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 methods have significant drawbacks, for instance, poor tracking capabilities and heavy computational load. Therefore, the aim of this work is to present a control algorithm that takes into account the connection between the solar array output power and the controller's PWM duty cycle of the MPPT boost converter. 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 any weather, 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, hydro energy, geothermal energy, tidal energy, biological energy, solar energy, and so forth, are getting 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 a number of 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 that is the regulation and optimization of PV systems under partial shading conditions [3], which has been a hot research topic in the field of PV power in recent years. Generally, to achieve the ideal output power in various situations is the main purpose of the maximum point tracking power (MPPT). This seeks to solve the issue caused by partial shading conditions of PV systems. Because of their low efficiency and relatively high capital cost per watt, PV energy systems are under-utilised. Therefore, there is still a long way to improve the reliability and efficiency of photovoltaic systems. The first step is to figure out how to increase 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].

A number of methods for monitoring maximum power in PV applications [5,6,7] have been documented. However, the majority of current approaches have shortcomings such as 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, but the difference is that the fixed voltage monitoring method follows constant voltage, while OVT follows voltage evolution. In short circuit current, the tracking mechanism of short circuit current monitors the variation of current. The common 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. With respect to particle swarm optimization, the Deep Learning algorithm for MPPT in partially shaded PV systems shows faster and more stable tracking. Although the desired and effectiveness is achieved, it still has a few disadvantages, such as a heavy calculation burden.

Therefore, the goal of this work is to discover more precise and dependable methods to generate the desired power that a PV system is capable of producing, under a variety of weather conditions. The shortcomings of the current approaches will be corrected by adopting a Customised CNN algorithm based MPPT technique. This technology has excellent modelling and inference capabilities. Since location data can be stored for deep learning in functions, its primary benefit is faster real-time optimization. In order 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 implies learning to do tasks from the data set provided for training.
2. Fault tolerance via Redundant Information Coding: Faults could be semi-destructive of the neural network that ultimately degrades network performance. However, retraining data can provide fault tolerance to a large extent.
3. Real Time Operation: The computations needed in Customised CNN can be done in real time, but require special hardware that needs to be designed specifically for the purpose.
4. Self-Organization: Customised CNN forms its own structure or representation that suits itself while processing information received from the training data set.

II. METHODOLOGY

A. PV Cell equivalent Circuit

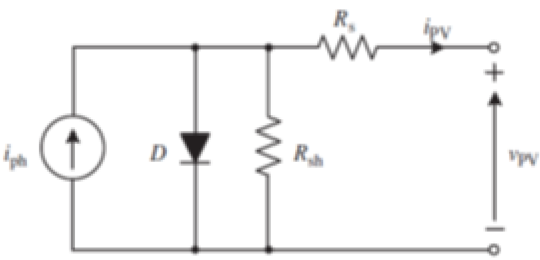

Figure 1: PV cell equivalent circuit

A PV module or cell's electrical properties are nonlinear and strongly influenced by temperature and solar irradiation. A photocurrent source connected in parallel to a diode, a shunt resistance R_{sh}, and a series resistance R_s can be used to electrically simulate the PV cell. The model of Figure 1 can be mathematically described by

$$i_{pv} = i_l - i_o\left[e\frac{e^{q(v_{pv}} + i_{pv}R_s}{nkT} - 1\right] - \frac{v_{pv} + i_{pv}R_s}{R_{sh}} \qquad (1)$$

Where v_{PV} is the output voltage of the PV cell, V

i_{PV} is photo generated current source, A

i_0 is leakage current of the diode, A

q is the charge of electron and numerically given as 1.6×102^{-19}C.

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

k is the Boltzman constant and is equivalent to 1.38×102^{-23} J/K,

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

R_s and R_P are the series and parallel resistance 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 input voltage. Output voltage is determined by the switching signal's duty ratio. The output voltage increases as the switch remains locked for longer.

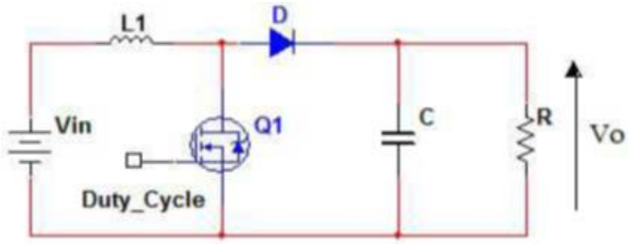

Figure 2: Boost Converter circuit schematic.

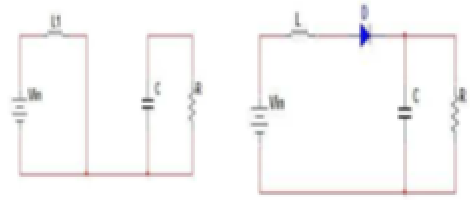

Figure 3: Boost Converter working modes

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

$$v_{in} = L\frac{di}{dt} \qquad (2)$$

Assuming that inductor current rise 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.

$$V_L = v_{in} - v_o \qquad (3)$$

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

$$L\frac{(\mathrm{I_2{-}I_1})}{\mathrm{t_2}} = v_{in} - v_o \tag{5}$$

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

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

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

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

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

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

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

The switching period T is

$$\Delta \mathrm{I} = t_1 + t_2 = \frac{\Delta \mathrm{IL}}{v_{in}} + \frac{\Delta \mathrm{IL}}{v_o - v_{in}} \tag{10}$$

The peak to peak ripple current can be found from

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

$$\Delta \mathrm{I} = \frac{Dv_{in}}{\mathrm{fL}} \tag{12}$$

The average capacitor current during time t_1 is $I_c = I_o$ and peak-to-peak ripple voltage of capacitor is

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

$$= \frac{1}{\mathrm{C}}\int_0^{t_1} I_c \mathrm{dt} = \frac{I_c}{\mathrm{C}} t_1 \tag{14}$$

C. Maximum Power Point Tracking (MPPT) Algorithms

The maximum power value varies as weather conditions such as temperature and irradiance varies. A real-time maximum power-point tracker is a crucial component of the PV system because solar arrays 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 operation pertaining to P and O Algorithm, also known as true 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, in order to find the MPP. To achieve 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 intrinsic steady state oscillation.

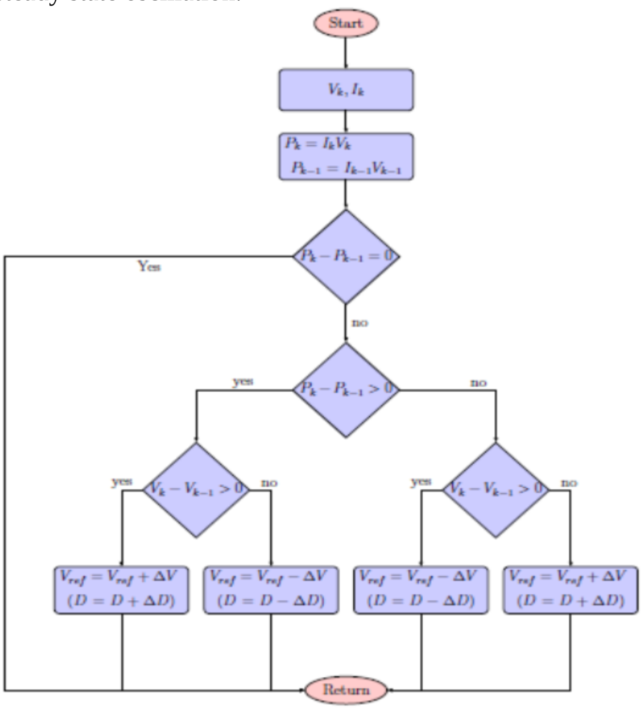

Figure 4: P & O based MPPT Algorithm

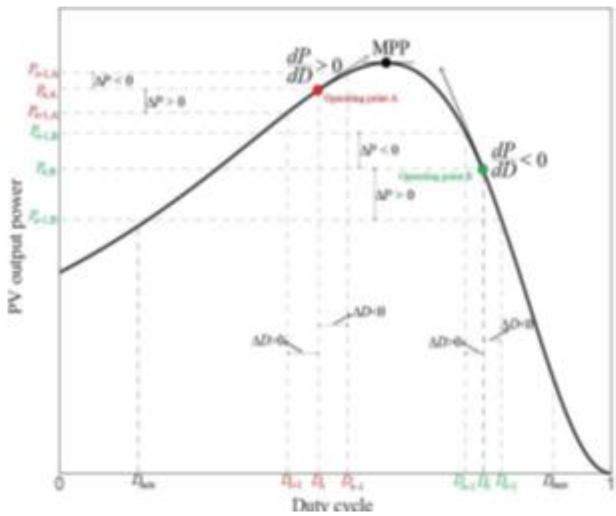

Figure 5: PV output power Vs Duty cycle D of the MPPT boost converter

An MPPT control algorithm based on duty cycle perturbation is implemented for quick response to the variation in ambient condition 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.

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2. Artificial Neural Network based MPPT

Artificial Neural Network has been used to improve the dynamic performance of MPP tracking. Concentrating on nonlinear characteristics of the PV arrays, the artificial Neural Networks provide a fast, and yet, computationally demanding solution for the MPPT problem. This method is based on extracting the MPP of the array from its output characteristics.

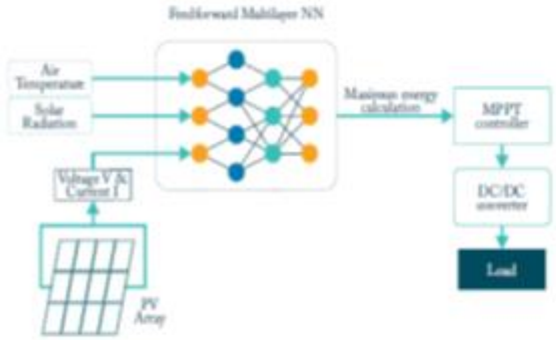

Figure 6: Artificial Neural network structure based MPPT Algorithm

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, weights of neurons in various levels are obtained. To acquire data, PV model programming in MATLAB is used. 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

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

3. Indirect method

The traditional algorithms (P&O, INC, & ANN) are not better enough to distinguish between the global peak and local peak under partial shading conditions. Particle swarm optimization (PSO), a stochastic search technique, is used to find the global peak, which is the maximum power point (MPP) of the array, because there are several local peaks with incomplete shading. The Particle swarm optimization (PSO) is a method of optimization that uses a community or a number 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 used as an MPPT method for multivariable function optimization with multiple local points.

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 best particle location rely on the PV module's power output. Thus, the duty cycle is determined by particle location. Each one's modification speed can be determined by the calculation agent and present speed. The distance to P_{best} and G_{best} is as follows.

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

Where,

V_i^k The speed of individual i when k is iterating,
X_i^k Individual i is in the position of k^{th} iteration,
W inertial weight
C_1 , C_2 acceleration factor,
P_{besti}^k The best position of individual i in k^{th} iteration
G_{best}^k Group's best position until k^{th} iteration.
r1, r2 Random number 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 falls between [1]. A concept known as velocity clamping is used in the Particle Swarm Optimization method, and it essentially aids the particle to remain inside the boundary and taking reasonable steps in order to comb through 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. 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.

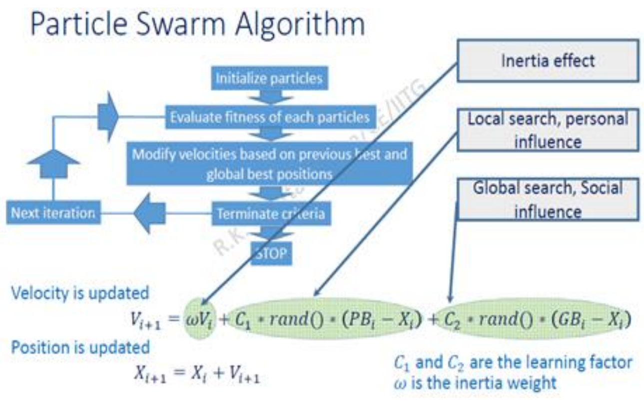

Figure 7: Particle Swarm Optimization Algorithms

1. Evaluate the fitness of each particle
2. Update individual and global best fitness and positions
3. Update 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 convolution neural network (CNN). This is used to deliver the intended output for the specific input task. The MPPT module's in the suggested design is broken down into three steps in Figure 8.

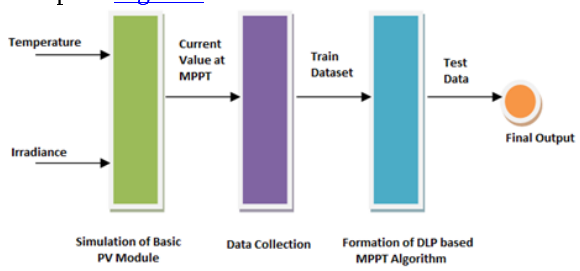

Figure 8: Work flow diagram of Proposed Methodology

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Temperature and Irradiance values are used as the basic PV module's input data, in the first stage [19, 20]. The procedure of gathering data in the second step is dependent on the outcomes of the simulation in the first step. The proposed multilayer 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 customized convolution network with two input layers, five hidden layers, and an output layer is suggested in this article. The illustration in figure 9 shows this.

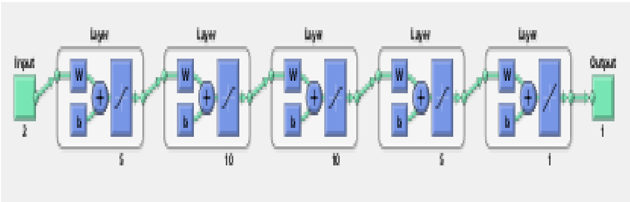

Figure 9: Deep Learning design consisting of 2 inputs, 5 hidden layers and 1 output layer

A dataset containing temperature and irradiance was produced following the execution of countless scenarios. The suggested technique calculates the duty ratio that can precisely follow the maximum output point in accordance with the irradiance and predicts the irradiance based on the output voltage/current and power of the photovoltaic (PV) system.

(a)

Name	Type	Activities	Learn Labels
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 8 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

The experimental data was used to train the deep learning model that was used in this work, and the performance of the suggested algorithm was assessed by contrasting it with the performance of the traditional algorithm in a range of input irradiance conditions. Comparing the suggested algorithm to existing algorithms for the same input conditions, 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 normalization layer, ReLU layer between the convolution layers serves to speed up the learning and training process while max pooling layer reduces feature space. Softmax layer used to assign a decimal probability which adds up to 1. Similarly, the pooling in CNN is demonstrated in Fig 11. In this, max pooling and average pooling explained by considering four convolution outputs. Maximum of all pixel values resulted in maxpooling, whereas average of all the pixel values resulted in average pooling.

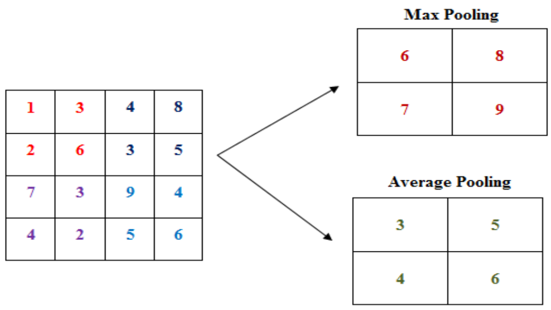

Figure 11 Pooling in CNN

III. SIMULATION RESULTS AND DISCUSSIONS

The proposed method was simulated under different operating conditions caused by solar irradiation and temperature variations. Performance analysis of voltages and power tracked by MPPT controller on the basis of various control system parameters such as ripples, stability, settling time and computation time. The comparison shows that the model implemented using Customized CNN based MPPT technique gives better performance with lesser voltage and current ripples as compared to P&O, PSO and Deep Learning model. In order 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 are varied at irregular Intervals with Irradiance between 600 to 1000W/m^2 and temperature between 20°C to 40°C.

1. Perturb and Observe Based MPPT Algorithm

Figure 10 and 11 illustrates output voltage, current and power waveforms of the Photo Voltaic system with P and O based Algorithm.

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It is observed that the P and O method will not instantly adapt the change in temperature and irradiance. The P and O method is suitable if both the inputs are linear. It works efficiently for lower frequencies. The ripple in the current and voltage are high due to low frequency operation. It requires more cycles to reach steady state values. It is also observed that there is high ripple in the current waveform which is reflected on the power waveform.

2. Particle Swarm Optimization (PSO) Based MPPT Algorithm

Figure 12 and 13 illustrates output voltage, current and power waveforms of the Photo Voltaic system with PSO based Algorithm. The initial adjustment of population position and velocity will give more oscillations on PSO method as shown in the figure 12. After proper velocity and positions update, the PSO will track proper MPP.

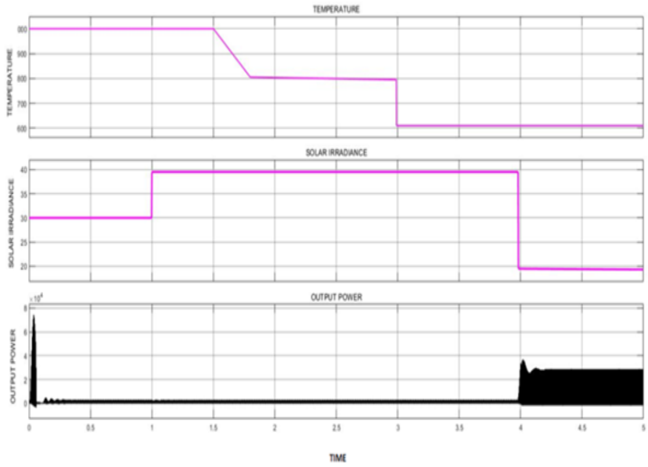

Figure 12 P and O Power Output for different values of Solar Irradiance and temperature

These values also affect the voltage and current values. Further, it is also observed that even after reaching steady state, small ripples are present on the voltage and current waveforms.

3. Deep Learning Based MPPT Algorithm

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

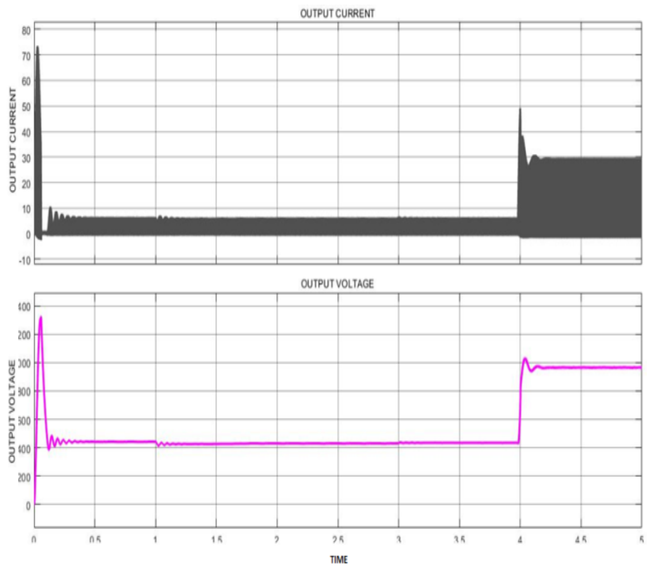

Figure 13: P and O Voltage and Current Output

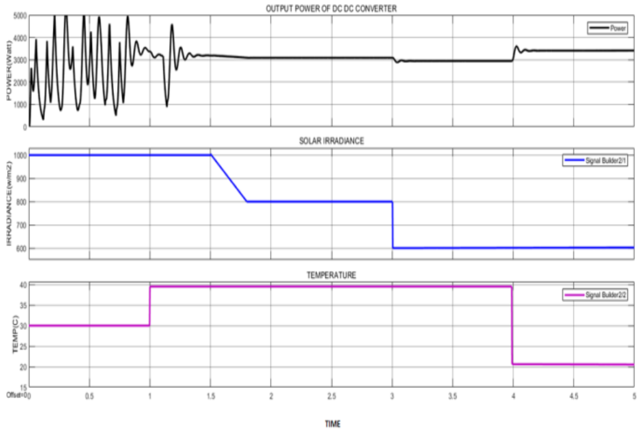

Figure 14 PSO Power Output for different values of Solar Irradiance and temperature

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

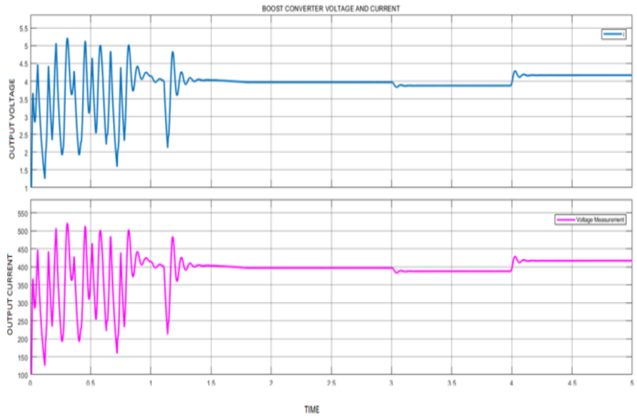

Figure 15: PSO Voltage and Current Output

Even though fast tracking, the Deep Learning method also has some ripples in voltage and current waveform. This is because the deep learning method will not change its weights with sudden change in irradiance and temperature, because it requires larger number of hidden layers.

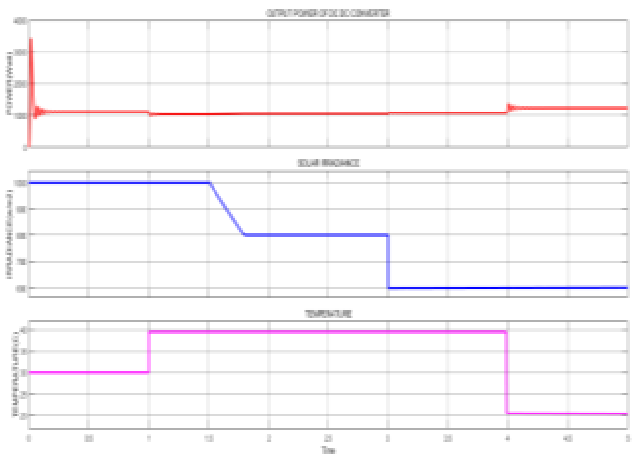

Figure 16: Deep Learning Power Output for different values of Solar Irradiance and temperature

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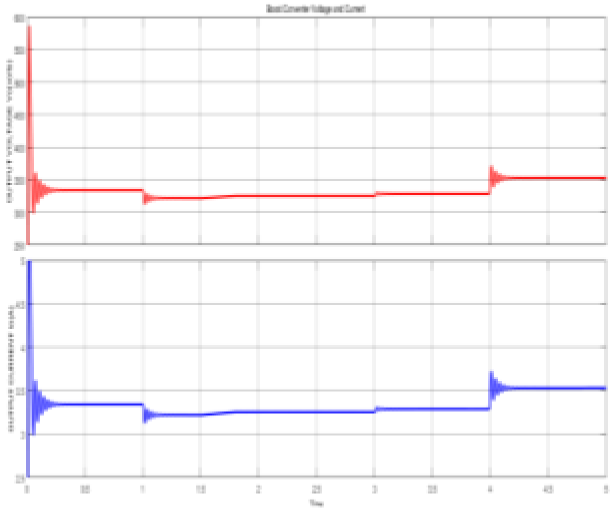

Figure 17: Deep Learning Voltage and Current Output

4 Customized CNN

The Deep Learning has some initial oscillations and some ripples due to adjustments of weights in hidden layers. This is overcome by proposed customized CNN, where convolution layers are selected according to the data available. Further, in proposed customized CNN, the number of hidden layers is chosen according to the available irradiance and temperature data. The proposed method out performs by removing the oscillations and reaching steady state conditions very fast with low ripple values compared toother methods. Figure 16, 17 and 18 shows the voltage, current and power waveforms of Customized CNN based MPPT algorithm with fast transient and steady state response.

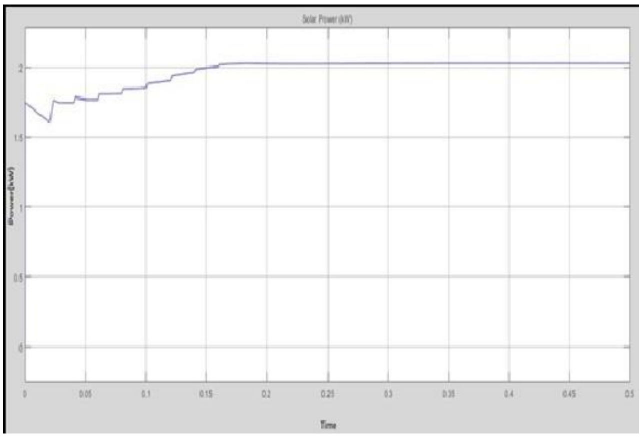

Figure 18: C-CNN Power out put

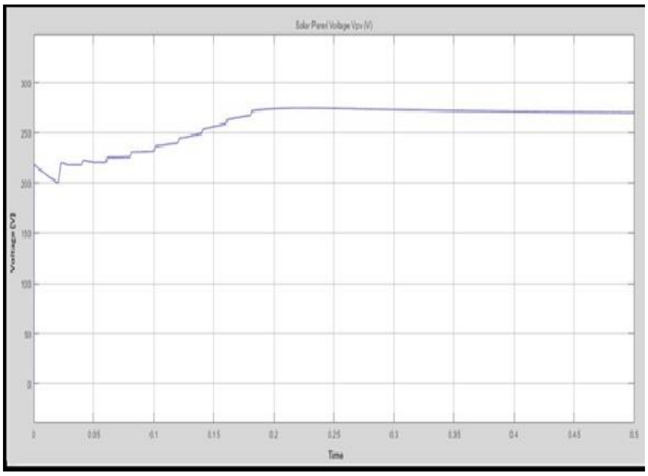

Figure 19 C-CNN Voltage Output

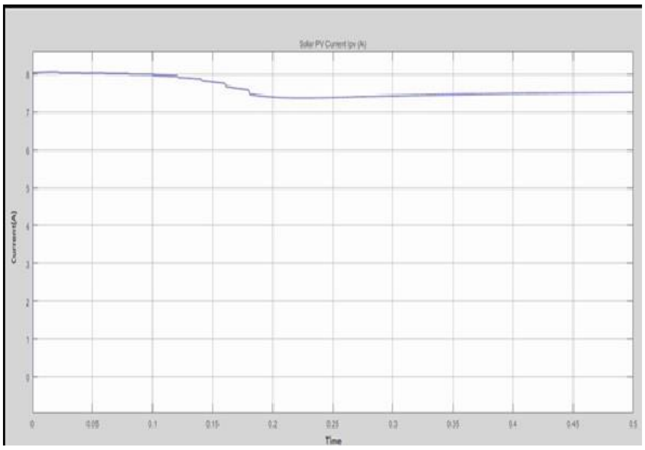

Figure 20 C-CNN Current Output

Table 1 depicts the settling and computational time required for different methods. It is seen that the proposed C-CNN method performs well compared to other methods.

Table 1 settling and computational time

Sl No.	MPPT Methods	Settling Time (sec)	Computational Time(sec)
1.	P & O	2.4	300
2.	PSO	1.3	195
3.	Deep Learning	0..25	225
4.	Customised CNN	0.17	155

IV. CONCLUSION

The proposed CNN will remove the initial oscillations and ripples in the power output. Because the layers adjustments in this method, will overcome the problems of the deep learning method. It out performs 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 customized Deep learning-based MPPT Algorithm is more effective, a fast tracking method with ideal settling and rise times, and resilient to changing weather conditions

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Authors Contributions	All authors have equal participation in this article.

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