Indian Journal of Pure & Applied Physics
Vol. 60, October 2022, pp. 892-898
DOI: 10.56042/ijpap.v60i10.62197

Machine Learning Based Maximum Power Prediction for Photovoltaic System

Anshul Agarwal[a*], Nitish Kumar[a] & Pawan Dubey[b]
[a]National Institute of Technology, GT Karnal Road, New Delhi 110 036, India
[b]Madhav Institute of Technology & Science, Gwalior, Madhya Pradesh 474 005, India

Received 19 April 2022; accepted 15 September 2022

This manuscript proposes a data-driven machine learning algorithm to track maximum power for PV (photovoltaic) panel systems. Data from the PV panel system connected to a boost converter has been collected. PV Voltage, current, temperature, irradiance, PI and power value have been collected for the supervised machine learning-based modeling. Where PV Voltage, PV current, temperature, and irradiance are the predictors, and PI (proportional integral) is the response of the machine learning-based model. The proposed system becomes more efficient with time while existing MPPT (maximum power point tracking) work on a specific logic for whole life. The model efficacy has been analyzed based on accuracy, scattering plot, and ROC (receiver operating characteristics) curve.

Keywords: Supervised machine learning; Data driven modeling; Boost converter; MPPT (Maximum power point tracking)

1 Introduction

India is a country having the enormous capability of solar energy and has several states where the average sunshine is more than 8 hours like Madhya Pradesh, Haryana, Bihar and West Bengal. As the world facing tremendous pressure to opt for renewable energy in the field of power generation, and transportation purpose. In these scenarios, India will have to massively enlarge its presence in the field of renewable energy, and solar energy is the best option.

1.1 Literature Survey

Solar energy has several shortcomings, such as efficiency, weather constraints, as well as partial shading[1,2]. A partial technique was used to overcome several constraints for MPP tracking[3]. One of the most popular methods is perturb and observe (P&O). The PV array voltage is adjusted in the (P&O) technique, and the change in power is measured[4]. If the change in power is positive, it indicates that maximum power exists on the left side of the graph, and maximum power does not exist on the right side[5,6].

Another method was to use an incremental conductance algorithm for MPP tracking. Dynamic instantaneous conductance ratios are being used to track MPP[7,8]. If somehow the ratio is positive, the MPP would be on the left side; otherwise, will be on the right side[9]. An MPPT technique of constant voltage and constant current is used in several loads where a specified voltage or rated current is required[10]. The current value is smaller than the presumed reference in this approach, and its value is adjusted to achieve MPP while keeping the voltage constant[11,12]. In another situation, the voltage is less than a predetermined reference value, and the voltage is changed to achieve MPP while keeping the current constant[13,14].

1.2 Research Gap and Motivation

These techniques based on the regression method, operate as real-time parameters affecting MPPT, (temperature, irradiance) changes their value[15,16]. The conventional technique becomes sluggish and inefficient in the short time disturbances like partial shading and moving shadow[17]. Even a fuzzy logic controller has been used to track maximum power point[18]. To design a fuzzy controller, complex mathematical modeling is required and technique becomes more complex for conditions like partial shading, moving shadow[19,20]. In order to overcome several intelligent MPP techniques like artificial neural network based on data collection[21,22]. But the system is plagued with the slow processing and has to retrain the model as the configurations of PV panel changes. In the proposed configurations a supervised machine learning based algorithm has been proposed. Several parameters will be collected from PV panel connected with boost converter, as per the previous data model will be trained. The trained and tested model will be used to predict the MPPT by varying the PI value.

*Corresponding authors: (Email: anshul@nitdelhi.ac.in)

1.3 Contribution and Paper Organization

In this manuscript, a data-driven model MPPT technique has been proposed, instead of using conventional technique based on regression, machine learning based algorithm has been used to track MPPT in boost converter with PV panel.

- The proposed data-driven model modifies itself as per the variation of irradiance and temperature. The data-driven model can predict PI value for maximum MPPT, which is used to predict the duty ratio for maximum power.
- The proposed system is experimentally validated using PV panel with boost converter.
- The data has been collected using current and voltage sensor integrated with Arduino Mega 2560.

2 Data Driven Based Maximum Power Point Tracking

In the proposed machine learning based model has been used to predict MPPT under various varying conditions. In PV based system variation of temperature, irradiance, partial shading, moving shading affects the power extraction of the system. Even the location of PV panel in same city, but at different locations may vary its output. In the proposed algorithm, the data has been collected from location under different conditions. It tested on several machine learning algorithm like support vector machine, KNN, trees, bagged ensemble, regression. The machine learning model having highest accuracy will be tested on a new set of data. The system operates with same accuracy, and then it is used to control the boost converter as shown in Fig.1. The key goal of the proposed (shown in Fig. 1) computer-based machine learning modeling, is to synthesize a power response of the PV panel with a boost converter. In this manuscript, the model should be capable of taking the various parameters power, voltage, temperature irradiance, load voltage, source current, *etc*. Time can also be an input parameter for the model. The implementation of machine learning will go through several process and steps as discussed below.

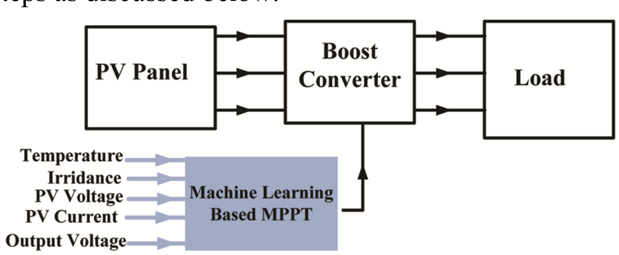

Fig. 1 — Machine Learning Based PV System

1. Data Collection
2. Data Processing
3. Machine Learning Algorithm
4. Model Verification
5. Model Implementation

2.1 Data Collection

The data has been gathered from the MATLAB Simulink models. The data has been collected using the MATLAB 2018 b PV block. The data was obtained from the PV panel to the boost converter at different irradiance and temperature conditions.

The strength of model is dependent on the data strength. As a result, collecting data is a vital step. The data has been collected using an MPPT model from MATLAB Simulink model. The simulation results have been used to collect the input voltage, output voltage, temperature, and power value as a function of irradiance fluctuations. For all situations, the input voltage has been set to 250V, 275V, and 300V. Different irradiance values of 200W/m^2, 300W/m^2, 250W/m^2, and 400W/m^2 have been taken, and PI values have been gathered as for MPPT based on the fluctuation irradiances.

2.2 Data Processing

All the collected data cannot be used directly. So, data must be converted into a desirable form. Input voltage, output voltage collected from Simulink and it is in time series form. While the data like PI value, reference and error are not in the time-series form. To use these data, it must be converted into time series form. The selection of parameters is also important in machine learning modeling. In the proposed MPPT, the data of PV current, load current has been neglected to protect from over fitting.

2.3 Machine Learning Algorithm

Supervised learning is a learning function that converts an input to an output based on example input-output pairs (SL). To infer a function, it uses labeled training data and a set of training examples. In supervised learning, each example consists of an input object (often a vector) and a desired output value (also called the supervisory signal). A supervised learning algorithm looks at the training data and creates an inferred function that can be used on new cases. In the best case scenario, the algorithm will be able to reliably estimate the class labels for unseen cases. This implies the use of learning algorithm to "reasonably" generalize from the training data to unknown conditions.

2.4 Model Verification

A PV panel with boost converter, MPPT at different irradiance of 200W/m^2, 300W/m^2, 250W/m^2, and 400W/m^2 has been tested. The model is verified with irradiance of 370 W/m^2, 470 W/m^2, 560W/m^2. PI value is collected from the simulation model for the MPPT at irradiance of 370 W/m^2 and 470W/m^{2}and then it is cross-verified through the data-driven model.

2.5 Model Implementation

Once the model is verified with the test data and machine learning model is producing satisfactory output for the operation of boost converter then the model is created using the classification learner application of MATLAB. Model code is generated from the classification learner app and used to predict the PI value for MPPT at different irradiance. PI value is compared with a triangular pulse and the output is given to the switch S_1 as shown in Fig. 1.

3 Results

The put voltage is taken from an inbuilt model from MATLAB 2018. The voltage is taken from at different irradiance value 200W/m^2, 300W/m^2, 250W/m^2 and 400W/m^2. As the irradiance varies, PV voltage also varies. PV voltage varies from 250V to 270V as shown in Fig. 2(a). PV voltage is taken as input at 25 ^{o}C and MPPT based machine learning technique has been used to track MPPT. Output voltage varies as per the variation of input voltage, power, and irradiance as shown in Fig. 2(b). The output voltage remains at 600V, 700V, 750V for t=1s, 2s, and 3s respectively. The irradiance is again increasing at t=3s and output voltage also increases to 800V. As irradiance increases to 275W/m^2 again so the voltage also changes to 800V. PI value varies to track maximum power under different conditions of irradiance. Fig. 3(a) shows the PI value 0.5, 0.6, 0.625, 0.650 and 0.675 to track power 1.75kW, 2.75kW, 2.25kW, 2.75kW and 3kW respectively at different irradiance conditions as shown in Fig. 3(b).

Figure 4 shows the power variation using the P&O method that has been used to track MPPT. With the variation of irradiance, value of power is also changes. The value of power is 1.75kW, 2.75kW, 2.25kW, 2.75kW and 3kW for t=1s, 2s, 3s, 4s, and 5s respectively.

4 Supervised Machine Learning Based Results

The same Simulink model is used, to take the same result in the form of data. 39846 (thirty-nine thousand eight hundred forty-six), data has been taken for the model implementation and, 20800 (twenty thousand eight hundred) used for the testing purpose. The

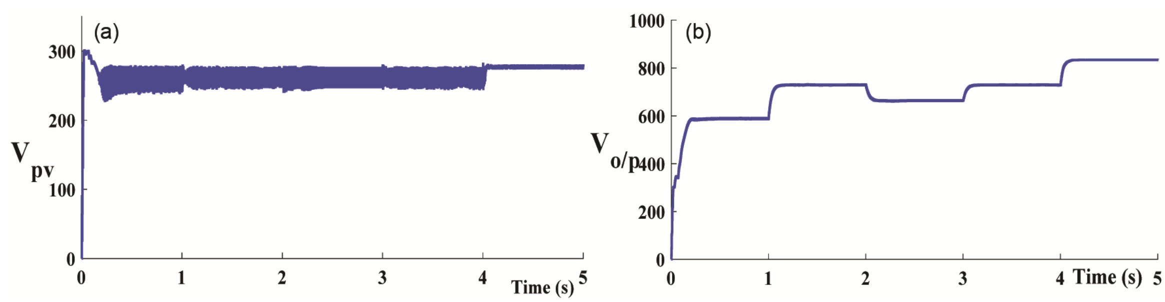

Fig. 2 — (a) Input Voltage for Boost Converter (b) Output Voltage of Boost Converter

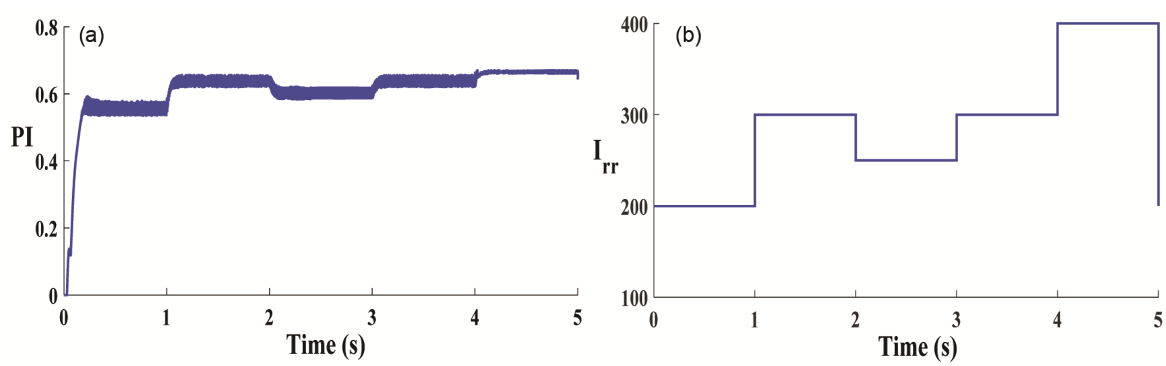

Fig. 3 — (a) PI Value for Different Power Value and (b) Irradiance Value

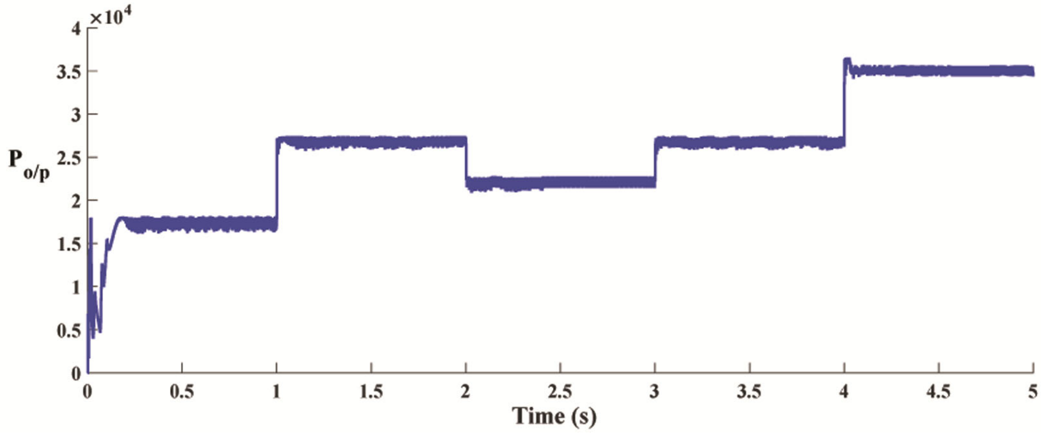

Fig. 4 — Power at Different Irradiance Value

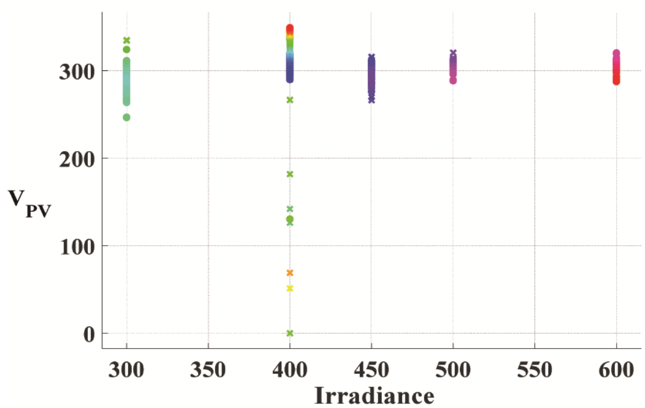

Fig. 5 — Scattering Plot.

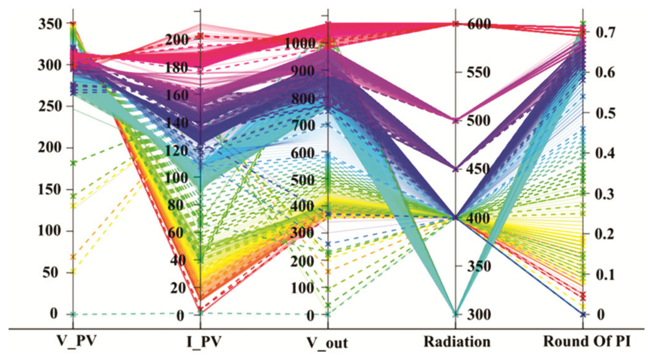

Fig. 6 — Parallel Coordinate Plot.

model behavior has been analyzed through parallel coordinates plots, ROC curve and scattering plot. The data has been tested on various machines learning algorithm and the most suitable model output result has been illustrated.

Scattering plot is used for numerical data plotting and shows the relationship between two variables used in data based modeling. In Fig. 5 show the relationship between irradiance and PV input voltage. As per the irradiance variation, PV input voltage (V_{PV}) varies. For the irradiance 300 W/m^2 PV voltage varies between 260V to 320V. For the irradiance for 400 W/m^2, 450 W/m^2, 500 W/m^2 and 600 W/m^2, PV voltage varies 400V to 600V.

As scattering plot shows the relation between two variables while parallel co-ordinates plot shows relation between all inputs parameters used in the modeling. In this model for MPPT forecasting for different irradiance conditions, inputs are temperature, irradiance, PV voltage, input current and PI value as shown in Fig. 6.

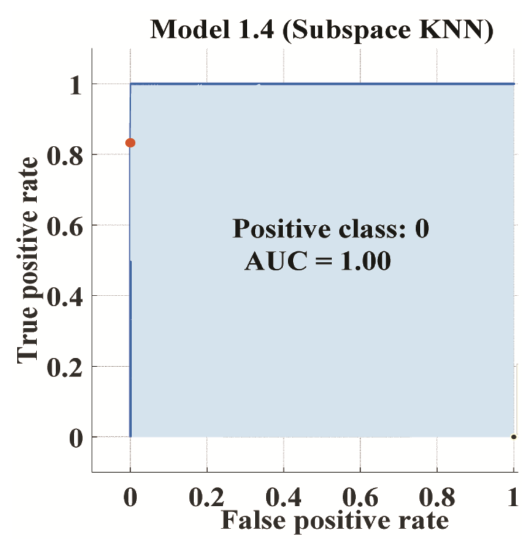

Fig. 7 — ROC (Receiver Operator Character).

The model accuracy is measured through ROC (receiver operator characteristics) as shown in Fig. 7. The true positive rate is plotted against the false positive rate on the receiver operator characteristics (ROC) curve. The true positive figure is shown on the

X-axis, while the false positive rate is shown on the Y-axis. The ROC curve for the bagged ensembled algorithm for predicting MPPT having threshold value 1.

5 Experimental Validation

The proposed machine learning-based algorithm has been experimentally validated using a 6X6 PV panel. The design of the boost converter consists of an inductor (SRR1216-60M) 56µh, an electrolytic capacitor 1000µF, MOSFET (IRF7410) and a rheostat for the loading purpose. MOSFET has been operated with the switching frequency of 100kHz, using an optocoupler (VO3120) based driver circuit. The switching pulse has been generated using AURDINO MEGA.

5.1 Collection of Data form experimental setup

Data has been collected for several parameters from the experimental setup. The data of voltage and temperature has been collected using voltage and temperature sensor using AURDINO MEGA. The variation of irradiances has been done by halogen light connected with a potentiometer. The alteration of potentiometer resistance varies irradiance and that changes power and voltage. The data of power has been taken from the load side by measuring voltage and current.

The PV voltage has been taken at different conditions. Initially, PV voltage is 62.08V taken at 39 °C and the output voltage of boost converter is 112.92 V at maximum power as shown in Fig. 8 and Fig. 9 respectively. The irradiance is changed through a potentiometer connected in series with halogen light and PV panel voltage changes to 42.92V and output voltage of boost converter is 87.05 V as depicted in Fig. 10 & Fig. 11 at 25 °C. PV panel voltage again changes to 55.42 V and output voltage of boost converter at maximum power is 100V illustrated in Fig. 12 and Fig. 13 respectively taken at temperature of 28 °C. The data has been collected from the same conditions and this real time data has been tested on the model developed through the Simulink model. Real time data also gives satisfactory result on the ensemble bagged trees and ensemble subspace KNN model for the PV system.

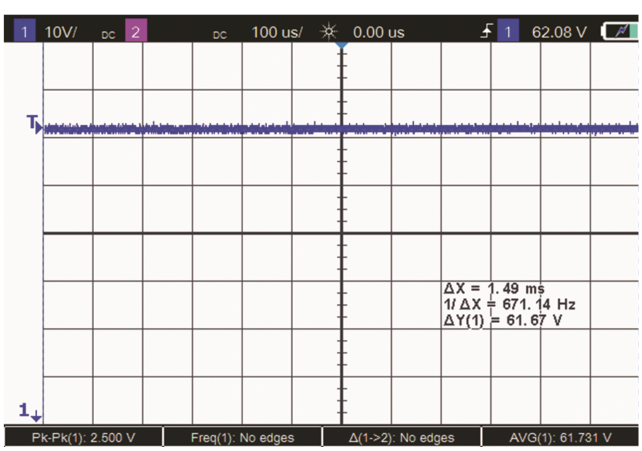

Fig. 8 — PV Panel Voltage at 39 °C.

6 Comparison of Machine Learning Algorithm

Data has been taken from the PV panel connected with boost converter. 59076 (fifty-nine thousand seventy-six) data has been taken for the model implementation and 24545 (twenty-four thousand five hundred forty-five) used for the testing purpose. The data has been tested on several machine learning algorithms. The accuracy for the fine tree, medium

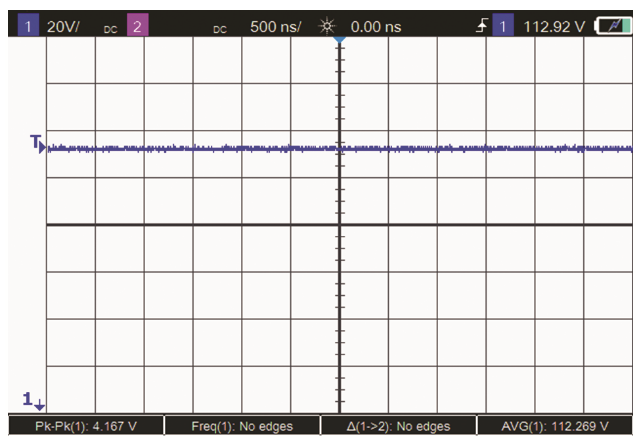

Fig. 9 — Output Voltage of Boost Converter at 39 °C

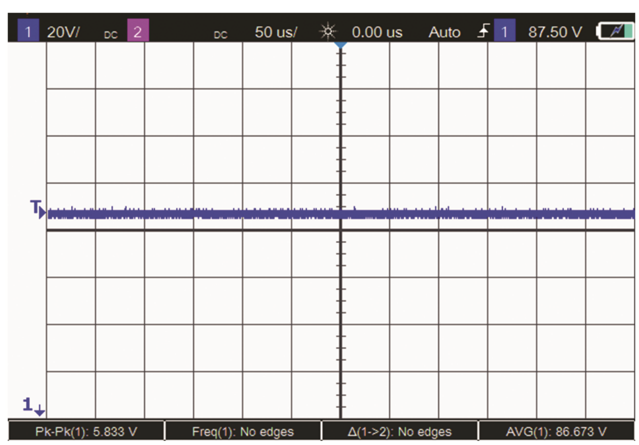

Fig. 10 — PV Voltage at 25 °C

tree, coarse tree, fine KNN, medium KNN, coarse KNN, cosine KNN, cubic KNN and weighted KNN are 96,82.9, 56.9, 93.8, 93, 90.4,92.9,92.6 and 94.3 respectively. The data has been also tested on ensemble which is the combination of several machine learning base models (KNN, Tree, and SVM). The accuracy of ensemble boosted trees, ensemble bagged trees and ensemble subspaces KNN are 94.6, 98.1 and 97 respectively as depicted in Fig. 14. Among these algorithms, ensemble bagged trees and ensemble subspace KNN has shown best result. The model behavior has been analyzed through confusion matrix, parallel coordinates plots, ROC curve and scattering plot. The most suitable model (ensemble bagged trees and

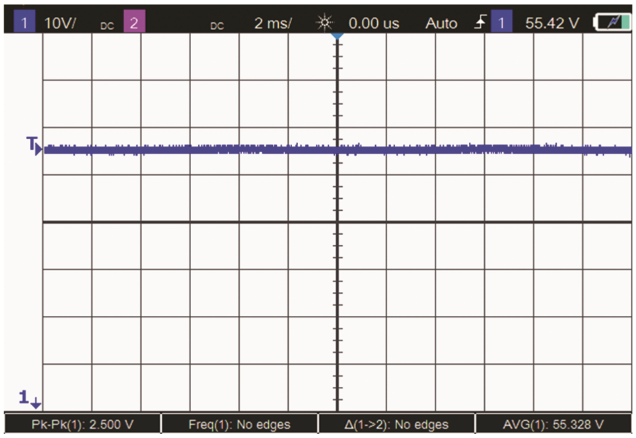

Fig. 11 — Output Voltage of Boost Converter at 25 °C.

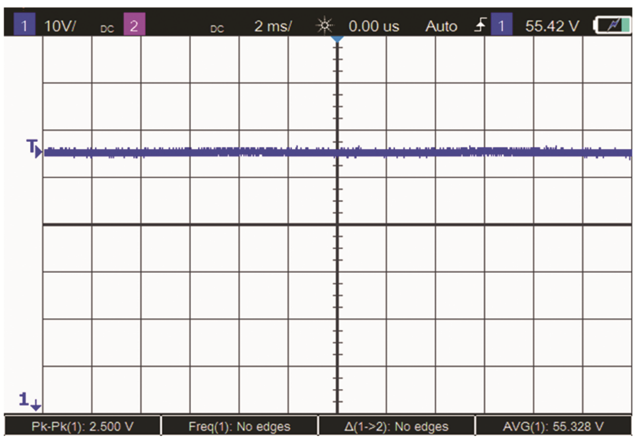

Fig. 12 — PV Voltage at 28 °C

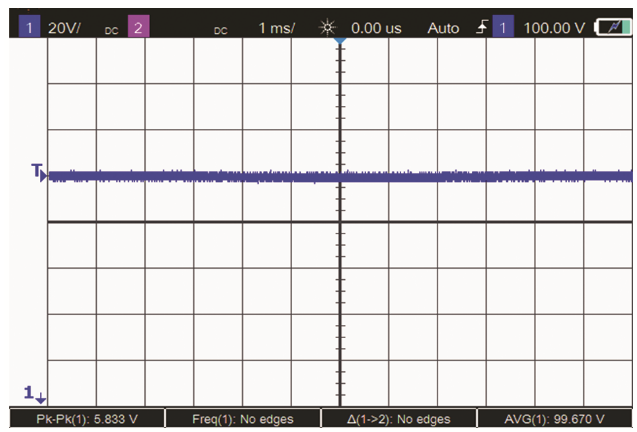

Fig. 13 — Put Voltage of Boost Converter at 28 °C

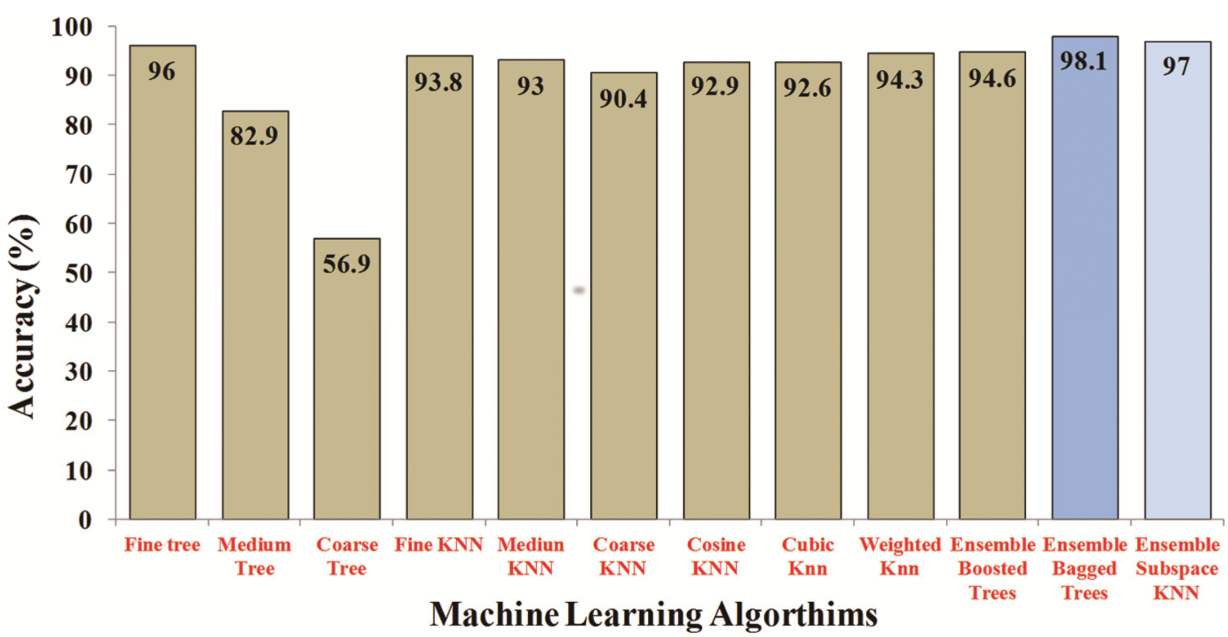

Fig. 14 — Accuracy of Several Machine Learning Algorithms

ensemble subspace KNN) output result has been shown in Fig. 5 to Fig. 7.

7 Conclusion

Several algorithms were employed, with bagged ensemble trees providing the highest accuracy of 98%. The model outperformed the earlier P&O and hill-climbing methods. The conventional approaches use a mathematical regression method to estimate the MPPT, which takes more time, but the machine learning model uses data-based modeling. The data-driven model can estimate the power value instantly based on its data or by using the power variation pattern as an input parameter variation. The work can be extended for the multiple renewable energy sources and machine learning-based algorithm will make the system robust.

References

1 Deshmukh L P, Shahane G S & Garadkar K M, *Indian J Pure Appl Phys*, 35 (1997) 560.
2 Singh N K, Agarwal A & Kanumuri T, *J Eng Res*, 9 (2021) 89.
3 Salman S, Ai X & Wu Z, *Prot Control Mod Power Syst*, 3 (2018).
4 Bollipo R B, Mikkili S & Bonthagorla P K, *IET Renew Power Gener*, 14 (2020) 1433.
5 Kermadi M, Salam Z, Ahmed J & Berkouk E M, *IEEE Trans Ind Electron*, 68 (2021) 2236.
6 Shengqing L, Fujun L, Jian Z, Wen C & Donghui Z, *Soft Comput,* 24 (2020) 6039.
7 Wang H, Vinayagam L, Jiang H, Cai Z Q & Li H, *Proc 2016 51st Int Univ Power Eng Conf, UPEC 2016*, 1 (2016).
8 Bouguerra S, Yaiche M R, Gassab O, Sangwongwanich A & Blaabjerg F, *IEEE J Emerg Sel Top Power Electron*, 9 (2021) 3114.
9 Islam M N, Rahman M Z & Mominuzzaman S M, *Proc 2014 3rd Int Conf Dev Renew Energy Technol ICDRET 2014,* (2014) 8.
10 Singh O & Gupta S K, *A review on recent Mppt techniques for photovoltaic system*, (2018) 1.
11 Tina G M, Ventura C, Ferlito S & Vito S D, *Appl Sci*, (2021) 11.
12 Miraftabzadeh S M, Foiadelli F & Longo M, *A Survey of Machine Learning Applications for Power System Analytics*, 34 (2019) 1.
13 Khandakar A, Chowdhury M E H, Kazi M-K, Benhmed K, Touati F, Al-Hitmi M & Gonzales A J S P, *Energies*, 12 (2019) 14.
14 Garoudja E, Chouder A, Kara K & Silvestre S, *Energy Convers Manag*, 151 (2017) 496.
15 Ibrahim A W, Ding M, Jin X, Dai X, Sarhan M A, Shafik M B & Zhou H, *Chin Control Conf CCC*, (2019) 6559.
16 Nkambule M S, Hasan A N, Ali A, Hong J & Geem Z W, *J Electr Eng Technol*, 16 (2021) 411.
17 Sreenu B, Kameswari S V, Naushad S M & Kutala V K, *Indian J Biochem Biophys,* 57 (2020) 245.
18 Kumar N R P & Shetty N S, *Indian J Biochem Biophys*, 57 (2020) 602.
19 Singh G, Kaur M, Singh M & Kumar Y, *Indian J Pure Appl Phys,* 60 (2022) 407.
20 Zicheng L, *et al*., *IEEE Trans Power Electron,* 37 (2022) 8767.
21 Shuai Z, Blaabjerg F & Wang H, *IEEE Trans Power Electron,* 36 (2020) 4633.
22 Abu-Rub, Omar H, *et al*. *IEEE Power Electron Mag*, 8 (2021) 28.