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Machine learning based maximum power point tracking in solar energy conversion systems

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Abstract

Extraction of solar energy from photovoltaic cells has different efficiencies corresponding to different algorithms. In the paper, a power efficient algorithm is suggested for tracking of maximum power point (MPP) in solar energy conversion systems by implementing machine learning (ML) in the pre-existing perturb and observe (P&O) methodology. P&O works on the principle of varying duty cycles step by step in the direction of the MPP and is the most feasible and accurate algorithm. However, the speed of convergence to the MPP is usually less in this method and it varies in different climatic conditions. This paper describes the application of ML in decreasing the perturbation time significantly leading to the significant increase in the efficiency to predict the MPP. The suggested algorithm predicts an MPP based on instantaneous values of solar irradiation, solar cell temperature and humidity as input features to the localized multivariate regression ML model and is used to fetch maximum available power (MAP). It is a self-learning algorithm and as the time progresses, the estimation becomes much closer to the theoretically available power. The simulation was done in python and yielded an average efficiency of 99.8% in estimating the MPP after 83 hours of training.

Keywords: Photovoltaic systems, solar energy conversion systems, maximum power point tracking, perturb and observe, machine learning.

1. Introduction

To date, fossil fuels are responsible for fulfilling eighty percent of the world's total energy demands. Fossil fuels being a non-renewable resource exist in limited amounts and their unchecked use will lead to complete consumption within the next few decades. Moreover, global warming is caused by greenhouse gases released as by-products as a result of generation of energy from fossil fuels [1]. Thus, it is high time to start looking for alternatives to fossil fuels. Solar energy being the earth's most readily available source of energy can turn out to be an excellent substitute and can help solve the energy crisis faced by the world. Photovoltaic cells are used to generate electrical energy from solar energy but being non-linear in characteristics, they are highly inefficient. Therefore, it is difficult to extract maximum power from solar PV cells in varying climatic conditions. The process of generating maximum possible power from the PV cells is known as maximum power point tracking (MPPT). A variety of MPPT algorithms like the method of incremental conductance [2], the method of fractional voltage [3], perturb and observe [4], fuzzy logic control [5], etc., have been developed and are being used in the industry over the years.

There is a need for an effective mechanism to quickly estimate the maximum power point due to continuously changing intensity of solar radiation. A solar energy conversion system is usually made up of a solar PV array, charger controllers and an interconnection framework to supply the power generated

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for further distribution. When the solar radiation falls on the PV array, the cells are excited leading to generation of photocurrents which are further directed to load impedances for power consumption. The photocurrent and power versus voltage characteristics of a solar cell for different intensities of irradiation are shown in Fig. 1[4].

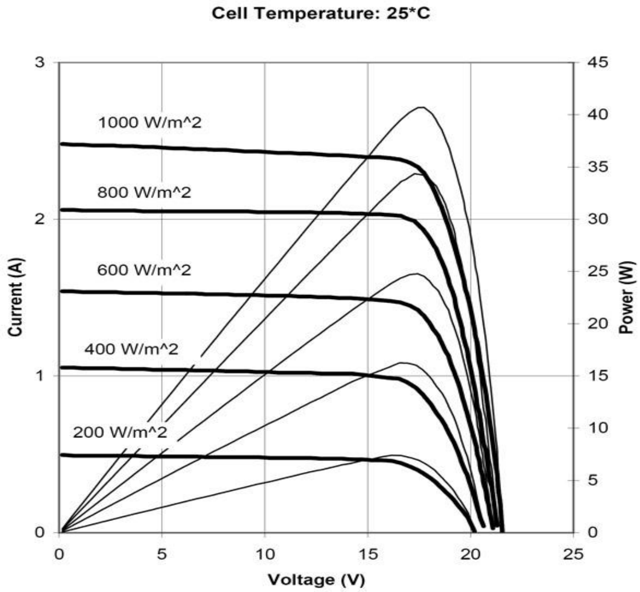

Fig. 1. Photocurrent and power versus voltage characteristics for different intensities of sunlight.

A charger controller fed with an efficient algorithm is responsible for carrying out MPPT. The generated power is optimized and controlled via its design. Commonly used MPPT algorithms have been compared in Table 1[6] based on their efficiency and complexity.

Table 1. Comparison of P&O with other MPPT techniques

MPPT Technique	Speed of Convergence	Implementation Complexity	Periodic Tuning	Sensed Parameters
Perturb and Observe	Varies	Low	No	Voltage
Incremental Conductance	Varies	Medium	No	Voltage, Current
Fractional V_{OC}	Medium	Low	Yes	Voltage
Fractional I_{SC}	Medium	Medium	Yes	Current
Fuzzy Logic Control	Fast	High	Yes	Varies
Neural Network	Fast	High	Yes	Varies

In this paper, an alternative method is described to overcome the limitations of the existing P&O methodology and other MPPT algorithms. The given model uses machine ML before the conventional P&O algorithm to estimate MPP. ML is a type of artificial intelligence that trains the system to learn and doesn’t require manual programming. Its main focus is on the improvement of systems that can learn on their own and vary accordingly on exposure to new information and data sets. Results have been analyzed and compared with the pre-existing methods on the basis of performance and efficiency.

2. System Model

The system consists of a solar panel coupled with a buck converter. A buck converter works on the concept of duty cycles using pulse width modulation (PWM) signal to control the ratio of input to output voltages thereby acting as a step-down DC to DC voltage converter. The PWM signal is managed by the MPPT charger controller. Fig. 2 describes the proposed solar energy conversion model and its functioning.

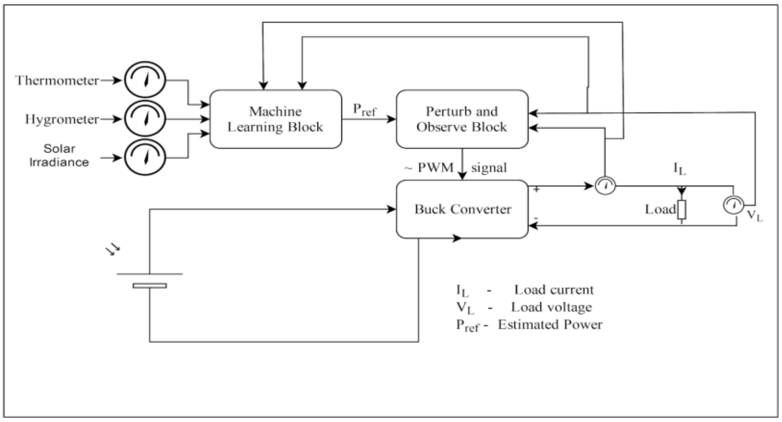

Fig. 2. Proposed solar energy conversion model and its configuration

2.1. The solar photovoltaic cell model

Photocurrents in the solar cells are generated by the photovoltaic cells and they act as variable current sources. A solar cell is nothing but a PN junction diode which generates current on exposure to sunlight [7]. The generated current depends linearly on the solar illumination/irradiance. Fig. 3 shows the basic circuit analogy for a solar PV cell.

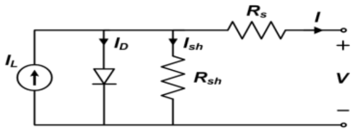

Fig. 3. Functional circuit of a singular solar PV cell

Here, I_L is the photocurrent (in Amps),

I_D is the diode current (in Amps),

R_{sh} is the shunt resistance (in ohms),

I_{sh} is the current passing through the shunt resistance (in Amps),

R_S is the series multiplier resistance (in ohms),

I and V are the output voltage and current.

Following sets of equations give the current-voltage characteristic of the solar PV circuit:

$$I_D = I_{SS}[e^{(q(V+IRS)/KT)}-1] \quad (1)$$

Here, the output current I is given by:

$$I = I_L - I_D - I_{sh} \quad (2)$$

thus,

$$I = I_L - I_{SS}[\exp(q(V+IR_S)/KT)-1] - (V+IR_S)/R_{sh} \quad (3)$$

Here, q is the charge on an electron (in coulombs), K is the Boltzmann constant (in Joule/Kelvin) and T is the solar cell temperature (in Kelvin).

2.2. Buck converters

Buck converters are essentially step-down DC-to-DC voltage converters that work on the principle of varying the output current using energy storage elements [8]. They work in the switched mode power supply (SMPS) and typically contain at least two semiconductors (a diode and a transistor), energy storage elements like an inductor, a capacitor or a combination of two for the step-down operation. Buck converters are remarkably efficient (up to 90%) and are therefore useful for a variety of computational operations. They control the duty cycles for the stepping down operation using a pulse width modulator (PWM) signal. The On and Off states responsible for changing the direction of duty cycles are controlled via SMPS as depicted in Fig. 4.

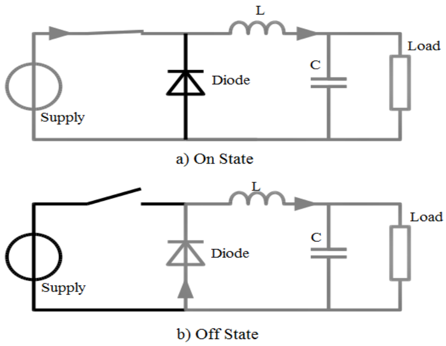

Fig. 4. Figure depicting On and Off states of a buck converter

2.3. The Perturb and Observe (P&O) Algorithm

P&O is one of the most simplistic and accurate algorithms for MPPT in solar energy conversion systems. A charger controller regulates the output supply of the solar PV array by controlling the pulse width modulation (PWM) based duty cycles of the buck converter and keeps a track of fall and rise in power constantly. If the power is incremented upon increasing the buck converter duty cycle, the duty cycle is increased in the same direction further till the MPP is achieved. Otherwise, if there is a fall in power, the direction of the duty cycle should be reversed and the same procedure has to be repeated. This point is the desired MPP and the characteristic parameters of this point are recorded and used for generating optimal power. This methodology is termed as P&O and is the most commonly used method in the electrical industry. A flow diagram demonstrating perturb an observe along with ML is shown in Fig 5.

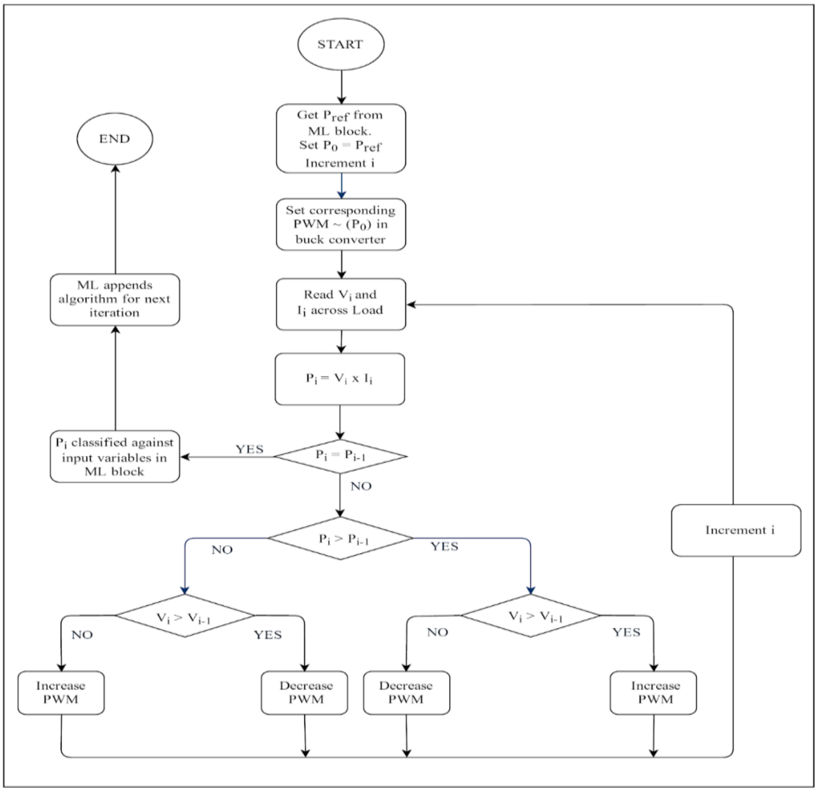

Fig. 5. Flowchart demonstrating P&O

2.4. MPPT algorithm

In this model, ML is used to estimate a power point (P_{ref}) close to the theoretical MAP based on a localized multivariate regression model [9] with the characteristic inputs (X_{ik} in Eq.5). The estimation is done to decrease the time of perturbation in P&O algorithm. At the end of every iteration, the inputs solar cell temperature, solar irradiance and humidity (X_k in Eq. 5) of the previously detected MPP(s) are fed into the ML module as training data along the MAP. This model learns by itself based on regression and pattern recognition of the MPP(s)from the characteristic parameters (b_k and X_k). The P&O upgrades the estimation dataset at the end of every iteration thereby reducing the error ($\epsilon_i$in Eq. 5). After every iteration, this model goes undergoes continuous refining using gradient descent algorithm as depicted in Fig. 5.

$$\phi_t = F_t(\phi_0,\ldots,\phi_{t-1}) \tag{4}$$

Here ϕ_t is the MPP at t^{th} iteration. The ML algorithm uses the $F_t(X_{il},\ldots,X_{ik}) = Y_t$ for estimation using the dataset of previous MPP(s) ($\phi_0,\ldots,\phi_{t-1}$). The calculated result is further taken for the next set of iterations as $P_{ref} = \phi_t$ after which the algorithm undergoes a regular P&O using a buck converter for learning and updating the algorithm. A localized regression model can be used to compute by Equation 5.

$$Y_i = b_0 + b_1X_{1k} + \ldots + b_kX_{ik} + \epsilon_i \tag{5}$$

Here, b_k are coefficients of regression, ϵ_i is the error at i^{th} iteration and X_{ik} are regressor/input variables. Y' is the mean MPP of all the MPP(s), Y_i using variable inputs X_{ik}(temperature, irradiance, humidity) and k predictor variables. The b_k values or the regression weights are compared to minimize the squared deviation sum as depicted in Equation 6. Here, N is the number of iterations.

$$\sum_{i=0}^{N}(Y_i - Y')^2 \tag{6}$$

The Gradient Descent algorithm [10] minimizes the sum of squared deviations as Cost Function J(θ) which allows the model to adapt to the dataset and give efficient and accurate outputs in further iterations.

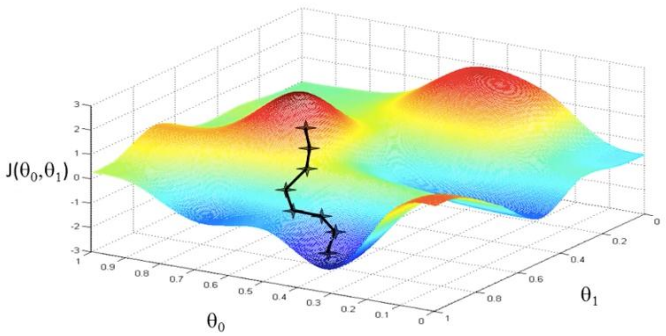

Fig. 6. Figure depicting Gradient Descent algorithm used by ML to minimize the Cost Function J(θ) with two cost parameters leading to reduced errors in further predictions

3. Experimental Results

Graph between estimated power point (blue) and maximum available power (red) is illustrated in Fig. 7 and Fig. 8. It can be clearly seen in the diagrams that the estimated power points are remarkably close to the actual available power in iterations ranging from 900 to 1000 as compared to iterations ranging from 0 to 100. These figures justify the learning accuracy of the algorithm. These results were obtained after 83 hours of training the ML model with all iterations being 5 minutes apart each.

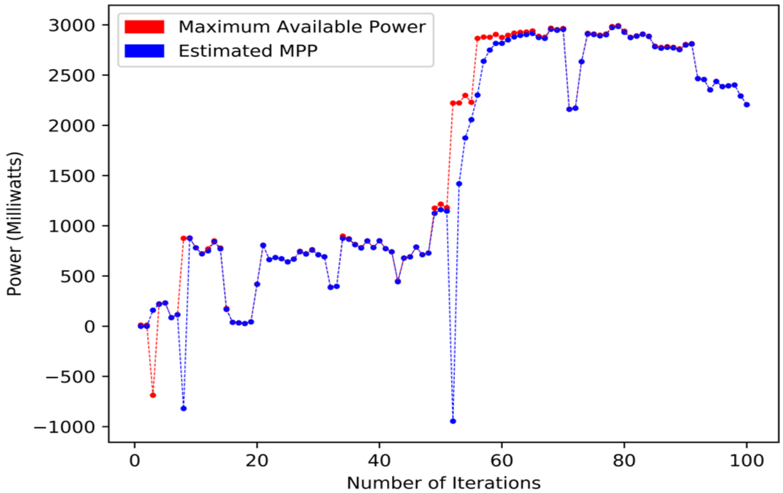

Fig. 7. Graph showing variation of MAP (P_t: Red) and Estimated MPPs (φ_t: Blue) with respect to time (0-100 iterations).

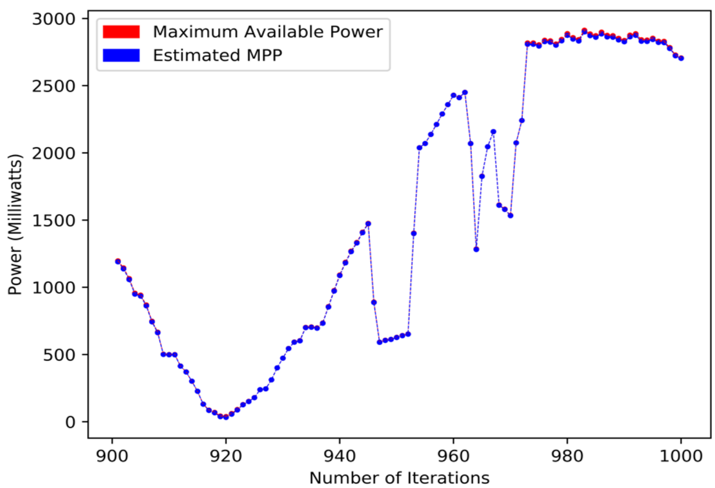

Fig. 8. Graph showing variation of MAP (P_t: Red) and Estimated MPPs (φ_t: Blue) with respect to time (900-1000 iterations).

$$\Delta = 100*|P_t - \varphi_t| / | P_t| \% \tag{7}$$

The percentage error Δ can be computed by using Equation 7. Average error for iterations 950-1000 is computed to be 0.2%. Fig. 9 shows the error percentage in the iteration set of 950-1000. This graph verifies the increase in efficiency after every iteration. Similarly, average efficiency can be calculated by using Equation 8.

$$\eta_t = (100 - \Delta_{t[avg]}) \% \tag{8}$$

The average efficiency of the model is at 99.8% after around 1000 iterations corresponding to 83 hours of training. Thus, Fig. 9 clearly depicts that more the training, lesser the likelihood of an error in prediction and the error threshold never crossed 0.5%. The training set included real time data from BITS Pilani K.K. Birla Goa Campus.

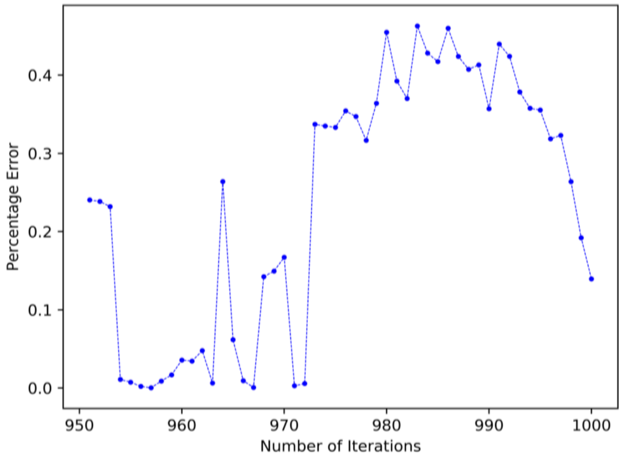

Fig. 9. Percentage error between MAP and Estimated MPP with respect to time (iteration 950-1000).

4. Advantages of Using Machine Learning

P&O combined with ML converges much faster to the MPP compared to the conventional P&O. The proposed model learns quickly and is much more efficient compared to similar AI algorithms such as artificial neural networks and deep learning. Moreover, they do not provide high performance and increased accuracy. Misclassification of input data by simple addition of small perturbations can easily confuse such algorithms resulting in prediction of inaccurate values. These perturbations occur practically all the time due to continuously changing climatic conditions. But in the proposed method, the learning is not affected because of the inclusion of supervised learning. The results' complexity with respect to the time taken for estimation is also directly affected by neural networks work on added hidden layers. The various features of the proposed algorithm are mentioned in Table 2.

Table 2. Comparison of MPPT Techniques with proposed model

Technique	Learning Phase	Complexity	Accuracy	Time Taken
ML into P&O	Yes (Supervised)	High	High	Low
P&O	No	Low	High	High
Fuzzy Logic Control	No	High	Medium	Medium
Neural Networks	Yes	High	Medium	Low

5. Conclusion

An efficient method to track maximum power point under varying climatic conditions is described in this paper. A python simulation of a solar energy conversion system has been carried out to validate the proposed MPPT method. The analysis showed that the proposed MPPT method estimated the MPP with higher frequency. Observations show that the performance and the accuracy of the proposed method is not affected by the variations in input data or small fluctuations and neither during nasty and rapid weather changes. The perturbation time decreases with each iteration. The proposed algorithm gradually learns and incorporates to the new data at the end of each iteration. Machine Learning in the proposed model overcomes overfitting that usually occurs in other AI based MPPT algorithms such as artificial neural networks and other deep learning algorithms. The main advantages of the proposed MPPT control method are faster convergence to the MAP, higher efficiency than its AI counterparts (ANN), robustness, ease of implementation and its ability to learn from previous data irrespective of the season of the year. Thus, much faster convergence speeds are obtained from the proposed algorithm which being a modified version of P&O can be directly cascaded to the existing P&O equipment with convenient setup.

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