

## Research Article

# Maximum Power Point Tracking of PV Grids Using Deep Learning

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Received 29 January 2022; Revised 10 April 2022; Accepted 12 April 2022; Published 25 May 2022

Academic Editor: V. Mohanavel

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In this paper, we develop a deep learning model using back propagation neural network (BPNN) that helps to obtain maximum power point. This deep learning model aims to maximise the output power from the solar grids when the panels are connected with the boost converter under different variable load conditions. BPNN-DL enables the prediction of reference voltage at different weather conditions for severing the various output power that ensures maximum power with stable output voltage. The proposed BPNN-DL is tested under different conditions to estimate the robustness of the modules under internal/external interferences. The results of the simulation show that the proposed method achieves maximum output power from each panel compared with existing methods in terms of regression analysis on training, testing, and validation.

## 1. Introduction

Electricity is a need in our day-to-day lives. Historically, the combustion of fossil fuels for the generation of electricity has resulted in serious environmental and human health issues [1]. Because of this, attempts have been made recently to identify new ways to generate clean energy using sustainable resources. Photovoltaic (PV) systems convert sunlight directly into energy that can be stored or even connected to the grid [2]. PV systems have a high initial implementation cost, which

is unfortunate. PV systems have a relatively low energy conversion efficiency [3]. Variations in the weather have an impact on energy output [4]. The effectiveness of a photovoltaic (PV) system can be affected by changes in humidity, temperature, and cloud [5]. This has led to numerous research efforts aimed at figuring out how to maximise the output power of PV panels regardless of the weather.

For a given set of solar insolation and ambient temperature, researchers studying the nonlinear properties of the PV system discovered a single operating point (output voltage)

where the PV system output power is maximised. The PV panel will produce less power than its maximum if the output voltage changes due to the load or for any other reason [6]. Solar radiation and temperature affect the output power [7]. All of the aforementioned make it extremely difficult to keep the system running at its maximum output power level for long periods of time. The goal here is to find a position where the PV panel maximum power output meets the demands of the system [8]. There have been a number of initiatives aimed at ensuring that PV systems operate at their maximum potential. One of the earliest approaches to the problem was the incremental conductance (IC) and the perturb and observe (PaO) [3]. As both strategies are simple to apply, they are frequently utilised in practise [3] [1, 9, 10].

The same problem was addressed in several ways in the literature, all with the goal of improving the PaO outcomes. The usage of machine learning was one attempt to solve the problem. The ability of deep learning to model nonlinear functions allowed for a precise estimate of the reference voltage in adherence with maximum power. Additionally, ANN-based approaches exhibited a rapid reaction in the testing phase, which was a significant advantage. In this paper, we develop a deep learning model using back propagation neural network (BPNN) that helps to obtain maximum power point. This deep learning model aims to maximise the output power from the solar grids when the panels are connected with the boost converter under different variable load conditions.

The main contribution of the work involves the following.

This deep learning model aims to maximise the output power from the solar grids when the panels are connects with the boost converter under different variable load conditions.

## 2. Background

Reproducing a neural network in association with parameters that connects to individual data points is the goal of the ANN model. There are no sophisticated mathematical equations or equations to mix multiple parameters in an ANN model [11]. When it comes to dealing with large numbers of unknown data points, an ANN technique requires less theoretical work than traditional methods [12]. Imported data is used to train ANNs, a process known as supervised learning or training. Like the human brain, the ANN is made up of many different types of neurons [13]. Weight [14] is the fractional number that connects these neurons. To be able to accurately forecast the results, the weights are adjusted during the training phase. Once the error surpasses a certain threshold, the weights are frozen [15].

It is possible to integrate the inputs into the network at various points. The data sets are divided into two groups based on the percentages of data points in each group. The datasets for training are used to train the deep learning. This data set is used to verify the trained deep learning, which is referred to as a validation data set [16]. The deep learning input-output parameters, as well as their training data, are

imported. In this network, an error is acceptable until it is accepted by the system.

Validation data set are associated with the relevant real data set output parameter projections. An optimum deep learning can be recommended if the error exists between actual and projected results is less than the permissible maximum. When the error magnitude falls below the acceptable value, an algorithm combination that has an acceptable error magnitude will be selected as the deep learning. Before a permitted error is attained, the deep learning is loaded with training algorithms, but with the same training methodology for larger error values [17]. Analyses from the ideal deep learning confirm the generalisation capabilities of deep learnings that have been trained.

The MPPT algorithms are also studied in another study [18]. Control variables, techniques of control, and other factors were grouped into categories. Simulink Frameworks were used in this work to perform hands-on evaluations of the most commonly used MPPT algorithms in PV voltage ripple dynamic reactivity [19]. A PI controller has been used to improve the results of classic MPPT algorithms. Simulating MATLAB results with environmental factors such as fluctuating irradiance or rising temperatures has been discussed by the authors in [19]. When irradiance varies unexpectedly, the authors suggest a new way to tighten P&O algorithm constraints [20]. Two algorithms are included in the proposed strategy. A revised P&O algorithm was proposed by the authors in [21]. To test the effects of adaptive measures and regular P&O methods, they conducted research and simulations.

Testing of the INC MPPT algorithm was done in [22]. Using an isolated PV pumping approach, the authors tested the INC algorithm and found that it had an effect on the reference voltage and service speeds. Due to sudden fluctuations in irradiance, the impact on phase and disturbance size for a previous disturbance has been explained here, which typically reveals the algorithm inaccuracy. Finally, the success is linked to the algorithm that was proposed. It is possible to track the PV characteristics. The INC MPPT approach was found to be less affected by noise and device dynamics than other MPPT strategies. Stability at rapidly changing irradiance has been improved by this phenomenon in the suggested device. Faster transitional responses at higher disruption speeds are observed with INC. Due to changes in noise or brightness, the algorithm can be disrupted and the MPP can recover more quickly. The PI controller has been employed in several MPPT algorithms to date.

An ANN controller for PV system construction was unnerving because it was a novel idea. There are various features including higher speed response, nonlinear mapping, and lower estimation delay in the ANN MPPT [23] develop and validate the NN model, we used MATLAB and Simulink to collect data from the P&O system. The proposed NN controllers swiftly shifting insulation showed enhanced monitoring precision, reaction time, and overflow in the simulation results. With artificial intelligence, it can be used to create electronic power networks that are both efficient and reliable.

Data extraction and training for artificial deep learnings are also covered in full. Another ANN in [24] performs in better MPPT than climbing algorithms [25]. The authors used the MATLAB NN-Tool to create a Levenberg-Marquardt backpropagation method to map the maximum highest point. Traditional MPPT algorithms should be used with a NN controller, according to the proposed methodology.

### 3. Proposed Method

In this section, we present how the BPNN-DL operates to determine the maximum power point and the operation is given in Figure 1.

In Figure 1, it is important to observe with the series of connections in order to obtain maximum power point tracking. The momentary changes in light intensity and temperatures are sent as input to the control and measurement unit. At the first stage, the MPP point is searched, and the obtained value is sent as feedback to the control and measurement unit. Simultaneously, the ANN unit receives the input from the MPP search unit, and this ANN unit helps in finding the maximum MPP value and send it as a feedback to the control and measurement unit. The process involves the control and measurement unit that provides the values to the MPP unit to search an optimal value, however, BPNN-DL interferes with the decision of the MPP unit and provides near-optimal solution of MPP. The local tracking results in a considerable reduction in power. The two-stage maximum power tracking approach provided in this paper identifies the maximum point for two serially connected modules.

Step one involves measuring the array radiation and temperature and calculating the PI curve. Finally, a MPP point search technique is deployed using ANN parameters at MPP. The search is redone if the weather conditions worsen beyond a particular point. If there have been any changes to the performance conditions, then, the actual characteristic curve will begin its MPP search from its previous performance point in step two rather than from its estimated point from the first stage. In the second stage, any of the MPPT process and then a BPNN network is employed.

**3.1. BPNN-DL Tracking.** The BPNN-DL is briefly described as follows:

Phase 1: the study will calculate the inaccuracy of the MPP output based on the ground truth. The inaccuracy can be traced back to every neuron in each layer of the brain.

Phase 2: The study then updates the weight to find the optimal solution.

In order to get the minimum error, the study defines the cost function:

$$C = \frac{1}{2} \sum_{j \in L} \|d_j - y_j^L\|^2, \quad (1)$$

where  $x$  is the input training data;  $d_j$  is the output of each layer;  $L$  is total layers, and  $y_j^L$  is the neural network output w.r.t  $x$ .

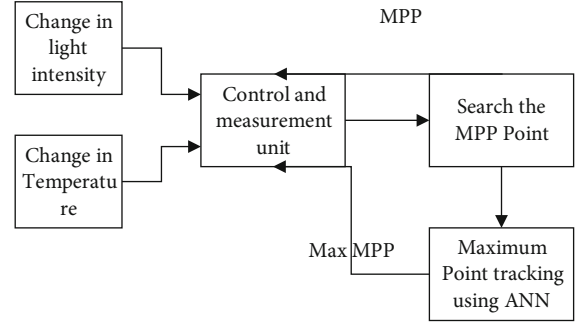


FIGURE 1: Schematic diagram of the proposed ANN MPPT.

The goal is to find the maximum power value and hence the study uses partial derivative as it helps in attaining minimal cost function w.r.t weights:

$$\frac{\partial C}{\partial W_{ij}^L} = 0. \quad (2)$$

Now, the study considers two cases: the node is an output node or it is in a hidden layer. In output layer, the study first computes the derivative of the difference of the ground truth and the output. That is,

$$\frac{\partial C}{\partial W_{jk}^L} = (d_k - y_k^L) \frac{\partial}{\partial W_{jk}^L} y_k^L. \quad (3)$$

Node  $k$  with weight  $W_{jk}^L$  enables the activation function output as  $y_k^L$  using sigmoid function as below:

$$\frac{\partial C}{\partial W_{jk}^L} = (d_k - y_k^L) \frac{\partial}{\partial W_{jk}^L} \sigma(x_k^L), \quad (4)$$

where  $x_k^L$  is the linear combination of inputs.

The sigmoid function derivative is given in the following form:

$$\frac{d}{dx} \sigma(x) = \sigma(x) - \sigma(x)^2. \quad (5)$$

The partial derivative based on the chain rule is defined as below:

$$\frac{\partial C}{\partial W_{jk}^L} = (1 - \sigma(x_k^L)) \sigma(x_k^L) (d_k - y_k^L) \frac{\partial}{\partial W_{jk}^L} x_k^L. \quad (6)$$

$x_k^L = \sum_{i \in L-1} W_{ik}^L y_i^{L-1}$ . Thus, the following expression is given as below:

$$\frac{\partial C}{\partial W_{jk}^L} = \sigma(x_k^L) (d_k - y_k^L) (1 - \sigma(x_k^L)) y_j^{L-1}. \quad (7)$$

In  $i \neq j$  case,  $\partial C / \partial W_{jk}^L$  is both linked  $y_j^{L-1}$  and unrelated  $y_i^{L-1}$ . This equation was used to discover the relationship between the  $j$  and  $k$  node.

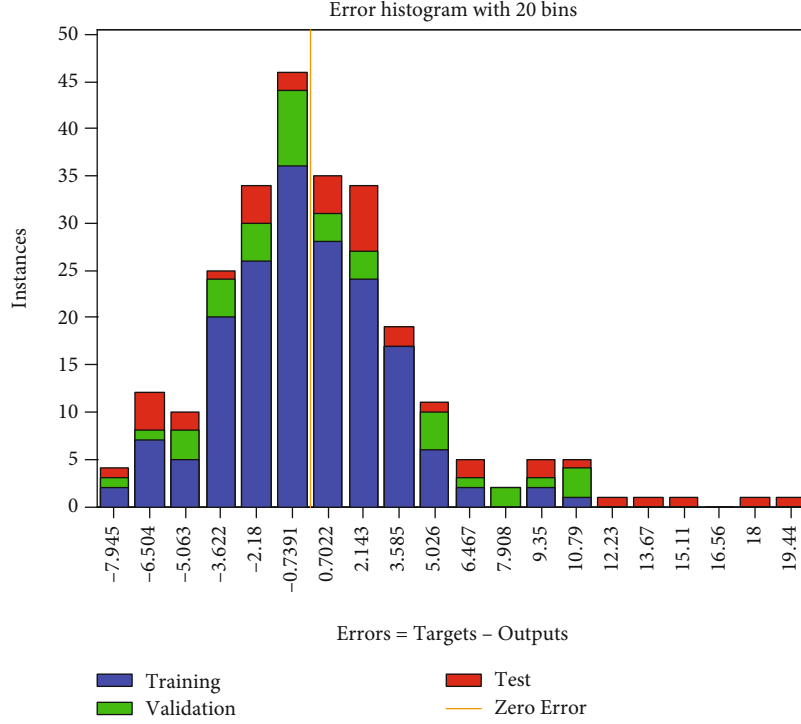


FIGURE 2: Error of proposed method during MPPT.

$$\delta_k = \sigma(x_k^L) (d_k - y_k^L) (1 - \sigma(x_k^L)), \quad (8)$$

as a way of representing the  $L$  layer  $k$  node. The equation is rewritten as below:

$$\frac{\partial C}{\partial W_{jk}^L} = \delta_k y_j^{L-1}. \quad (9)$$

Finally, the hidden node is examined. To begin, the study looks at layer  $L - 1$ , which is shortly before the output layer. It is necessary to use a partial derivative on the cost function as well. Only the hidden layer nodes have been weighted.

$$\frac{\partial C}{\partial W_{ij}^L} = \sum_{k \in L} (d_k - y_k^L) \frac{\partial}{\partial W_{ij}^L} y_k^L. \quad (10)$$

In the  $L$  layer, there is a summation over  $k$ , so keep that in mind. So why does it matter if hidden layer weights  $W_{ij}^L$  are varied. Because the neural network output  $y_k^L$  is affected. The study used the chain rule and came up with the following results:

$$\frac{\partial C}{\partial W_{ij}^L} = \sum_{k \in L} \sigma(x_k^L) (d_k - y_k^L) (1 - \sigma(x_k^L)) \frac{\partial}{\partial W_{ij}^L} x_k^L. \quad (11)$$

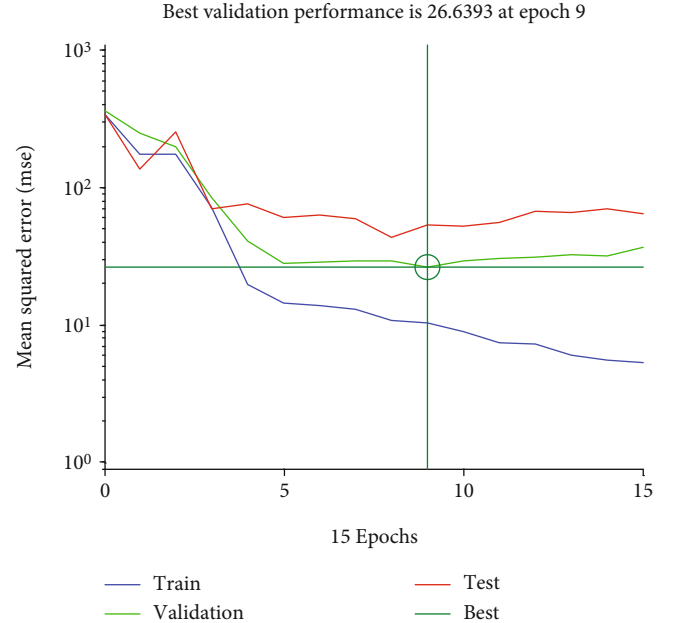


FIGURE 3: MSE of proposed method during MPPT.

Then, the study uses the chain rule to alter the last derivative term:

$$\frac{\partial C}{\partial W_{ij}^L} = \sum_{k \in L} (d_k - y_k^L) \sigma(x_k^L) (1 - \sigma(x_k^L)) W_{jk} \frac{\partial y_j^L}{\partial W_{ij}^L}. \quad (12)$$

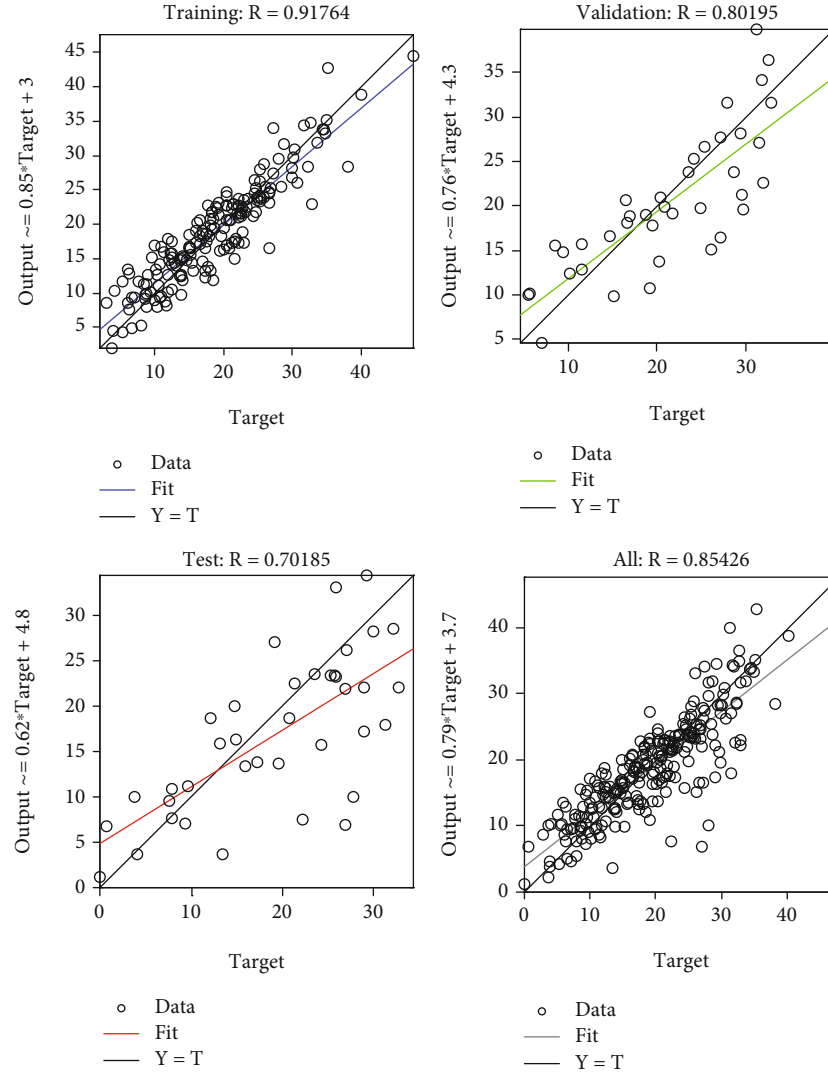


FIGURE 4: Fitness of proposed method during MPPT at all stages.

Line 2 in Eq. (14) originates from the fact that input is a linear combination  $x_k^L$  of the outputs from nodes in the preceding layer with a weight. According to the new findings, the derivative term has nothing to do with the  $L$  layer's  $k$  node. The chain rule is used again to simplify the derivative term, as seen in the following example:

$$\frac{\partial C}{\partial W_{ij}^L} = \sigma(x_j^L) (1 - \sigma(x_j^L)) y_i^{L-1} \sum_{k \in L} \delta_k W_{jk}. \quad (13)$$

Aside from  $y_i^{L-1}$  as  $\delta_j$ , the study is able to define all concepts. As a result, the equation is as follows:

$$\frac{\partial C}{\partial W_{ij}^L} = \delta_j y_i^{L-1}. \quad (14)$$

The equation for the output node of layer  $k$

$$\frac{\partial C}{\partial W_{jk}^L} = \delta_k y_j^{L-1}, \quad (15)$$

where

$$\delta_k = (d_k - y_k^L) (1 - \sigma(x_k)) \sigma(x_k). \quad (16)$$

The equation for the output node of layer  $k$

$$\frac{\partial C}{\partial W_{ij}^L} = \delta_j y_i^{L-1}, \quad (17)$$

Where

$$\delta_j = (1 - \sigma(x_j)) \sigma(x_j) \sum_{k \in L} \delta_k W_{jk}. \quad (18)$$

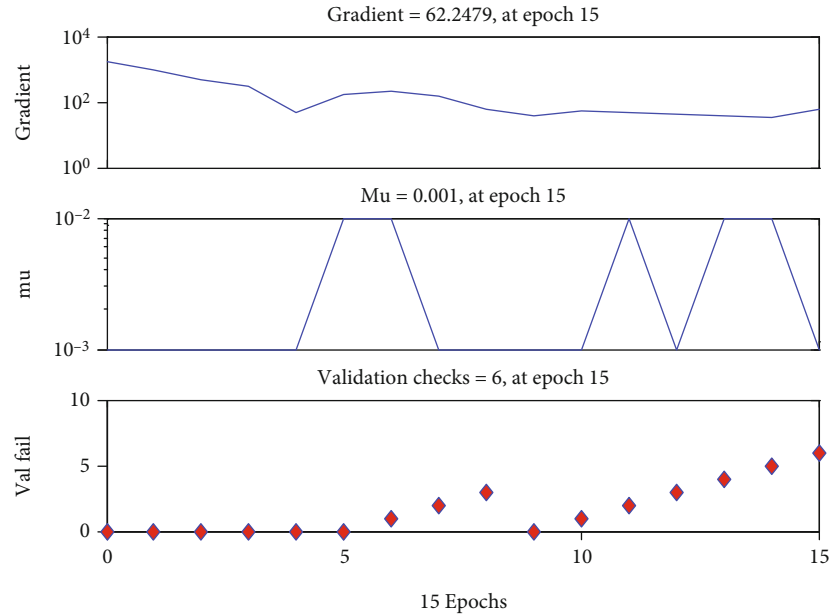


FIGURE 5: Fitness during training state of proposed method during MPPT.

Faintly, the cost function gradient at bias is given below:

$$\frac{\partial C}{\partial \theta_l} = (d_k - y_k^l) \sigma(x_k^l) (1 - \sigma(x_k^l)) = \delta_l. \quad (19)$$

## 4. Results and Discussions

The model is simulated in Simulink to correlate with the input data from PV array. Rather than using a continuous simulation, a discontinuous simulation is performed. ANN ability to accurately forecast the future depends on the size of the training dataset. The ANN predictions are generally accurate because of the enormous amount of data they have been trained on. From the lookup table, a clock synchronises the solar panel input data with the lookup table data. Figure 2 shows error of proposed method during MPPT.

An ANN prediction model is evaluated and validated using one or more specified error metrics. A continuous error matrix is used by the ANN algorithm to complete a function approximation task. No matter how many inputs and outputs are compared, all errors are rounded to the nearest integer.

Figure 3 shows the results of MSE of proposed method during MPPT, where the proposed method achieves reduced rate of error during testing process. The fitness of proposed method during MPPT in Figure 4 shows that the proposed method achieves better fit at all stages of the classifier. The results show that the proposed method moves to zero errors as the number of iterations getting increased, and it approaches towards the targeted solutions.

The average error (Figures 2–5) is the square root of the difference between the estimated and actual values, and this is what the mean square error measures. At each data point, the entire predictive model process is optimised by squaring the loss function and averaging it. Error minimization, or

backpropagation, is used by the ANN to alter its anticipated output with respect to its actual output.

## 5. Conclusions

In this paper, BPNN-DL obtains maximum power point and maximises the output power from the solar grids when the panels are connected with the boost converter under different variable load conditions. BPNN-DL enables the prediction of reference voltage at different weather conditions for severing the various output power that ensures maximum power with stable output voltage. The proposed BPNN-DL under different conditions shows that it is capable of achieving maximum output power (98% accuracy) from each panel compared with existing methods. In future, the reduction of implementation cost can be focused while adopting the machine learning modules.

## Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

## Acknowledgments

The authors thank Arba Minch University, Ethiopia, for providing help during the research and preparation of the manuscript. The author appreciates the assistance from Government College of Engineering, Salem, Aditya Engineering College, SIMATS, in completing this work.

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