \frac{(v_o - v_{in}) t_2}{L}$$
(7)

Substituting $t_1 = DT$ and $t_2 = (1 - D) T$, the average output voltage,

$$v_o = \frac{v_{in}}{1 - D} \tag{8}$$

for lossless converter, $V_oI_o = V_{in}I_{in}$, hence

$$I_{in} = \frac{I_o}{1 - D} \tag{9}$$

The switching period T is

$$\Delta I = t_1 + t_2 = \frac{\Delta IL}{v_{in}} + \frac{\Delta IL}{v_o - v_{in}} \quad (10)$$

The peak-to-peak ripple current can be found from

$$\Delta I = \frac{v_{in}(v_o - v_{in})}{fLV_o} \tag{11}$$

$$\Delta I = \frac{Dv_{in}}{fL}$$
(12)

The average capacitor current during time t_1 is $I_c = I_{o}$, and the peak-to-peak ripple voltage of the capacitor is

$$\Delta I = v_c - v_c (t = 0) = \frac{1}{C} \int_0^{t_1} I_c dt$$
 (13)

$$= \frac{1}{C} \int_{0}^{t_{1}} I_{c} dt = \frac{I_{c}}{C} t_{1}$$
(14)

C. Maximum Power Point Tracking (MPPT) Algorithms

The maximum power value varies with changes in weather conditions, such as temperature and irradiance. A real-time maximum power-point tracker is a crucial component of the PV system because the solar array's maximum available energy is constantly affected by atmospheric conditions. Three distinct categories of Maximum Power Point Tracking MPPT schemes can be found in the technical literature.

- 1. Direct method.
- 2. Artificial intelligence method.
- 3. Indirect method.

1. Direct method

Perturb and Observe (P&O) [13,14] Hill Climbing (HC) [14], and Incremental Conductance (INC) schemes [8] fall into this group and are frequently used in PV systems. The sequence of operations for the P and O Algorithm, also known as the accurate seeking method, is shown in Figure 4. Voltage is continuously perturbed, and power is observed in the direct technique. The operating point is located on the PV characteristics of the PV array to find the MPP. To achieve

Retrieval Number:100.1/ijeat.D40840412423 DOI: <u>10.35940/ijeat.D4084.0412423</u> Journal Website: <u>www.ijeat.org</u> the MPP, the P&O scheme varies the PV array's operating voltage. Hill climbing technique varies the duty cycle of the DC-DC interface converter [18]. These techniques can only be used in low-power situations due to the intrinsic steady-state oscillation.



Figure 4: P & O-based MPPT Algorithm



Figure 5: PV output power vs. duty cycle D of the MPPT boost converter

An MPPT control algorithm based on duty cycle perturbation is implemented to provide a quick response to variations in ambient conditions on the PV array. Figure 5 shows the variation of PV power with the change of duty cycle D of the MPPT boost converter. In this technique, the operating point oscillates around the MPP, and the duty cycle is adjusted based on perturbation power.

2. Artificial Neural Network-based MPPT

Artificial Neural Networks have been used to improve the dynamic performance of MPP tracking. Concentrating on the

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nonlinear characteristics of PV arrays, Artificial Neural Networks offer a fast yet computationally demanding solution for the MPPT problem. This method is based on extracting the MPP of the variety from its output characteristics.



Figure 6: Artificial Neural Network Structure-Based MPPT Algorithm

Figure 6 illustrates how a three-layer neural network is used to achieve MPP. The input factors for the Artificial Neural Network (ANN)are temperature and irradiance, and the output variable is the voltage of the MPP $V_{mpp}[15,16,17]$. To train the neural network, data must be obtained as input and output variables. As a result, the weights of neurons in various levels are obtained. To acquire data, PV model programming is used in MATLAB. There are numerous ways to teach an ANN. The ANN's output, for any T and G as inputs, is the V_{mpp} after training and setting the neuron weights. Now, using the P-V characteristic of the PV model, it is possible to determine the power at the highest power point, P_{mpp} . The duty cycle of the Boost Converter is calculated as

$$D = 1 - \sqrt{\frac{\nu_{mpp}}{I_{mpp}} \times \frac{I_{out}}{V_{out}}}$$
(14)

3. Indirect method

The traditional algorithms (P&O, INC, and ANN) are not sufficiently accurate to distinguish between the global peak and local peak under partial shading conditions. Particle swarm optimisation (PSO), a stochastic search technique, is employed to locate the global peak, which corresponds to the maximum power point (MPP) of the array, as there are several local peaks with incomplete shading. The Particle swarm optimisation (PSO) is a method of optimisation that uses a swarm or a group of particles. These particles are initially and randomly dispersed throughout a particular search area. Finally, these particles travel in the direction of the actual MPP and locate it. In this instance, it can be utilised as an MPPT method for multivariable function optimisation with multiple local minima.

Particle location update and velocity update are two operators of the PSO technique. The output of this algorithm is the duty cycle for the switch of the boost converter, and both the velocity update and the best particle location rely on the power output of the PV module. Thus, the duty cycle is determined by particle location. Each individual's modification speed can be determined by the calculation agent and their current speed. The distance to P_{best} and G_{best} is as follows.

 $V_i^{k+1} = W \times V_i^k + C_1 \times r_1 \times (P_{besti}^k - X_i^k) + C_2 \times r_2 \times (G_{best}^k - X_i^k) \quad (15)$ Where,

Retrieval Number:100.1/ijeat.D40840412423 DOI: <u>10.35940/ijeat.D4084.0412423</u> Journal Website: <u>www.ijeat.org</u> V^k_i, the speed of individual i when k is iterating, X^k_i Individual i is in the position of the kth iteration, W inertial weight

 C_1, C_2 acceleration factor,

 ${P_{\text{besti}}}^k{\!\!\!}^k$ The best position of individual i in the k^{th} iteration

G_{best}^k Group's best position until the kth iteration.

r1, r2 Random numbers between 0 and 1.

Accelerate coefficients C1, C2 and the inertial weight W are predefined during the speed update, and r1, r2 are produced at random whose values fall between [1]. A concept known as velocity clamping is used in the Particle Swarm Optimisation method, and it essentially helps the particle remain within the boundary and take reasonable steps to explore the search space. Because the process could explode and the particle's location could change suddenly in the absence of velocity clamping, which is crucial for stability. Maximum velocity establishes a rapid equilibrium between local and global exploration, which in turn regulates the granularity of the search area. The three stages of the PSO algorithm are repeated until the stopping condition is satisfied, as shown in Figure 7.



Figure 7: Particle Swarm Optimization Algorithms

- 1. Evaluate the fitness of each particle
- 2. Update individual and global best fitness and positions
- 3. Update the velocity and position of each particle

4. Proposed Customized CNN(C-CNN) for MPPT

A class of neural networks in the deep learning method is called a convolutional neural network (CNN). This is used to deliver the intended output for the specific input task. The MPPT module in the suggested design is broken down into three steps, as shown in Figure 8.



Figure 8: Workflow diagram of Proposed Methodology Temperature and Irradiance values are used as the basic PV module's input data, in the first stage [19, 20]. The procedure

for gathering data in the second step depends on the outcomes of the simulation in the first step. The proposed multilayer

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perceptron can be trained using the entire dataset once it has been formed and trained, and it can then be used to discover the final output from our test data [21]. Without using a large network model, the CNN network design could be modified and adjusted. A customised convolutional network with two input layers, five hidden layers, and an output layer is proposed in this article. The illustration in Figure 9 shows this.



Figure 9: Deep Learning design consisting of 2 inputs, five hidden layers and one output layer

A dataset containing temperature and irradiance data was generated after executing numerous scenarios. The suggested technique calculates the duty ratio that precisely follows the maximum output point based on irradiance and predicts the irradiance based on the output voltage, current, and power of the photovoltaic (PV) system.

imageinput. ImageinputLayer	+ convolution2dt	batchnorm_1 batch/łórmaiza	+ relu_1	# maxpool_1 maxPooling2dl	eenv_2 convolution2dL	¢ batchnorm_2 batchNormaiza	relu_2 relu_2	fo fullyConnected	eoftmaxLayer	class/fcationLa
X	E.			:: *				X	1	1

(a)

Learn

Labels

Туре	Activities
Temperature and Irradiance	Data
Convolution	1600x1600

Name

Data input	Temperature and Irradiance	Data		
Conv_1 8 convolutions with stride [1 1] and padding same	Convolution	1600x1600	Weights 1600x8 Bias 1x1x8	
Batchnorm_1 Batch Normalization with eight channels	Batch Normalization	1600x1600	Offset 1x1x8 Scale 1x1x8	
Relu_1 ReLU	ReLU	1600x1600		
maxpool 2x2 maxpooling with stride [2 2] and padding [0 0 0 0]	Max pooling	800x800		
Conv_2 16 3x3x1 convolutions with stride [1 1] and padding same	Convolution	800x800	Weights 800x16 Bias 1x1x16	
Batchnorm_2 Batch Normalization with 16 channels	Batch Normalization	800x800	Offset 1x1x16 Scale 1x1x16	
Relu_2 ReLU	ReLU	800x800		
fc 2 fully connected layers	Fully Connected	1x1x2	Weights 2x64000 Bias 2x1	
Softmax	Softmax	1x1x2		

(b)

Figure 10 Proposed Customized CNN (C-CNN) (a) Architecture (b) Layer details

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The experimental data were used to train the deep learning model employed in this work, and the performance of the proposed algorithm was assessed by comparing it with the traditional algorithm under various input irradiance conditions. Comparing the suggested algorithm to existing algorithms for the same input conditions, the former performs well.

Figure 10 shows the proposed C-CNN model architecture and layer details. It consists of two convolution layers, fully connected layers, and a classification layer. The batch normalisation layer and ReLU layer, located between the convolution layers, serve to speed up the learning and training process, while the max pooling layer reduces the feature space. The softmax layer is used to assign a decimal probability that adds up to 1. Similarly, the pooling in CNN is demonstrated in Fig. 11. In this, max pooling and average pooling are explained by considering four convolution outputs. The maximum of all pixel values resulted in max pooling, whereas the average of all pixel values resulted in average pooling.



Figure 11: Pooling in CNN

III. SIMULATION RESULTS AND DISCUSSIONS

The proposed method was simulated under various operating conditions resulting from solar irradiation and temperature variations. Performance analysis of voltages and power tracked by an MPPT controller based on multiple control system parameters, including ripples, stability, settling time, and computation time. The comparison shows that the model implemented using a customised CNN-based MPPT technique yields better performance with lower voltage and current ripples compared to the P&O, PSO, and Deep Learning models. To validate the performance of different MPPT Techniques, a Solar Panel and a boost converter are included in the Simulink/MATLAB model. The Solar Irradiance and temperature vary at irregular Intervals, with Irradiance between 600 and 1000 W/m² and temperature between 20 °C and 40 °C.

1. Perturb and Observe-Based MPPT Algorithm

Figures 10 and 11 illustrate the output voltage, current, and power waveforms of the Photo Voltaic system with the P and O-based algorithm.

It is observed that the P and O method does not instantly adapt to changes in temperature and irradiance. The P and O method is suitable if both inputs are linear. It works efficiently for lower frequencies.

The ripple in current and voltage is high due to low-frequency operation. It requires more cycles to

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reach steady-state values. It is also observed that there is a high ripple in the current waveform, which is reflected in the power waveform.

2. Particle Swarm Optimization (PSO) Based MPPT Algorithm

Figures 12 and 13 illustrate the output voltage, current, and power waveforms of the Photo Voltaic system with a PSO-based algorithm. The initial adjustment of population position and velocity will result in more oscillations using the PSO method, as shown in Figure 12. After updating the proper velocity and positions, the PSO will track the proper MPP.



Figure 12: P and O Power Output for different values of Solar Irradiance and temperature

These values also affect the voltage and current values. Furthermore, it is also observed that even after reaching a steady state, small ripples remain on the voltage and current waveforms.

3. Deep Learning Based MPPT Algorithm

Figures 14 and 15 illustrate output voltage, current and power waveforms of the Photo Voltaic system with Deep Learning based MPPT Algorithm.



Figure 13: P and O Voltage and Current Output



Figure 14 PSO Power Output for different values of Solar Irradiance and temperature

The Deep Learning method will decrease the initial oscillations caused by temperature and irradiance changes on PV Panels, as shown in Figure 14.



Figure 15: PSO Voltage and Current Output

Even though it is fast-tracked, the Deep Learning method also has some ripple effects on the voltage and current waveforms. This is because the deep learning method does not adjust its weights in response to sudden changes in irradiance and temperature, as it requires a larger number of hidden layers.



Figure 16: Deep Learning Power Output for different values of Solar Irradiance and temperature



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Figure 17: Deep Learning Voltage and Current Output 4 Customized CNN

Deep Learning exhibits initial oscillations and ripples due to adjustments of weights in the hidden layers. This is overcome by a proposed customised CNN, where convolutional layers are selected according to the available data. Furthermore, in the proposed customised CNN, the number of hidden layers is chosen based on the available irradiance and temperature data. The proposed method outperforms other methods by eliminating oscillations and achieving steady-state conditions rapidly, with minimal ripple values. Figures 16, 17, and 18 show the voltage, current, and power waveforms of the customised CNN-based MPPT algorithm, which exhibits fast transient and steady-state responses.



Figure 18: C-CNN Power output



Figure 19 C-CNN Voltage Output

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Table 1 illustrates the settling and computational times required for various methods. It is observed that the proposed C-CNN method outperforms other approaches.

Table 1: settling and computational time

SI No.	MPPT Methods	Settling Time (sec)	Computational Time(sec)
1.	P & O	2.4	300
2.	PSO	1.3	195
3.	Deep Learning	025	225
4.	Customised CNN	0.17	155

IV. CONCLUSION

The proposed CNN will eliminate the initial oscillations and ripples in the power output, as the layer adjustments in this method address the issues inherent in the deep learning method. It outperforms P and O, PSO, and Deep learning in terms of oscillations, settling time, and computational time. The simulation results make it abundantly clear that the proposed customised deep learning-based MPPT Algorithm is more effective, a fast-tracking method with ideal settling and rise times, and resilient to changing weather conditions.

DECLARATION

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REFERENCES

- Li D, Li J and Wang N (2021) "A Novel Technique Based on Peafowl Optimization Algorithm for Maximum Power Point Tracking of PV SystemsUnder Partial Shading Condition". Front. Energy Res. 9:801571. doi: 10.3389/fenrg.2021.801571 [CrossRef]
- Hiren Patel & Vivek Agarwal. "Matlab-based modelling to study the effects of partial shading on PV array characteristics". *Energy Conversion, IEEE Transactions on*, vol. 23, no. 1, pp. 302-310, 2008. [CrossRef]
- M. Irwanto et al., "Analysis simulation of the photovoltaic output performance", Power Engineering and Optimization Conference (PEOCO) 2014 IEEE 8th International, pp. 477-481, 2014. [CrossRef]
- Faranda, Roberto & Leva, S, "Energy comparison of MPPT techniques for PV Systems". J. Electromagn. Anal. Appl.2008.
- Geoff Walker. "Evaluating MPPT converter topologies using a MATLAB PV model". *Journal of Electrical & Electronics Engineering*, Vol. 21, Issue 1, pp.49–56, 2001.
- Sah Bikram & GVE Kumar" A comparative study of different MPPT techniques using different DC-DC converters in a standalone PV system", IEEE Region 10 Conference, 2016 [CrossRef]
- A. Arora, P. Gaur, "Comparison of ANN and ANFIS based MPPT Controller for grid connected PV systems", *Annual IEEE India Conference (INDICON)*, pp. 1-6, 2015. [CrossRef]
- Abdelaziz et al.," A novel approach in stand-alone photovoltaic system using MPPT controllers & NNE", Ain Shams Engineering Journal, Vol. 2, pp.1973-1984,2021. [CrossRef]
- Maind, S.B. & Wankar, P.," Research paper based on Artificial Neural Network". International Journal on Recent and Innovative Trends in Computing and Communication. Vol. 2, pp. 96-100, 2014.
- I.A Basheer, M Hajmeer, "Artificial neural networks: fundamentals, computing, design, and application, Journal of Microbiological Methods, Vol. 43, Issue 1, Pages 3-31, 2000. [CrossRef]
- Munish Manas et al.," An Artificial Neural Network based Maximum Power Point Tracking Method for Photovoltaic System", IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2016), pp. 23-25, 2016. [CrossRef]
- Khare A. & S. Rangnekar, "A review of particle swarm optimization and its applications in solar photovoltaic system. *Applied Soft Computing, Vol.* 13, pp.2997-3006, 2013 [CrossRef]
- Sriranjani, R et al.," Design of Cuk Converter Powered by PV Array". Research Journal of Applied Sciences, Engineering and Technology. Vol. 6, pp. 793-796, 2013. [CrossRef]
- B. Masood, M. S et al., "Maximum power point tracking using hybrid perturb & observe and incremental conductance techniques," 2014 4th International Conference on Engineering Technology and Technopreneurship (ICE2T), pp. 354-359, 2014, [CrossRef]
 Noppadol Khaehintung et al.," FPGA implementation of MPPT using
- Noppadol Khaehintung et al.," FPGA implementation of MPPT using variable step-size P&O algorithm for PV applications". *International Symposium on Communications and Information Technologies*, *ISCIT*'06, pp. 212–215.IEEE, 2006. [CrossRef]
- Y. -H. Liu et al.,, "A Particle Swarm Optimization-Based Maximum Power Point Tracking Algorithm for PV Systems Operating Under Partially Shaded Conditions," in *IEEE Transactions on Energy Conversion*, vol. 27, no. 4, pp. 1027-1035, 2012,. [CrossRef]
- Munish Manas & Ananya Kumarib, Sanjeev Das," An Artificial Neural Network-Based Maximum Power Point Tracking Method for Photovoltaic System", IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2016), pp.23-25, 2016. [CrossRef]
- G.Neelakrishnan et al.," Transformer Less Boost DC-DC Converter with Photovoltaic Array", IOSR Journal of Engineering, Vol. 3, Issue 10, pp. 2278-8719, 2013. [CrossRef]
- N. Pindi, S. Joshi and B. Mehta, "Neural Network based MPPT system for Standalone PV system," IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society, pp. 1866-1871, 2020. [CrossRef]
- O. A. Kumar et al., "Cascaded Artificial Neural Network Based MPPT Algorithm for PV Application," 2019 3rd International Conference on Electronics, Communication and Aerospace Technology (ICECA), pp. 296-300, 2019. [CrossRef]
- L. P. N. Jyothy & M. R. Sindhu, "An Artificial Neural Network based MPPT Algorithm for Solar PV System," 4th International Conference on Electrical Energy Systems (ICEES), pp. 375-380, 2018 [CrossRef]

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