Design and Analysis of an Artificial Neural Network-based Maximum Power Point Tracking Algorithm for PV System

Apurba Kumer Saha, Md. Rifat Hazari and Mohammad Abdul Mannan

Abstract— The demand for renewable energy integration into the electrical grid is growing day by day. Solar photovoltaic (PV) generation is crucial for battery charging, grid-tied applications, and other uses. It is critical to find the maximum feasible energy harvest from PV panels to increase the output power of a solar PV system. Therefore, to obtain maximum power from the PV system, this paper proposes an artificial neural network (ANN)-based maximum power point tracking (MPPT) controller for a solar PV system. The proposed ANN system can track a PV system's maximum power point (MPP) under quickly changing irradiance conditions at a fast and accurate rate. The performance of the proposed ANN system has been verified through simulation analysis, and it is compared with the perturbation and observation (P&O) algorithm. The simulation result indicates that the proposed ANN system effectively extracts maximum power from the PV panel under varying atmospheric conditions..

Index Terms— Artificial neural networks (ANN), perturbation and observation (P&O), solar photovoltaic (PV) system, proportional-integral-derivative (PID) controller

1 INTRODUCTION

Solar PV systems are more efficient than other renewable energy sources due to environmental and economic benefits Photovoltaic power generation is the most encouraging sustainable energy source since it's perfect, boundless, creates less contamination, and requires less maintenance. [1]

Solar photovoltaic cell energy is a clean source of energy that is always regarded as a valuable renewable resource. Solar photovoltaic cells have nonlinear internal resistance and nonlinear I-V characteristics, making them photon-dependent power sources because the solar panels must be operated at full power for economic reasons, the source's internal resistance must be equalized with the load resistance. [2] The source's internal resistance must be equalized with the load resistance since the solar panels must be operated at full power for economic reasons. [3] There are a total of nine MPPT algorithms accessible, however only a few can be designed practically. Perturb and Observe, Constant Voltage, Constant current, Incremental Conductance, Parasitic Capacitance, Fuzzy Logic-based, and others are some of the algorithms. There have been many ANN-based algorithms developed so far. [4]

In this piece of the presentation, another related exploration that has been recently led is momentarily talked about from an overall perspective. Likewise, the distinctions of this exploration in connection to prior work are introduced. Past writing introduced and analyzed diverse greatest PowerPoint following (MPPT) calculations for different PV frameworks. There are in a real sense a great many reports that account for MPPT calculations, and they are too various to even think about naming here.[10] Later in this proposition, different MPPT calculations are clarified. Also, the two calculations that are utilized in this theory research are genuinely conventional and have been investigated by different specialists. Be that as it may, in this postulation, these two calculations are examined in more detail than most. Furthermore, various sorts of force converters have been utilized to control these kinds of frameworks.[11] For example, different DC-to-DC converters, for example, the buck, support, buck-help, forward, SEPIC, thunderous, fly back, and others, just as DC-to-AC inverters have been utilized in the execution of a MPPT framework. Interleaving techniques such as the one described here have also been used, but to a lesser extent. Certain components of the interleaved boost converter are studied and discussed in further depth in this thesis. The MPPT algorithms are synthesized using the Xilinx block set within Simulink and other Xilinx tools, which is a unique component of this research.[12] The algorithms are then placed onto an FPGA and used. To put it another way, this thesis makes a unique contribution by presenting both simulations and experiments of two digitally implemented MPPT approaches that use an interleaved boost converter. Furthermore, the author's level of depth in presenting these themes adds to the reader's understanding of these topics.[13]

A few recently developed MPPT approaches will be covered in this section. It may appear that MPPT is a solved problem, given the multiple approaches that have been devised and tested. However, there is still a lot of work being done in this subject to improve the MPPT approach and improve tracking accuracy and converter efficiency. This is basic for rapidly changing climatic conditions, to some extent concealed PV cluster settings, more current semiconductor gadgets on high-recurrence power converters, and differed DC-DC converter geographies with low homeless people. The conventional P&O technique is as yet being improved and changed by analysts to address its imperfections. The upgraded versatile bother and notice (EA-P&O) MPPT technique was presented by Ahmed and Salam in [14] They guarantee that the EA-P&O can effectively follow the worldwide MPP (GMPP) in fractional shade circumstances, tackle the difference issue, and decrease power misfortune in a consistent state. The EA-P&O professes to have a 99 percent general productivity rating.

This study offers an ANN-based controller that will solve most of the drawbacks that prior algorithms had, such as non-linearity, uncertainty, and parameter fluctuations in both controlled and uncontrolled environments. A similar ANN-based approach for tracking the optimal operating point is provided in this paper. The objective of this study is to make and simulate an ANN-based MPPT conspire for solar PV systems with different environmental circumstances as well as to compare the outcomes to the traditional P&O strategy.

2 PV MODELING

A solar cell is a device that absorbs solar irradiation and converts it to electrical energy using semiconductor-based PV technology. [5] These are joined in series and parallel to construct PV modules to provide the appropriate output voltage or current of PV. The equivalent circuit of a solar cell is shown in Fig. 1. [6]

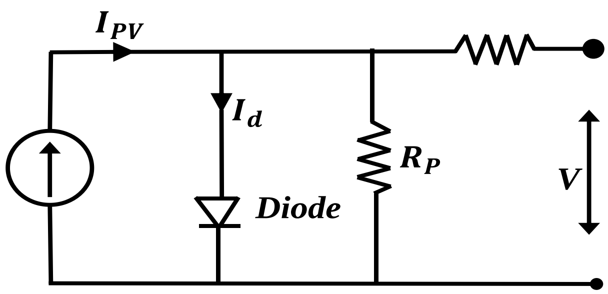

Fig. 1. PV cell equivalent circuit model

3 PRINCIPLES OF MPPT

ANN is generally recognized as a technology that can help tackle complex problems differently. It is made up of several simple, densely interconnected processors called neurons. Pattern recognition and learning capacities are outstanding in such networks. In ANN applications, four primary processes must be completed like Data generation, Input selection, ANN architecture selection, and Training & testing.

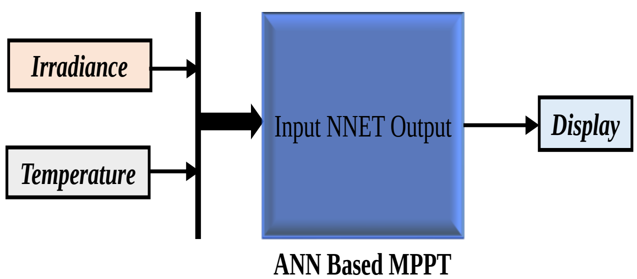

Fig. 2. ANN-based MPPT Block

MSE is a technique for determining how close estimations or projections are to actual values. The lower the MSE, the more accurate the forecast. For regression models, this is employed as a model evaluation metric, with a lower value indicating a better fit. [7]

$$MSE = \frac{1}{Q}\sum_{K=1}^{Q} e(k)^2 \quad (1)$$

$$MSE = \frac{1}{Q}\sum_{K=1}^{Q}(t(k) - a(k)) \quad (2)$$

The ANN takes two input variables: an array of irradiance levels and an array of ambient temperature levels. The training data for ANN learning is obtained by simulating the selected PV Module characteristics and recording the maximum power point voltages for each sample. The PI controller's next task is to smooth out the erroneous signal variance. [8]

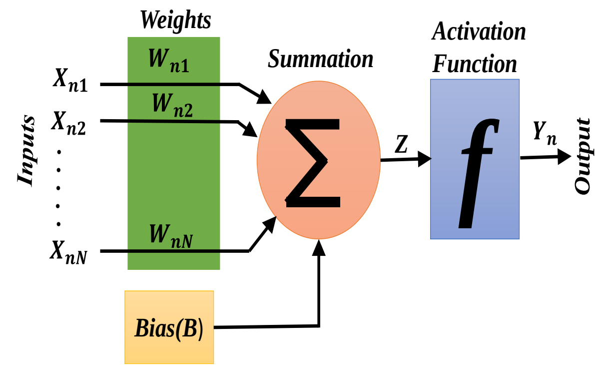

Fig. 3. Neuron Module

As shown in Fig. 5, two neurons make up the input layer thirty neurons make up the hidden layer and one neuron makes up the output layer. A total of 590 training point combinations of temperatures and irradiances are delivered to the input layer, ten neurons make up the hidden layer, and one neuron makes up the output layer (V_{mpp}).

As shown in Fig. 4, The output of the ANN block & the PV operating voltage are taken into a comparator. The controller receives gate pulse and then the output is again compared with the ANN output in another comparator.

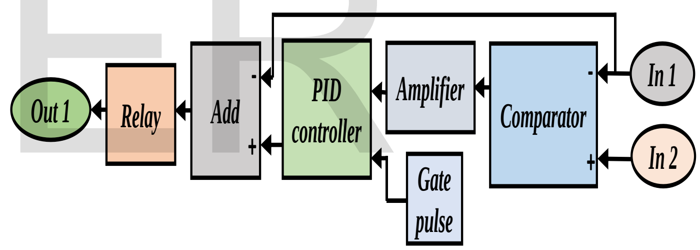

Fig. 4. Representation of controller

4 IMPLEMENTATION OF THE ENTIRE SYSTEM

The ANN block provides a voltage at maximum power point for that fixed temperature & irradiance as output. The output of the ANN block & PV array operating voltage is taken into a comparator & then the difference is fed to a PID controller. The DC-DC converter maintains the operating voltage of the PV array to its MPP voltage so that maximum power can be obtained from the PV array in all load condition

Challenges faced in implementing the entire model.

- Designing/ Selecting a PV array.
- Creating a Data set for different irradiance & temperature for the PV array.
- Training the ANN model with the data set.
- Using a Controller block to feed PWM pulse to the switch of the converter.

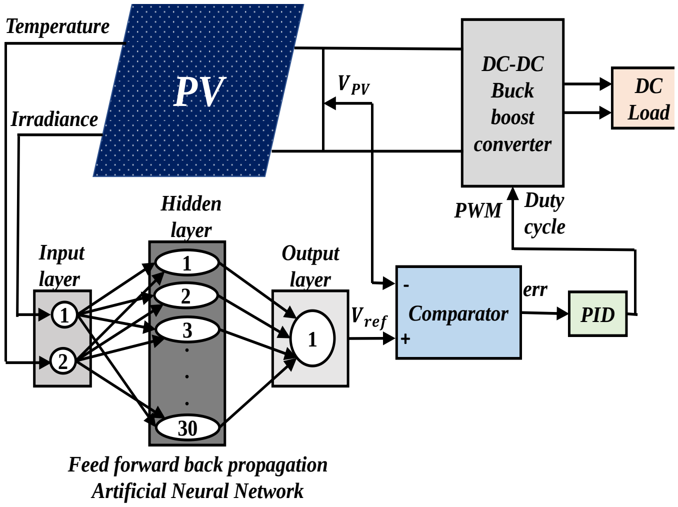

Fig. 5. An ANN-based MPP tracker that has been proposed

5 ANN BASED MPPT

For designing & simulating the performance of ANN-based MPPT we need to design & combine some basic blocks in the MATLAB/ Simulink environment. We have used the feed-forward back propagation technique.

TABLE 1
TRAIN PARAMETERS

No. of the input point	2
No. of the output point	1
No. of hidden layers	30
No. of Data in Data set	590
No. of epochs	1000
Goal	1e-25
Learning rate	0.01

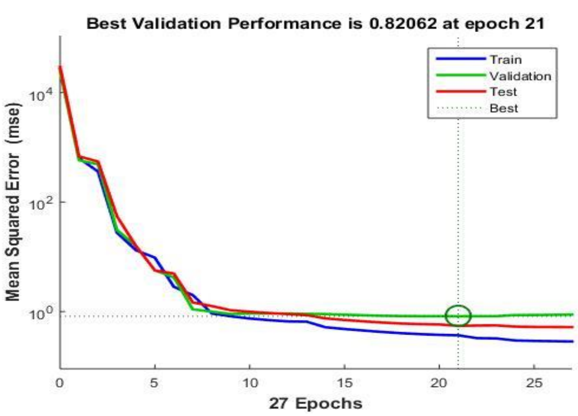

Fig. 6. ANN training best validation performance

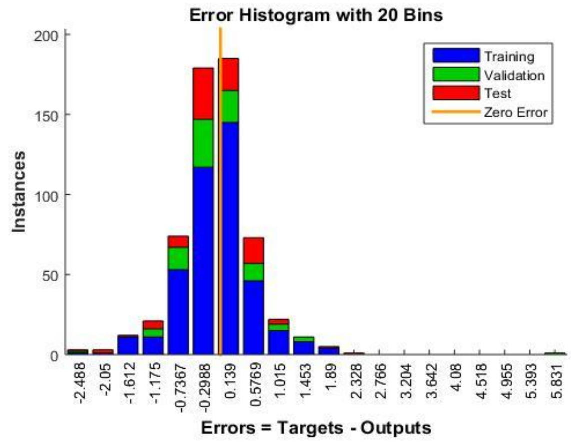

Fig. 7. ANN Training error histogram

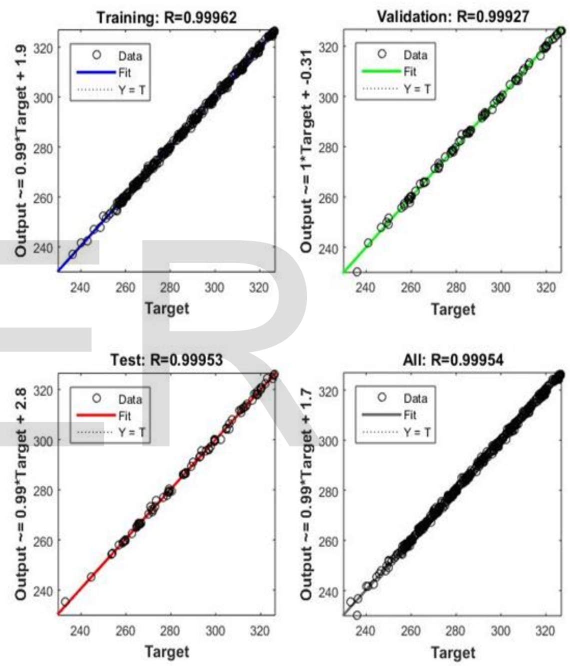

Fig. 8. ANN training Regression.

A well-trained artificial neural network will have a very low mean squared error after training, as shown in Fig. 6. Following the training procedure, the ANN-based MPPT controller should be able to provide the MPP voltage in any weather condition.

6 SIMULATIONS AND RESULTS

For 1000 Watt/m^2 irradiance & 25℃ temperature the maximum output power of the experimental model is 8.856×10^4 watts on 290 volts. Here, the system is supplying power to 200Ω active loads.

TABLE 1
TRAIN PARAMETERS

Parameters	***Values***
Parallel strings	40

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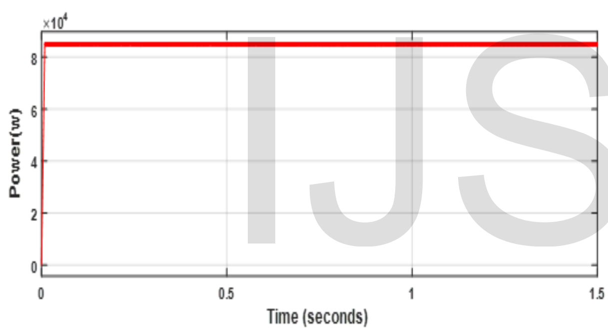
Parameters	*Values*
Series-connected modules per strings	10
Maximum power(w)	213.15
Cells per module (Ncell)	60

6.1 Comparison of ANN and P&O method:

If the active load is fed from the output of the DC-DC converter which is controlled by the implementation of ANN-based MPPT techniques then it will be visible that the PV array operating voltage remains fixed around 290V (Maximum Power Point Voltage). The standard atmospheric condition is considered to be solar irradiance of 1000 Watt/m^2 & temperature of 25℃. But the solar irradiance & temperature vary. So, the variable signal is generated for both irradiance & temperature. In Fig. 11, the atmospheric condition (irradiance & temperature) was considered to be constant. But actually, the condition varies from time to time. So, the MPPT technique should have fast tracking speed, high accuracy & it must not oscillate around the maximum PowerPoint. In this section, the performance of the ANN-based MPPT technique will be compared with the most widely used MPPT technique, Perturb & Observation (P&O) method.



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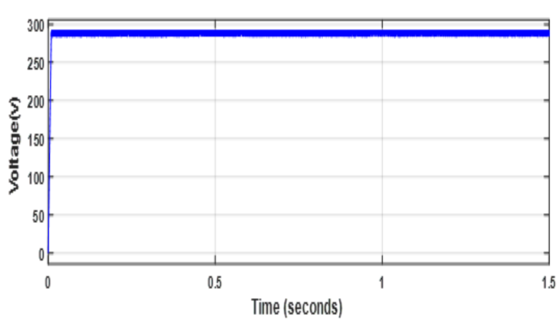

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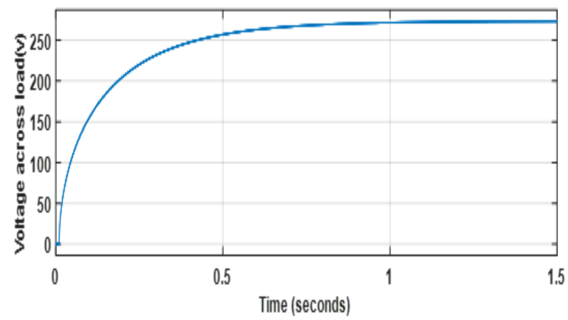

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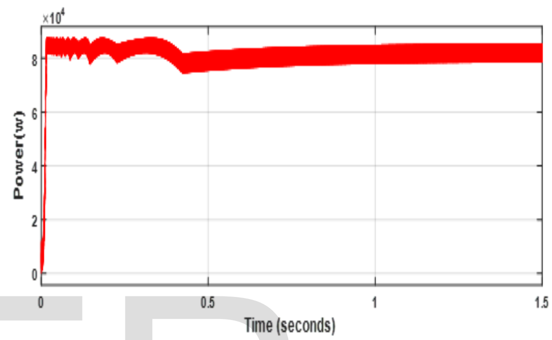
Fig. 9. Simulation result from ANN method (a) output power, (b) output voltage, (c) voltage across the load



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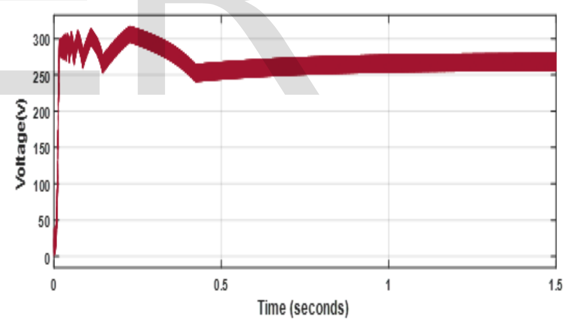

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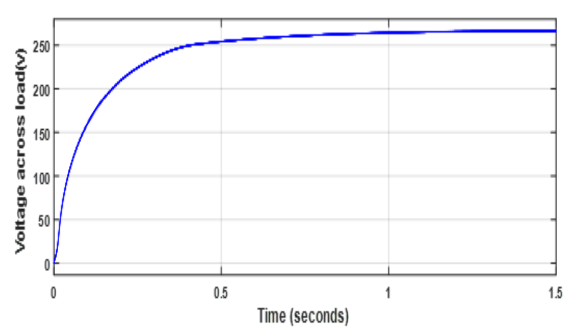

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Fig. 10. Simulation result from P&O method (a) output power, (b) output voltage, (c) voltage across the load

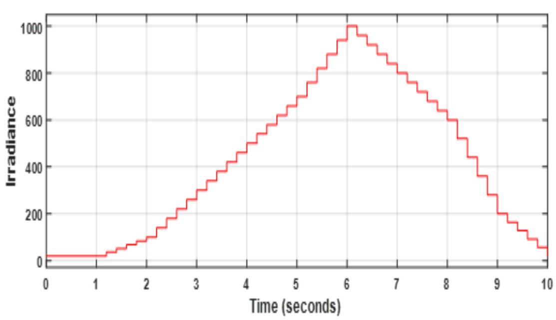


Fig. 11. Signal for variable irradiance

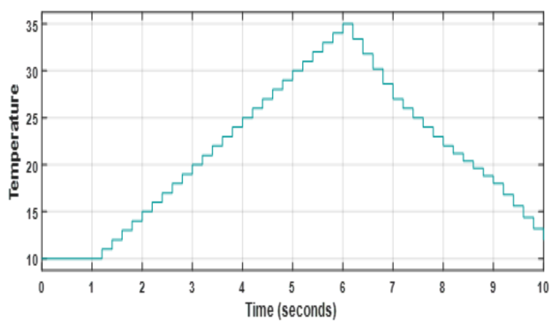
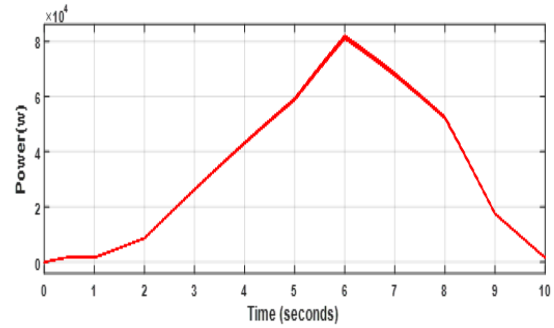


Fig. 12. Signal for variable temperature

To assess the performance of the P&O and ANN MPPTs when irradiation is rapidly changing, The signal shown in Fig. 11 and Fig. 12 is used to simulate solar irradiation and temperature. Fig. 13 and Fig. 14 depict the simulation results for the P&O and ANN approaches at a variable atmospheric condition. As shown in Fig. 13 and Fig. 14, the ANN technique can rapidly follow the MPP when the irradiation changes rapidly, whereas the P&O method fails to attain MPP when the irradiation varies rapidly. Furthermore, after reaching MPP, ANN has a minor oscillation around it, whereas the oscillation in the P&O approach is very strong, resulting in power loss in a steady state. As shown in Fig. 9 and 10, the ANN technique has a very tiny oscillation when the solar irradiation is constant, whereas the P&O method has a significant oscillation, which results in a high-power loss when the solar irradiation is constant or slowly changing.

The solar irradiance is varied from 10 Watt/m^{-2} to 1000 Watt/m^2 & then again fall back to 10 Watt/m^2. The total simulation period is 10s. So, in the first 5 seconds the irradiance will be 10 to 1000 Watt/m^2. For the second 5s interval the irradiance value will be 1000 to10 Watt/m^2 . Thus for each 1s interval, the value of irradiance will change. This signal was built using the signal builder block from the Simulink library file. More variation could have been brought. But this is enough to check the performance of the entire system. Now a variable temperature signal is built in the signal builder block Simulink like before. For simulation period of 10s, the temperature varies from 10°C to 35°C.



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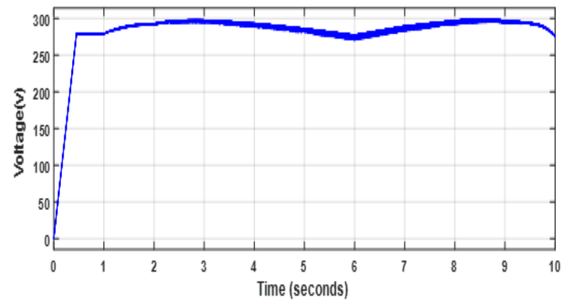

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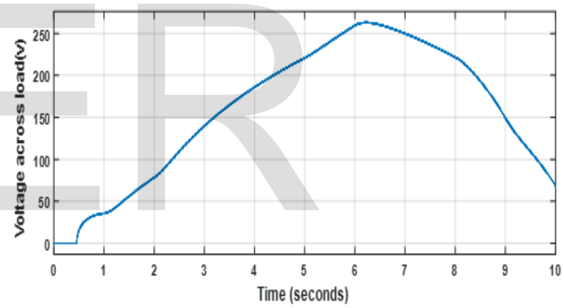

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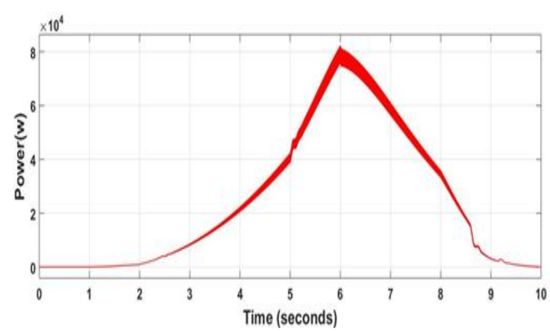
Fig. 13. (a)Output power, (b) PV operating voltage, (c)Output voltage across load using ANN-based MPPT technique.



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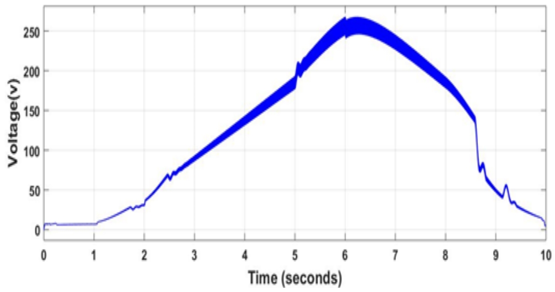

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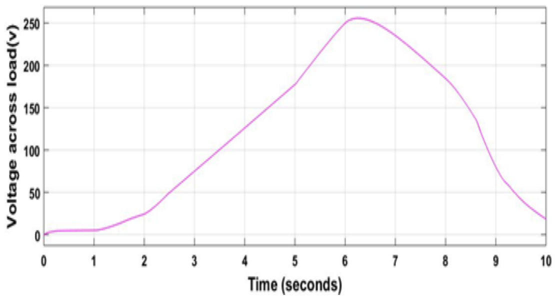

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Fig. 14. (a) Output power delivered to load, (b) PV operating voltage, (c) Output voltage across the load, using P&O technique

7 Conclusion

The simulation results for the ANN and P&O approaches provided in this work show that in the scenario of rapidly changing solar irradiation, the ANN method is particularly fast and exact in locating and tracking the MPP. Furthermore, with slowly changing solar irradiation, our approach can reliably extract the maximum powerpoint. When irradiation changes rapidly over a short period, however, the P&O approach fails to track the MPP. Furthermore, with slowly changing solar irradiation, this approach exhibits considerable oscillation around MPP, resulting in high power loss over time. Observations from the performance graphs are given below:

- The tracking speed of the P&O method is very low. ANN has a faster tracking speed.
- ANN-based MPPT has better accuracy than the P&O method.
- P&O oscillates around the maximum power point, but ANN provides almost stable output.
- Implementation of the P&O method is much easier than ANN as ANN is a complex method.

From the above observation of the wave-shapes, it is evident that the ANN provides better output than the P&O technique.

References

[1] H. Attia, "Artificial Neural Networks Based Maximum Power Point Tracking photovoltaic System for Remote Park LED Lighting Applications," *International Review on Modelling and Simulations,* vol. xx, December 2018

[2] M. Farhat, "Photovoltaic Maximum Power Point Tracking Based on ANN Control," *International Review on Modelling and Simulations (I.RE.MO.S.),* vol. 7, pp. 474-480, June 2014

[3] L. B. Prasad, "An Improved Method for MPPT using ANN and GA with Maximum Power Comparison Through Perturb & Observe Technique," in *Uttar Pradesh Section International Conference on Electrical, Computer and Electronics Engineering*, 2016.)

[4] R. E. idrissi, "Artificial Neural-Network-Based Maximum Power Point Tracking for Photovoltaic Pumping System Using Backstepping Controller," in *59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University*, 2018

[5] B. Bendib, "A survey of the most used MPPT methods: Conventional and advanced algorithms applied for photovoltaic systems," *Renewable and Sustainable Energy Reviews,* vol. 45, pp. 637-648, 2015

[6] R. Khanaki, "Comparison of ANN and P&O MPPT Methods for PV Applications under Changing Solar Irradiation," in *IEEE Conference on Clean Energy and Technology (CEAT)*, 2013.

[7] Z. O. a. J. AYMEN, "Comparison of Hill-Climbing and Artificial Neural Network Maximum Power Point Tracking Techniques for Photovoltaic Modules," in *Second International Conference on Mathematics and Computers in Sciences and in Industry*, 2015.S.P. Bingulac, "On the Compatibility of Adaptive Controllers," *Proc. Fourth Ann. Allerton Conf. Circuits and Systems Theory*, pp. 8-16, 1994. (Conference proceedings)

[8] H. Goto, Y. Hasegawa, and M. Tanaka, "Efficient Scheduling Focusing on the Duality of MPL Representation," *Proc. IEEE Symp. Computational Intelligence in Scheduling (SCIS '07)*, pp. 57-64, Apr. 2007, doi:10.1109/SCIS.2007.367670. (Conference proceedings)

[9] S. Messalti, "A New Neural Networks MPPT controller for PV Systems," in *6th International Renewable Energy Congress (IREC)*, 2015.

[10] A. Jäger-Waldau, "Snapshot of Photovoltaics—March 2017," *Sustainability,* p. 783, May 2017

[11] C. W. C. C. E. C. a. Y. S. S. Jiang, "Distributed photovoltaic," *CSEE Journal of Power and Energy Systems,* pp. 263-272, September 2018

[12] A. R. H. H. A. M. D. B. a. S. R. T. R. McNutt, "Silicon Carbide Power MOSFET Model and Parameter Extraction Sequence," *IEEE Transactions on Power Electronics, vol. 22, no. 2,* pp. 353-363, March 2007.

[13] H. Attia, ""Artificial Neural Networks Based Maximum Power Point Tracking photovoltaic System for Remote Park LED Lighting Applications,"," *International Review on Modelling and Simulations, vol. xx, ,* December 2018.

[14] G. P. G. S. N. Femia, "Optimization of perturb and observe maximum power point tracking method," *IEEE Transactions on Power Electronics, vol. 20, no. 4,* p. 963–973, , Jul. 2005.