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Hybrid MPPT for PV Converter: Integrating Long Short-Term Memory (LSTM) Networks with Perturb and Observe (P&O) Technique for Real-Time Optimization

by

Rachhak Shahu

A THESIS

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Rachhak Shahu

(079MSPDE018)

Thesis Supervisor

Assist. Prof. Yuba Raj Adhikari

Department of Electrical Engineering, IOE, Pulchowk Campus

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Electrical Engineering Department
Pulchowk Campus

CERTIFICATE OF APPROVAL

The undersigned certify that they have read and recommended to the Institute of Engineering for acceptance, a dissertation entitled **"Hybrid MPPT for PV Converter: Integrating Long Short-Term Memory (LSTM) Networks with Perturb and Observe (P&O) Technique for Real-Time Optimization"**, submitted by **Rachhak Shahu** in partial fulfillment of the requirement for the award of the degree of **Master of Science in Power Electronics and Drives Engineering**.

Assist. Prof. Yuba Raj Adhikari
Supervisor
Department of Electrical Engineering

Assoc. Prof. Jeetendra Chaudhary
Program Coordinator
M.Sc. in Power Electronics and Drives Engineering

Assoc. Prof. Dr. Basanta K. Gautam
Head of Department
Department of Electrical Engineering

Er. Thark Bahadur Thapa
External Examiner
Director, NEA

APRIL, 2025

Tel: +977-1-5443081, Email: doee@pcampus.edu.np, Website: www.doee.pcampus.edu.np

ABSTRACT

Integration of renewable energy with power system is getting popular due to the environmental concerns, economic benefits and technological advancements. Solar PV generation has significant role in charging the battery, helping in grid tied application and so on. To strengthen the output power of a solar photovoltaic arrangement, it is crucial to attain the maximum possible energy output from the photovoltaic (PV) panel. This research aims for exploring the integration of Long Short-Term Memory (LSTM) and the widely used traditional method, Perturb and Observe (P&O) approach for the Maximum Power Point Tracking (MPPT) in Photovoltaic (PV) system. This hybrid approach for the MPPT in PV converter integrates the predictive capability of the LSTM network with the straightforward and the stability capability of the P&O algorithm. The aim of this research is to design a hybrid LSTM-P&O MPPT algorithm evaluating its performance in changing environment conditions like fluctuating irradiance and temperature. In this research, the proposed hybrid MPPT was designed, implemented and tested in MATLAB/Simulink by training the LSTM model with one-year real world dataset of a PV system with 200W maximum power output solar array. After the training of LSTM model, the RMSE and the loss of the model obtained is 0.0975 and 0.048 respectively. It is found that the proposed hybrid LSTM-P&O MPPT algorithm is capable to effectively track the maximum power point efficiently under changing environmental conditions and also performs better than the traditional MPPT method P&O. Also, to determine the effectiveness of the proposed hybrid MPPT algorithm, artificial neural network based MPPT method was implemented for the comparison. The ANN based MPPT model was used as a benchmark for validating the responsiveness and the accuracy of the proposed hybrid MPPT system under changing irradiance and cell temperature. Simulation results presented that the proposed method matched closely with the results from ANN based MPPT despite being slower than the ANN based MPPT but provided more output power from the PV array.

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LIST OF ABBREVIATIONS

- AI: Artificial Intelligence
- ANN: Artificial Neural Network
- DNN: Deep Neural Network
- LSTM: Long Short-Term Memory
- MPPT: Maximum Power Point Tracking
- MSE: Mean Squared Error
- P&O: Perturb and Observe
- PV: Photovoltaic
- RNN: Recurrent Neural Network
- RMSE: Root Mean Squared Error

CHAPTER ONE: INTRODUCTION

1.1. Background

Modern advancements in solar photovoltaic (PV) systems have been seen due to rising worldwide need for clean and renewable energy. As the technology is advancing rapidly, the reliability of the PV panels is increasing and the PV modules costs are decreasing [1]. PV systems working as sustainable energy source benefit from efficient power generation methods whose operation are affected by the dynamic environmental factors such as: rapidly changing irradiance, temperature, humidity, cloud cover and precipitation. To strengthen the output power of a solar photovoltaic arrangement, it is crucial to obtain the maximum possible energy output from the photovoltaic panel. MPPT algorithms plays as an important component that improves the PV system performance by continuously monitoring operating points to get the maximum available power.

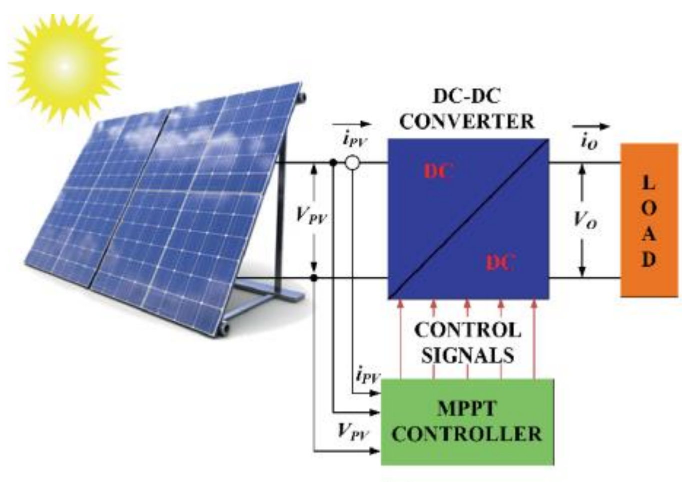

Figure 1.1: Block diagram of PV system

The predictive models improve the dependability of the device, limiting the effect of performance of PV and the extra equipment maintenance costs. The main features of I-V properties of a solar PV array are irradiation and temperature. For the optimal performance of the solar cell arrays, an MPPT controllers are used. There are many MPPT algorithms for harvesting maximum power from the solar cell arrays. Perturb and Observe (P&O), being one of the conventional MPPT techniques with simple implementation and easy operation, is widely used. However, the technique lacks performance as the convergence speed is not enough to settle inside MPP proximity and has poor accuracy for changing environment conditions.

1.1.1. Recent Advancements in MPPT

In past years, artificial intelligence (AI) methods in combination with machine learning (ML) tools have been effective tools for improving the performance of MPPT system. LSTM neural networks have such an exceptional feature, that they can process time series data and also can detect about the complex relation between data points. LSTM networks are able to process time series data, and can therefore be used to predict how PV systems should operate in terms of historical and real time information. LSTM predictive nature adds on to tracking efficiency performance which is also used to achieve stability alongside adaptability to offset the difficulties encountered in the traditional MPPT techniques.

This research presents a combination of the MPPT controller which uses an LSTM network along with the P&O to optimize PV converters in real-time. This combination of predicting feature of LSTM with the P&O algorithm produces a synergistic solution which provides a robust adaptability with practical simplicity to improve the PV system efficiency. P&O technique is applied to LSTM networks that can overcome different incapability faced by traditional MPPT approaches during operation. It yields several advantages, which include optimized stability in the MPP region and fast-tracking response as well as power dissipation during stability. The system can make advance modification through predictive features of its LSTM model that helps it to be able to respond quickly to changing environmental conditions.

1.2. Problem Statement

The maximum power extraction from PV system becomes challenging because of the non-linear characteristics exhibited by the PV arrays also supported by the dynamic environmental conditions such as fluctuation in temperature and irradiance. This results in shifting of the Maximum power point in unpredictable nature which limits the energy conversion efficiency.

There are convention methods of Maximum Power Point Tracking like Perturb and Observe (P&O) which have gained popularity due to their simplicity and convenience.

However, this technique is significantly affected by the issues of slow convergence to MPP, power losses due to oscillations around MPP and decrement of tracking accuracy under dynamic conditions. These drawbacks led to the need of the more accurate, fast and reliable system for MPPT.

With the increasing need for advanced MPPT approach for predicting and dynamically adjusting the PV operating point in real-time for achieving the efficient, stable, responsive and enhanced power tracking, integration of advanced AI models like Long Short-Term Memory (LSTM) with the conventional method P&O came into light. This hybrid approach is derived from conventional methods to overcome constraints while putting the machine learning predictive skills to achieve maximum performance in different environmental conditions.

1.3. Objectives

The main objective of this research is:

- To design a hybrid LSTM-P&O MPPT algorithm and evaluate its performance under changing environmental conditions

The specific objective of this research is:

- To train the LSTM network using historical data of the PV system
- To integrate the trained LSTM model with perturb and observe (P&O) algorithm
- To validate the proposed hybrid system using simulation and compare the proposed method with traditional MPPT method P&O

1.4. Scope of the research

This research focuses on the analysis of a hybrid MPPT technique by integrating the LSTM network with P&O algorithm for a 200W photovoltaic (PV) array under changing irradiance. The research emphasizes leveraging this PV system for research into hybrid Maximum Power Point Tracking (MPPT) methods. The integration of machine learning techniques, like Long Short-Term Memory (LSTM) networks, with traditional approaches like Perturb and Observe (P&O), aims to optimize the energy extraction process.

1.5 Report Organization

This thesis report consists of five comprehensive chapters for presenting the research work starting from the background and ending with the conclusions.

The opening Chapter one provides the background for the topic, namely, describing photovoltaic systems and what has recently been developed for the improvement of the MPPT techniques, by means of, for example, power electronics. It also presents the research problem, the objectives and the scope of the study.

Chapter two includes a literature review of the basic concepts relating to photovoltaic systems, traditional MPPT techniques and limitations of the Perturb and Observe (P&O) methods. Additionally, it covers Artificial Intelligence namely Long Short-Term Memory (LSTM), as well as hybrid systems and predictive control.

This report includes a methodology in chapter three. The full system components including a PV array, sensors, a controller, a boost converter and a load are presented. It also explains the process of data collection, development of the LSTM model and integration of the hybrid LSTM-P&O MPPT algorithm.

Results and performance of the proposed system are discussed in Chapter Four. Results analysis of the evaluation of the predicted values of the LSTM model, the comparison of actual and predicted outputs, and the simulation results with the traditional P&O, ANN based and the proposed hybrid algorithm are presented.

The work concludes in Chapter Five with summary of findings and its contributions. In addition, it gives future recommendations concerning possible enhancement of MPPT techniques by more advanced learning methods.

There is also a final section at the back of the report with supporting materials including references and appendices, for additional context or data.

CHAPTER TWO: LITERATURE REVIEW

2.1. Equivalent circuit and characteristic of photovoltaic (PV)

A basic representation of an ideal solar cell contains a current source and a diode connected in parallel. [2]. The ideal solar cell model is completed by connecting a shunt and a small value series resistance as shown in the Figure 2.1. The series resistance accounts for the internal resistance caused by the flow of the current, while shunt resistance reflects the losses from leakage currents.

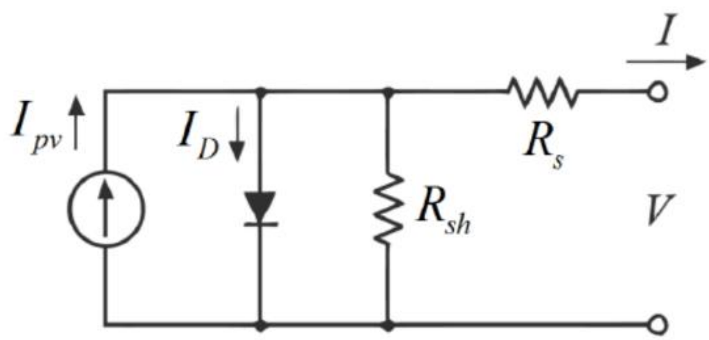

Figure 2.1: Equivalent circuit of a solar cell

From the equivalent circuit of the solar cell, the I-V curve if a solar cell or a solar panel can be will reproduced which is shown in the Figure 2.2.

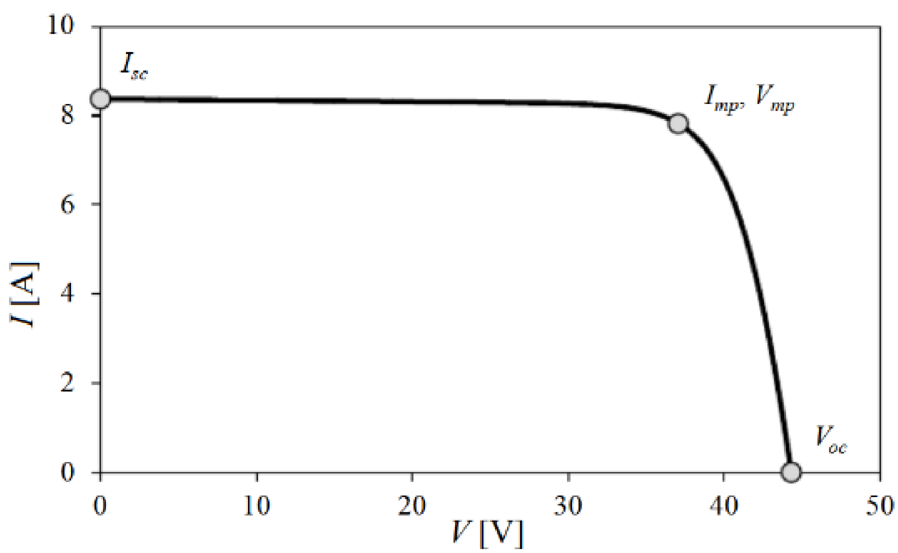

Figure 2.2: I-V curve of a solar cell/solar panel

The I-V characteristic of the equivalent circuit of a solar cell formed by a diode, series resistor and a shunt resistor can be defined by the equation given below:

$$I = I_{pv} - I_o \left[\exp\left(\frac{V + IR_s}{aV_T}\right) - 1\right] - \frac{V + IR_s}{R_{sh}}$$

Where, I_{pv} = photocurrent provided by the constant current source

I_o = Diode reverse saturation current

R_s = Series resistor which considers the loss in the solder bonds of the solar cell, junctions, interconnections and so on

R_{sh} = A shunt resistor which considers the leakage current through high conductivity shunts across pn junction

a = Ideality factor representing the deviation of behavior of the diode from the Shockley diffusion theory.

V_T = Diode thermal voltage which depends on the charge of electron

The main parameters in the I-V curve are open-circuit voltage (V_{oc}), short-circuit current I_{sc}, and the maximum power point (MPP) [3]. The power produced by the solar cell is zero at both the short-circuit current and the open-circuit voltage. The maximum energy extracted by a solar cell is available only at an operating point of the I-V, P-V characteristic. The point at which the power is maximum is defined as the maximum power point (MPP).

2.2. Traditional P&O and Its Limitations

Because of its simplicity and ease of implementation, the most widely used MPPT algorithm even this far is still mostly based upon the Perturb and Observe (P&O) method [4].

The main goal for this control strategy is to have the PV system continuously adjust the operating point in order to extract the maximum power that is available in the system depending on the environmental conditions such as: the irradiance and the temperature [5]. The P&O algorithm uses a small perturbation on the DC-DC converter duty cycle or directly on the voltage or current of the PV plant, which allows the output power to be measured and to discover the local maximum value.

The algorithm assumes that: if the system response to perturbation is in the direction of an increased power for a small increase in voltage, then system is in the direction of a slow change to the Maximum Power Point (MPP) and the perturbation should continue in the same direction [6]. When a small increase in voltage causes the power to drop the system is away from the MPP and the perturbation direction must be reversed [5]. It iteratively repeats this process, which ultimately leads to convergence of the system to the MPP.

The flowchart for the working of the P&O algorithm is shown in the Figure 2.3.

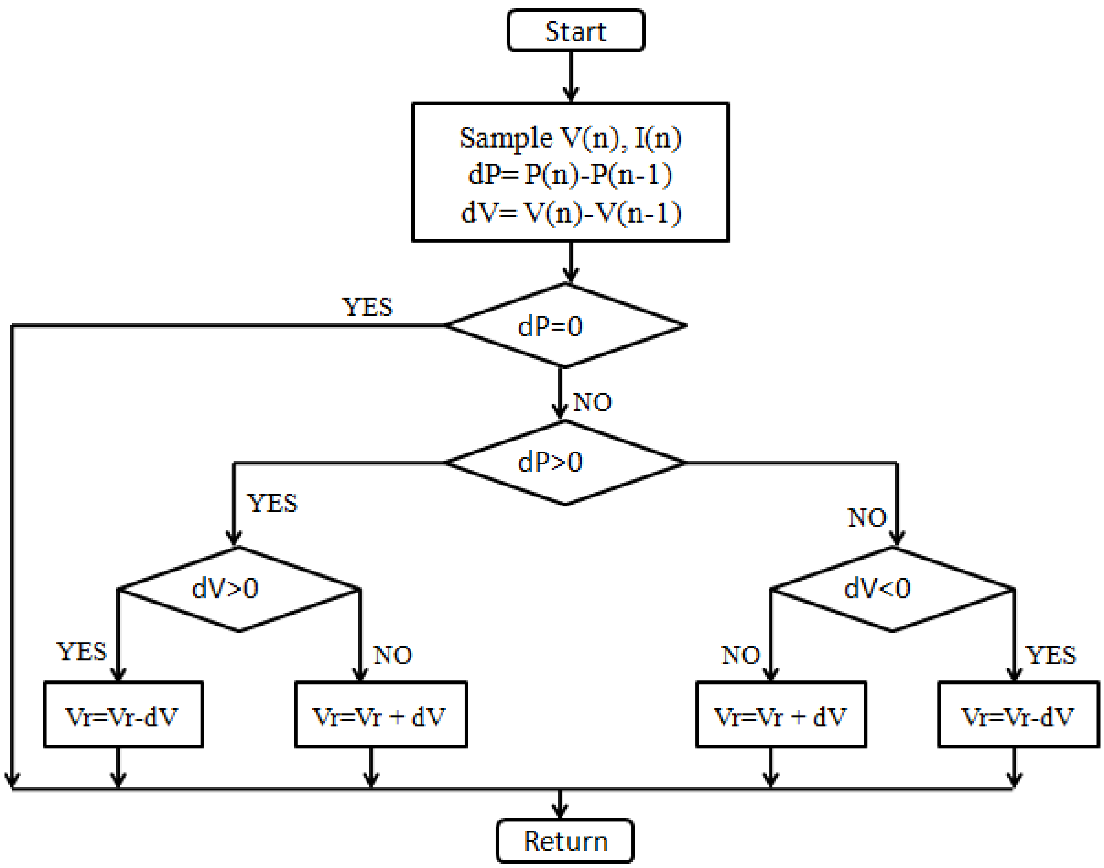

Figure 2.3: Flowchart of P&O algorithm [7]

However, its efficiency greatly falls off as we change the environmental condition such as: irradiance and temperature levels. As a result, a notable power loss is caused by the oscillations that takes place around the MPP and has a slow convergence time. As mentioned in [8], the conventional MPPT method P&O cannot properly handle the conditions of partial shading and dynamic irradiance. It is limited in the application to the advanced PV systems. The adaptability of P&O technique is restricted by its incapability of prediction future trends and it depends solely on current measurements.

2.3. AI Techniques for MPPT Enhancement

In recent years, artificial intelligence (AI) methods in combination with machine learning (ML) tools have been effective tools for improving the performance of the MPPT system. AI-based MPPT algorithms like FLC and ANN have been used widely for tracking the MPP in solar based PV systems [9] [10]. These techniques present good performance for partial shading condition because of their resilience, dependability and adaptability despite their complexity and high implementation costs [11]. Different advanced machine learning and deep learning (ANN, RNN) based MPPT methods have been studied for fast tracking and efficient performance of the PV system. However, conventional neural networks and RNNs struggles with the long-term dependencies because of the gradient vanishing problem. But this problem can be resolved by using the structure of the gating of the Long short-term memory (LSTM) networks [12].

Artificial Neural Networks (ANNs), along with Long Short-Term Memory (LSTM) networks, have been tested for their predictive abilities in recent studies. In [13], it was shown that sequential data could be used by LSTM networks to predict solar irradiance trends and improve the energy harvesting accuracy as compared to regular AI models. In a similar way [14] highlights the usage of AI to overcome the deficiencies of conventional approaches by making use of the LSTM based MPPT controllers to produce a better accuracy and stability. AI’s capability to learn complicated patterns and change to dynamic situations is a best alternative for precise MPPT techniques.

Two Deep Neural Network controllers has been employed by the authors of [15] for a 40kW wind/solar hybrid system. The system included a custom deep neural network MPPT with two features, one target, 66 thousand of data points and one thousand hidden neurons. But the essential steps for the data pre-processing and data visualization are not provided which are required for the DNN approach. The authors of [16] presented the deep reinforcement learning by integrating deep learning into the MPPT. For optimizing the maximum power point under the partial shading conditions, they have also included deep deterministic policy gradient and deep learning method. But the deep reinforcement learning techniques have higher training complexity and they are computationally expensive as well in comparison with the simple and low computational requirements of the Long Short-Term Memory networks.

2.4. Long Short-Term Memory

LSTM Networks further enable training of photovoltaic systems by using a future power value prediction capability and environmental adaptation to track for Maximum Power Point faster and smooth power oscillations while at the same time maximizing energy harvested across changing environment conditions. While standard RNN architectures differ in their Deep Learning (DL) structure due to their unique structure consisting of memory cells with three regulating gates for information transfer between the time steps named the input, forget and output gates. The design approach of LSTM makes them suitable to address issues during the training sessions regarding the gradient problems and to effectively work on lengthy time series.

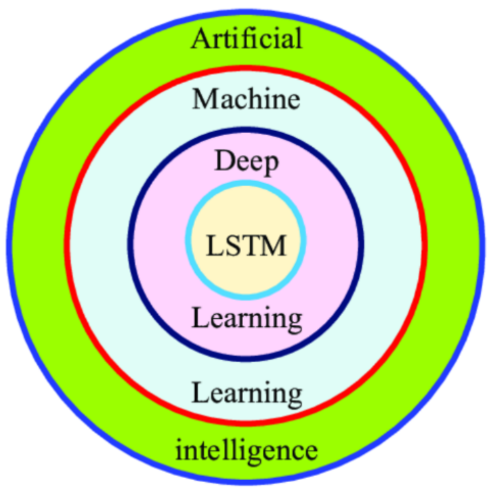

Figure 2.4: Long Short-Term Memory [17]

The advantages of using LSTM networks for MPPT in photovoltaic systems are as evident as the fact that they provide significantly fast convergence to the Maximum Power Point, reduce oscillations, and yield better energy harvesting under varying irradiance and temperature conditions due to their ability to predict future power values, adapt to dynamic environmental changes, and even handle nonlinearity.

2.4.1. Architecture of LSTM

The architecture of a basic LSTM cell includes of a memory cell and three primary gates namely; forget gate, input gate, and output gate [18]. These gate work together for managing the flow of the information.

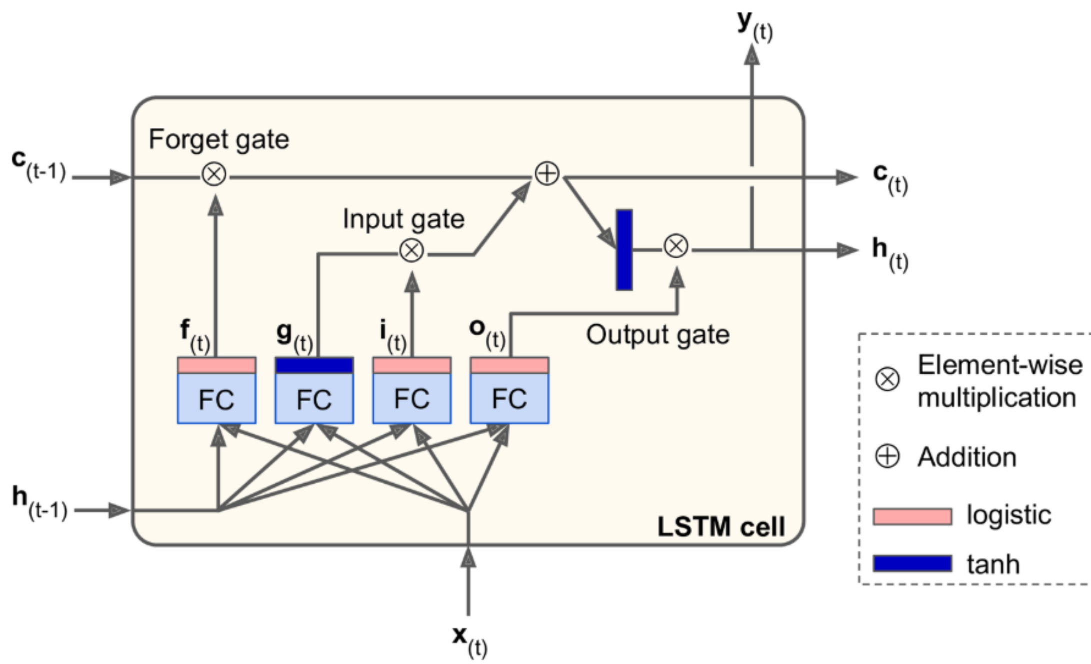

Figure 2.5: Architecture of the basic LSTM cell [18]

The Figure 2.5 illustrates the structure of a basic cell of Long-Short Term Memory (LSTM).

- Memory Cell: Stores information over time, maintaining a balance between retaining important data and discarding irrelevant information.
- Input Gate: Regulates the amount of new input information stored in the memory cell.
- Forget Gate: Identifies which information from the memory cell needs to be forgotten or retained determined by the current input to the network and the previous hidden state.
- Output Gate: It controls the information that is sent as the cell's output for the current time step and contributes to the hidden state for the next step.

The combination of these gates and the cell state allows LSTM to selectively memorize or forget information, making it highly effective for modeling sequential and time-series data.

The equations for computing the short-term state, the long-term state, and the output at every time step for an individual instance are provided below:

$$i_{(t)} = \sigma\left(W_{xi}^{T}.x_{(t)} + W_{hi}^{T}.h_{(t-1)} + b_i\right)$$

$$f_{(t)} = \sigma\left(W_{xf}^{T}.x_{(t)} + W_{hf}^{T}.h_{(t-1)} + b_f\right)$$

$$o_{(t)} = \sigma\left(W_{xo}^{T}.x_{(t)} + W_{ho}^{T}.h_{(t-1)} + b_o\right)$$

$$g_{(t)} = tanh\left(W_{xg}^{T}.x_{(t)} + W_{hg}^{T}.h_{(t-1)} + b_g\right)$$

$$c_{(t)} = f_{(t)} \otimes c_{(t-1)} + i_t \otimes g_t$$

$$y_{(t)} = h_{(t)} = o_{(t)} \otimes \tanh\left(c_{(t)}\right)$$

where,

W_{xi}, W_{xf}, W_{xo}, W_{xg} = The matrices of weight for each of the four layers, representing their connection to the input vector $x_{(t)}$.

W_{hi}, W_{hf}, W_{ho}, and W_{hg} = The matrices of weight of the four layers that connect to the previous short-term state $h_{(t-1)}$.

b_i, b_f, b_o, and b_g = The bias terms associated with each of the four layers.

2.5. Hybrid Systems

Hybrid systems have been introduced in recent research that combines traditional methods with AI-based approaches to achieve greater advantages. The authors of [13] presented a LSTM MPPT control system able to both accelerate system convergence speed and reduce MPP point oscillation magnitude. Furthermore, [19] highlighted incorporation of deep learning with conventional method realizing hybrid architectures that showcases significant improvements in efficiency and reliability, especially in large-scale grid-tied PV systems.

2.6. The Role of Real-Time Data and Predictive Control

The optimization of MPPT depends on immediate data acquisition and predictive control operations. By processing real-time irradiance and temperature data with LSTM networks users achieve precise forecasting and adapted control methods. The predictive abilities of

LSTM networks according to [12] provide optimal processing of dynamic environmental conditions to reduce power loss while improving system reliability. The implementation of stacked LSTM architectures for real-time control shows how deep learning models can drive MPPT technology forward resolving efficiency and scalability challenges.

CHAPTER THREE: METHODOLOGY

3.1. Method Overview

The figure below shows the block diagram of the methodology employed for this study. The system operates as a hybrid MPPT controller by combining the predictive capabilities of the LSTM model with the traditional P&O technique implemented in the predictive controller. This approach enhances the speed, stability, and accuracy of MPP tracking, especially under rapidly changing environmental conditions.

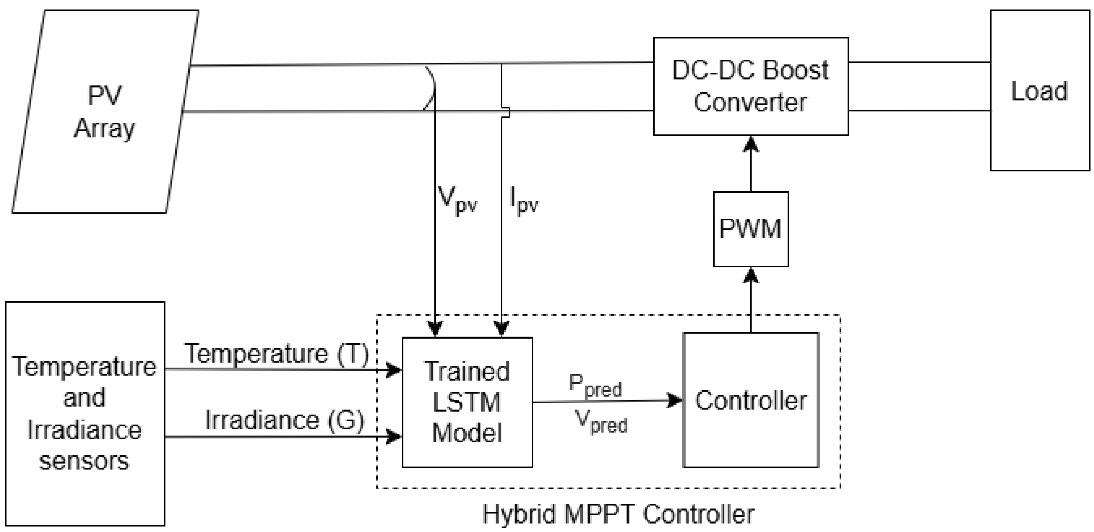

Figure 3.1: Block Diagram of the Proposed Hybrid MPPT Controller

3.1.1. PV Array

The main electrical power supply in the system is provided by the PV (Photovoltaic) array. It works as a converter of sunlight into the DC electricity. And these vary with environmental conditions like: cell temperature and irradiance, the output voltage V_{pv} and current I_{pv} are supplied to the rest of the system. The maximum power tracking starts from the PV array.

3.1.2. Temperature and Irradiance Sensors

This block measures the environmental conditions that affect the performance of the PV array. Panel temperature is given by the temperature sensor (T) and the irradiance sensor measures the intensity of sunlight (G). The necessary parameters are essential input to the trained LSTM model, which requires them to be properly calculated in order to optimize the prediction and readjusting of the operating point.

3.1.3. Trained LSTM Model

The trained LSTM (Long Short-Term Memory) model is an AI-based predictive component. It takes in real-time inputs, including the PV voltage (V_{pv}), current (I_{pv}), temperature (T), and irradiance (G). It predicts the maximum power $P_{pv,pred}$ and the voltage $V_{pv,pred}$ by fetching the information like irradiance and cell temperature, needed to shift the PV operating voltage toward the Maximum Power Point (MPP). The model is helpful in the dynamic adaptation to environmental changes.

3.1.4. Controller

The PV array's operating point is adjusted by using the perturbation step size (ΔV) which is predicted by the LSTM model. It uses the P&O algorithm and tries to fine-tune the duty cycle of the Pulse Width Modulation (PWM) block so that the system converges to the MPP as fast as possible with minimum oscillations.

3.1.5. PWM (Pulse Width Modulation)

The DC-DC boost converter is supplied with precise switching signals produced by the PWM block. The converter's duty cycle is controlled by these signals according to controller's signals. The duty cycle is adjusted to obtain the optimal point for the PV array working at a given voltage to maximize the power extraction.

3.1.6. DC-DC Boost Converter

DC-DC boost converter increases the generated voltage of PV array to the required voltage of the connected load. The PWM signals control its operation and keep the device at or near the desired operating point at or at the MPP. This block is very important in power transfer efficiency from the PV array to load.

3.1.7. Load

The electrical device or system consuming the generated power by the PV system is load of the system. The hybrid MPPT controller gives priority to the load by continuously changing the working point of PV array so that the load receives maximum power. As a result, there is an improved efficiency and better utilization of available solar energy.

3.2. Hybrid LSTM-P&O

Under dynamic environments, the maximum power point tracking (MPPT) efficiency and stability can be improved by integrating both the predictive capability of the LSTM model and the conventional Perturb and Observe (P&O) technique in the hybrid LSTM-P&O MPPT technique. Overall methodology adheres to a structured flow which is shown in the flowchart below:

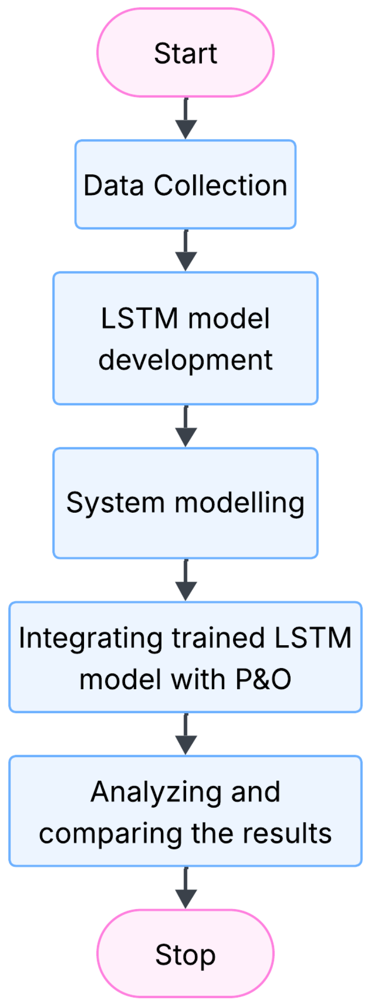

Figure 3.2: Overall flowchart for the research

3.2.1. Data Collection

The first task in the research is gathering in depth historical data from photovoltaic (PV) systems. These data will be used to train and validate the hybrid MPPT system. The required parameters include:

- PV array voltage (V_{pv}): The voltage at the input of the PV converter.
- PV array output Power (P_{pv}): The power output of the PV system.
- Environmental Factors: Key external factors such as solar irradiance (G) and cell temperature (T_{cell}) which affect the PV system's performance.

The research data was collected from an open dataset IEEE provided [20]. The data collection consists of dependable measurements obtained from a 200W photovoltaic (PV) system which provides standardized measurements. A total of 98080 datapoints were obtained which consists of daily logged data in 5 minutes of time interval for a year for different environmental and operational conditions. The system logs the data such as date, time, irradiance, cell temperature, PV voltage, PV current, output current, output voltage, output power, and other different parameters. The PV system's performance evaluation under different operating conditions depends on these distinct set of parameters. The dataset has multiple operational circumstances which help the model understand seasonal patterns and achieve better accuracy prediction results. The application of an IEEE dataset represents an essential method to increase both the study's credibility level and its robustness measures.

3.2.2. LSTM Model Development

In the previous step, time series data is acquired and the Long Short-Term Memory (LSTM) is trained on these time series data. The flowchart for training LSTM model for the hybrid MPPT technique is shown in the Figure 3.3.

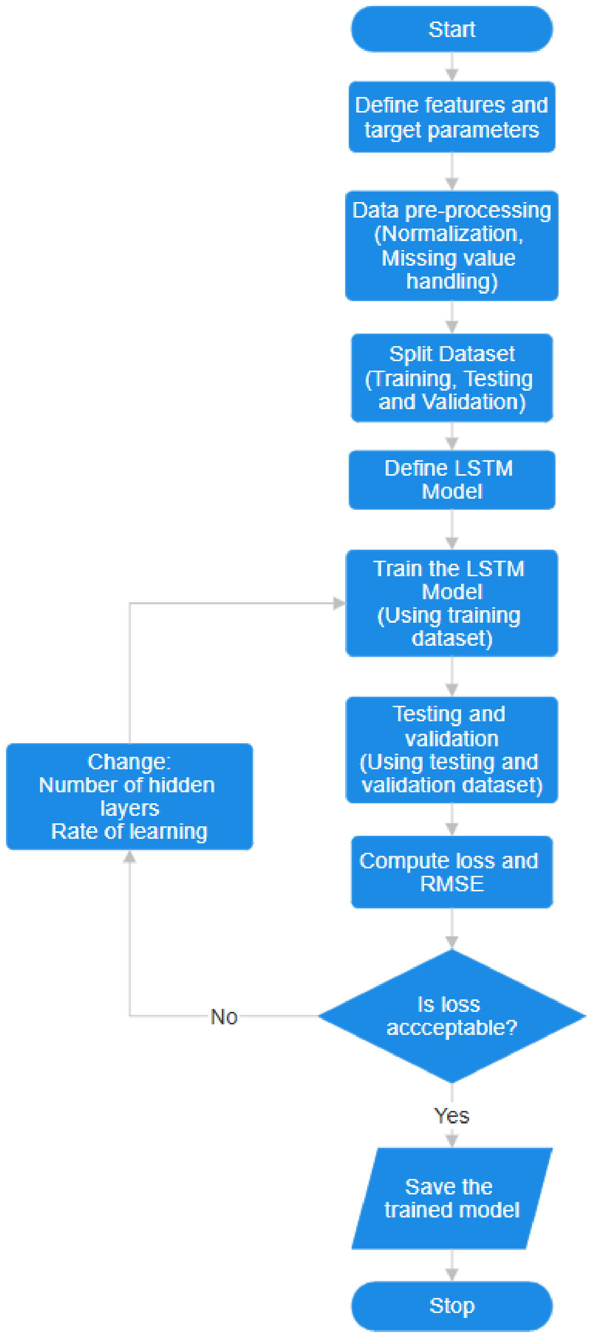

Figure 3.3: Flowchart for training the LSTM model

<u>Defining the feature variables:</u>

In the model designed, the historical series of solar irradiance (G) and cell temperature (T_{cell}) are taken as the feature variables. These inputs are fed into the model and train the model to learn patterns and dependencies over time.

Defining the target Outputs:

The LSTM is modeled to predict key outputs, that includes the next power value (P_{t+1}) and the next PV voltage (V_{pv}), necessary for fine-tuning the MPPT process.

Data pre-processing:

- Normalization

  Normalizing the data is necessary in machine learning and deep learning as the normalization process scales the data to a uniform range which improves the performance and stability of the models.

  Minmax Normalization is used for the normalization process for training the LSTM model. This normalization scales the provided data to range of [0,1] which is suitable for the data collected for this research as the values in the dataset doesn't contain negative values.

  The Min-Max normalization can be performed using the formula,

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{min}}$$

- Missing value handling

  If the dataset contains invalid data or data which results indefinite entries then those irrelevant and faulty data are neglected or omitted and removed from the set for the training process of the LSTM model.

Splitting the dataset

The whole dataset is split into several dataset namely, training dataset, testing dataset and the validation dataset for the proper modelling of the LSTM model and evaluate the model's performance and preventing the overfitting.

Defining the LSTM model parameters

The design of LSTM model includes:

- An Input Layer: Accepts sequences of past values as input.
- Hidden Layers: LSTM cells with a number of units that are carefully chosen in terms of the model complexity and computational efficiency.
- An Output Layer: Generates predictions for the future values

The training process involves finding the model with minimum prediction errors using suitable loss function, optimization algorithm, and the activation layer so that the model will predict the desired parameters correctly under different condition.

As per [21], the RMSE and loss was minimum for 3 layers with 256 total hidden units. Also, the most optimal learning rate is 0.001. So, the detail info on the training parameters is shown below:

Table 3.1: Training Parameters

Feature variables	2
Targets	2
Training dataset	70%
Testing dataset	15%
Validation dataset	15%
Optimizer algorithm	Adam
Number of layers	3
Total hidden units	256
Learning rate	0.001
Max epochs	20

<u>Compute loss and RMSE</u>

Calculating the loss and RMSE of the trained model is required in machine learning and deep learning for measuring the performance of the model. The loss function used for training the LSTM model in this research is Mean Squared Error (MSE).

$$MSE = \frac{1}{N} \times \sum_{i}^{N} (x_i - m_i)^2$$

And the Root Mean Squared Error can be calculated as,

$$RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N} (x_i - m_i)^2}$$

<u>Save the trained model</u>

After training the model, the trained model was saved as a ".mat" file along with the parameters such as standard deviation and mean of the features and targets. The trained model and the model parameters are used for the prediction purpose during the simulation and testing of the proposed hybrid LSTM-P&O MPPT model.

3.3. System Modeling

A photovoltaic (PV) system has been modeled in MATLAB/Simulink. A 200W PV system with a boost converter of output voltage 60V with switching frequency of 10kHz has been modeled. The feature variables used for training the LSTM model are irradiance (G) and cell temperature (T_{cell}). The output from the model are $V_{pv,pred}$, $I_{pv,pred}$ and $P_{pv,pred}$. These predicted values are then used for integrating with P&O technique.

The block-diagram of the modeled system is shown in the Figure 3.4 below:

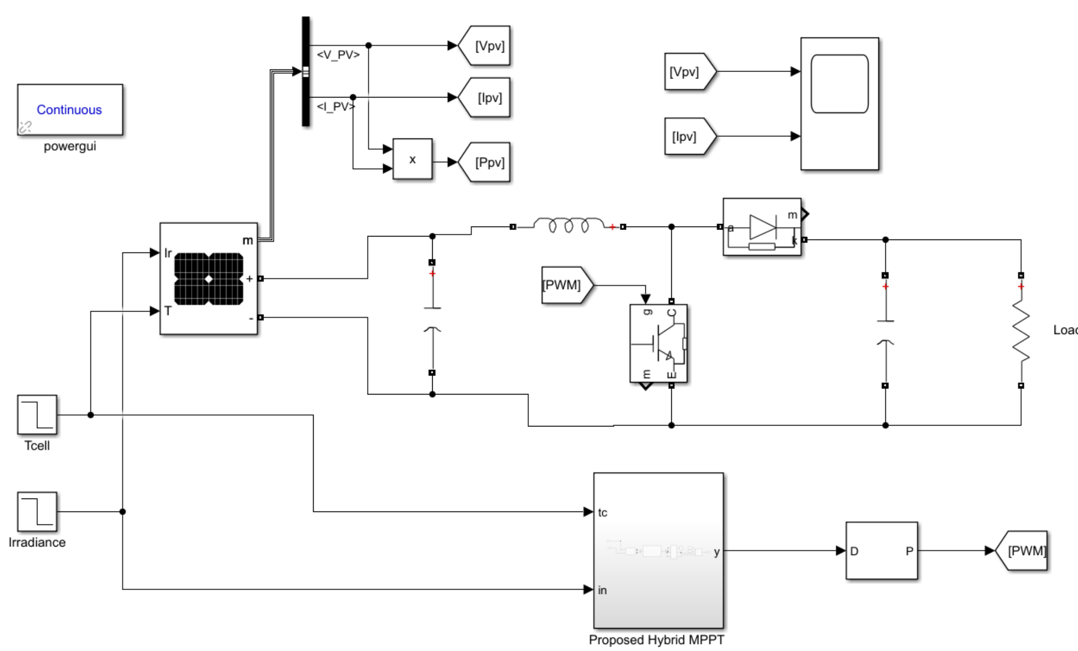

Figure 3.4: Simulink model of proposed Hybrid MPPT system

The Figure 3.5 shows the proposed hybrid MPPT algorithm where the trained LSTM model predicts the V_{MPP} and P_{MPP} for feeding the P&O block. The input values to the trained LSTM model needs to be in the range that was used during the training phase. So, the irradiance and temperature input at an instant is feed to the normalization block which normalizes the input values of irradiance and the cell temperature in the range that was used for the training of the LSTM model.

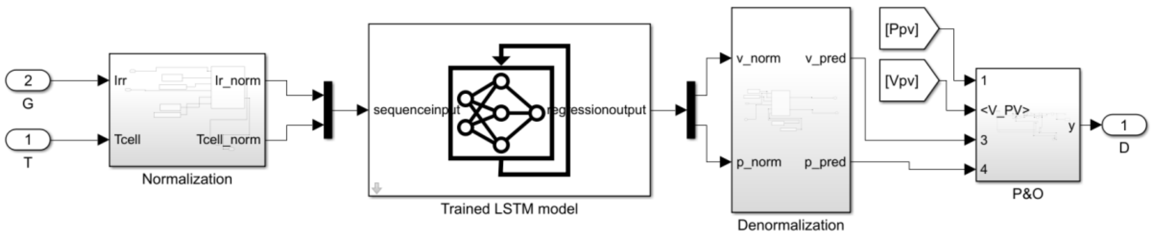

Figure 3.5: Proposed block diagram of Hybrid MPPT algorithm

After normalizing the inputs, the normalized values are fed as features to the trained LSTM model which then predicts the V_{MPP} and P_{MPP}. The predicted output from the trained LSTM is also in the range of normalized form and it needs to be denormalized to get the actual outputs. So, it is fed to the denormalization block which calculates and outputs the actual values of $P_{MPP,\ pred}$ and $V_{MPP,\ pred}$.

This predicted V_{MPP} and P_{MPP} are then passed to the P&O block along with the actual V_{PV} and P_{PV} output from the solar array for determining the optimized duty cycle for attaining the V_{MPP} at the provided irradiance and cell temperature at that instant.

3.3.1. Design Specifications

The data obtained for the training of the LSTM model was obtained from the PV module "Kyocera Solar KC200GT". The design specification of this PV module is given in the Table 3.2.

Table 3.2: PV module Specifications

Rated power	200.143 W
Voltage at Maximum Power Point (V_{MPP})	26.30 V

Current at Maximum Power Point (I_{MPP})	7.61 A
Open Circuit Voltage (V_{OC})	32.90 V
Short Circuit Current (I_{SC})	8.21 A
Cells per module (N_{cell})	54

Design of DC-DC boost converter

The purpose of DC-DC boost converter is to get the required power output from the solar PC array to the load at desired voltage level. As the voltage provided by the solar panel at MPP is 26.3V, the output voltage required for the load is 60V. So, a DC-DC boost converter is required. The selection of the components such as inductor, capacitor, etc. are done using the calculations as depicted in [22]. The input current of the converter will be, $i_L = \frac{P}{V_s}$ and, $\Delta i_L = 20\%$ of the average value.

For the DC-DC boost converter, $V_o = \frac{V_s}{1-D}$

Where, V_o=Load voltage

The value of the inductor can be calculated as, $L_{min} = \frac{V_s D}{f \Delta i_L}$

Where, f = switching frequence (10kHz)

The value of capacitance (C) = $\frac{D \times I_o}{f \times \Delta V_o}$, where ΔV_o is taken as 1% of V_o

The values obtained for the DC-DC boost converter are shown in the Table 3.3 below:

Table 3.3: DC-DC boost converter parameters

Switching frequency (f_s)	10kHz
Inductor (L)	2.2mH
Capacitor (C)	324.07 µF
Duty Cycle (D)	0.5833

3.3.2. Integration with the P&O Algorithm

A hybrid MPPT system is formed by the trained LSTM network integrated with the Perturb and Observe (P&O) algorithm. The integration with LSTM is to improve the performance of P&O method by leveraging the vision of predictive capability.

Guidance for the P&O Algorithm: The predictions made by the LSTM model guide the P&O algorithm by:

a. Predicting the maximum Power ($P_{t, pred}$):

   LSTM predicts the next power output:

   $P_{t+1,pred} = f_{LSTM} (G_t, G_{t-1}, T_t, T_{t-1})$

   where, f_{LSTM} represents the trained LSTM model.

b. Predicting V_{MPP}:

   LSTM predicts the voltage at maximum power point (V_{MPP}):

   $V_{MPP} = g_{LSTM} (G_t, G_{t-1}, T_t, T_{t-1})$

   where, g_{LSTM} represents another output of the LSTM model.

Predicting the Direction of Perturbation (+ or −): Based on the predicted power $P_{t, pred}$ and the current power P_t, the P&O algorithm decrement or increment of the boost converter duty cycle.

Fine-Tuning the Duty Cycle: DC-DC converter duty cycle is modified by the P & O algorithm on the basis of the outputs of LSTM. It thus maintains system operation in the Maximum Power Point (MPP) more efficiently and under varying environmental conditions.

Dynamic Perturbation Adjustment:

If $P_{t+1,pred} > P_t$, check $V(t) > V(t-1)$:

If yes: $D=D-\Delta D$ Else, $D=D+\Delta D$

If $P_{t+1,pred} < P_t$, check $V(t) > V(t-1)$:

If yes: $D=D+\Delta D$ Else, $D=D-\Delta D$

Optimization Criteria:

The convergence of hybrid system occurs when the change in predicted power becomes negligible:

$$| P_{t+1,pred} - P_t | < \epsilon \qquad \text{where, } \epsilon \text{ is a small threshold value.}$$

The optimization objective of the proposed hybrid LSTM-P&O MPPT approach is given as,

$$\max_{V(t)} P(V(t)) \quad where\ V(t) \approx V_{MPP}(t+1)$$

The hybrid LSTM-P&O MPPT approach optimizes the PV output by predicting the optimal voltage using the predicting power of LSTM as:

$$V_{MPP} = LSTM(X_1, X_2)$$

And refines the output through the perturbation steps as:

$$V_{t+1} = V_t \pm \Delta V$$

CHAPTER FOUR: RESULTS AND DISCUSSION

This chapter of the report presents the results obtained during the training process of the LSTM model with a year of dataset for the 200W PV system and the simulation results obtained after modeling and performing the analysis of the proposed hybrid MPPT method for the PV converter.

4.1. Performance metrics result of the LSTM model

The training progress of the LSTM model with one year of data is shown in the Figure 4.1.

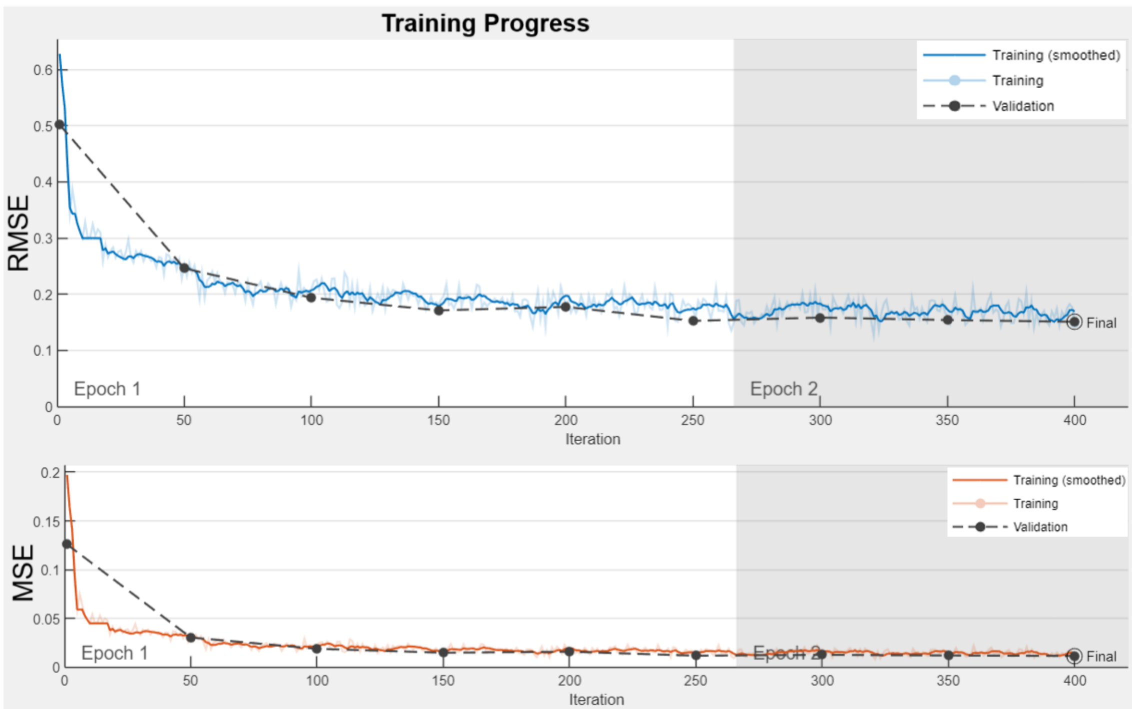

Figure 4.1: Result obtained after training the LSTM model

Evaluation results of the LSTM model reveal both training loss and RMSE decreasing persistently which indicates occurrence of correct learning. The training of the model up to epoch 2 is shown in the Figure 4.1, however the training progress was continuing up to Epoch 20 for the improved results. The training RMSE starts with an initial high value which then decreases steadily throughout each epoch of training before the validation RMSE reaches stable levels at 0.0975 and loss at 0.0048 for epoch 20 indicating effective generalization ability. During training both validation and training loss values decrease progressively which shows the model achieves stable convergence. Some level of training process noise appears in both loss and RMSE measurements despite the fact that optimized batch sizes or gradient clipping could help reduce it.

4.2. Comparison of actual V_{pv} and predicted V_{pv} by the trained model

The predicted V_{pv} values track actual values effectively since the LSTM model reproduces the global trend patterns well. The model effectively learns the periodic oscillations that appear in the dataset because it demonstrates strong pattern detection capabilities.

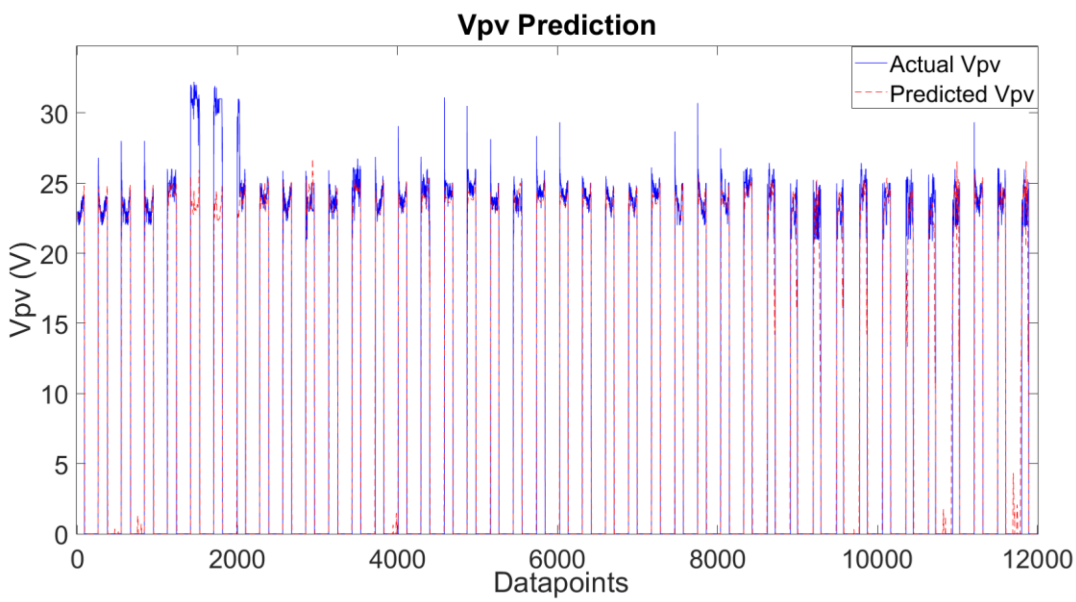

Figure 4.2: Actual V_{pv} and Predicted V_{pv}

Most high and stable regions show matching predicted and actual values making these portions consistent. The LSTM demonstrates effective tracking ability for voltage variations indicating its suitable performance for accurate forecasting. The model shows acceptable conformity to actual behavior although it reveals some minor deviations from the true system behavior. Learning sequential dependencies becomes possible through the periodic data representation of the model. The model shows competent performance in forecasting V_{pv} which enables it to be a useful tool for time-series prediction purposes.

4.3. Comparison of actual P_{pv} and predicted P_{pv} by the trained model

The visual graph correlation between actual and predicted P_{pv} dominates to demonstrate the LSTM model's capacity to capture power fluctuations properly. These actual values are very well predicted by the model which suggests that the model has learnt the underlying patterns of PV power generation.

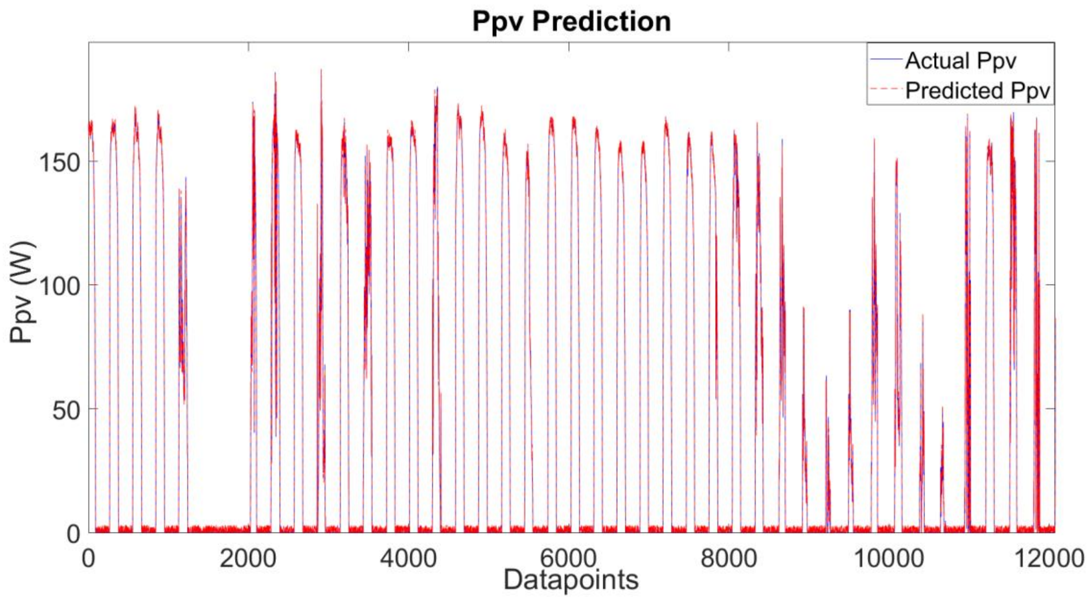

Figure 4.3: Actual P_{pv} and Predicted P_{pv}

The visual graph correlation between actual and predicted P_{pv} dominates to demonstrate the LSTM model's capacity to capture power fluctuations properly. These actual values are very well predicted by the model which suggests that the model has learnt the underlying patterns of PV power generation. A good track of the rapid change of PV system behavior (high peaks of power output) is exhibited by the predicted values. With this, it is maintained that the power output follows the overall trend; thus, the model seems to generalize well in different irradiance and temperature conditions. The predictions reflect the periodic nature of the fluctuations in PV power. The model has reasonable accuracy – deviations are reduced for most cases even in complex variations of power. The consistency of prediction across different power levels exhibits the model's robustness and potential for real-time MPPT applications.

4.4. Results obtained after simulating the modeled PV system

This section includes the results obtained after simulation of the model 200W PV system with a DC-DC boost converter. The output voltage of the PV array (V_{pv}) and the output power of the PV array (P_{pv}) along with the changing irradiance is discussed in this section.

4.4.1. Results obtained using P&O algorithm

4.4.1.1. Output voltage from PV array for different irradiance values

The output voltage from PV array with changing irradiance values using P&O algorithm is shown in the Figure 4.4.

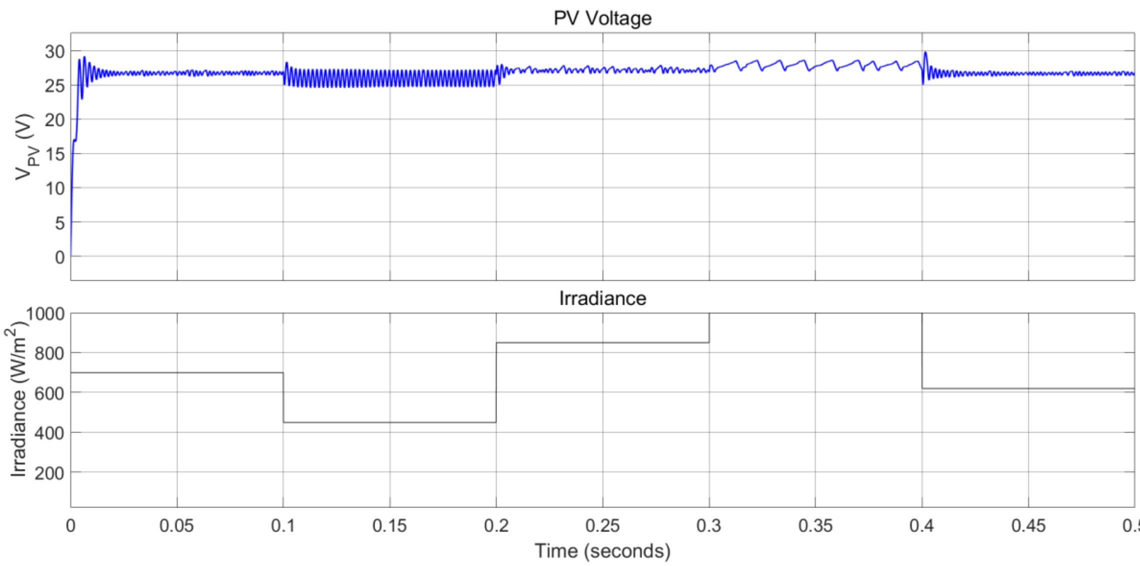

Figure 4.4: V_{pv} output with varying irradiance using P&O algorithm

The cell temperature of the PV array is kept constant at 25°C and the irradiance input to the PV array is changed in an interval of 0.1 seconds. In the first 0.1 seconds of the simulation time, the irradiance value was 700W/m^2 for which the output voltage of the PV array is seen to reduce huge oscillations within 0.026 seconds but keeps oscillating around the V_{MPP}. For the simulation time interval between 0.1 seconds and 0.2 seconds, the irradiance input to the PV array is 450W/m^2. The P&O algorithm seems to be facing difficulty in maintaining the V_{MPP} for this irradiance value as the oscillation around the MPP region is high. Similarly, for time interval 0.2 seconds to 0.3 seconds, 0.3 seconds to 0.4 seconds and 0.4 seconds to 0.5 seconds, the irradiance inputs are 850W/m^2, 1000W/m^2, and 620W/m^2 for which it maintains the V_{PV} around the V_{MPP} but a significant amount of oscillation is present as seen from the Figure 4.4.

4.4.1.2. Output power from PV array for different irradiance values

The Figure 4.5 depicts the output power of the PV array for changing irradiance values.

Similar to the output voltage of the PV array, the output power from the PV array keeps oscillating and doesn't attain a constant output power.

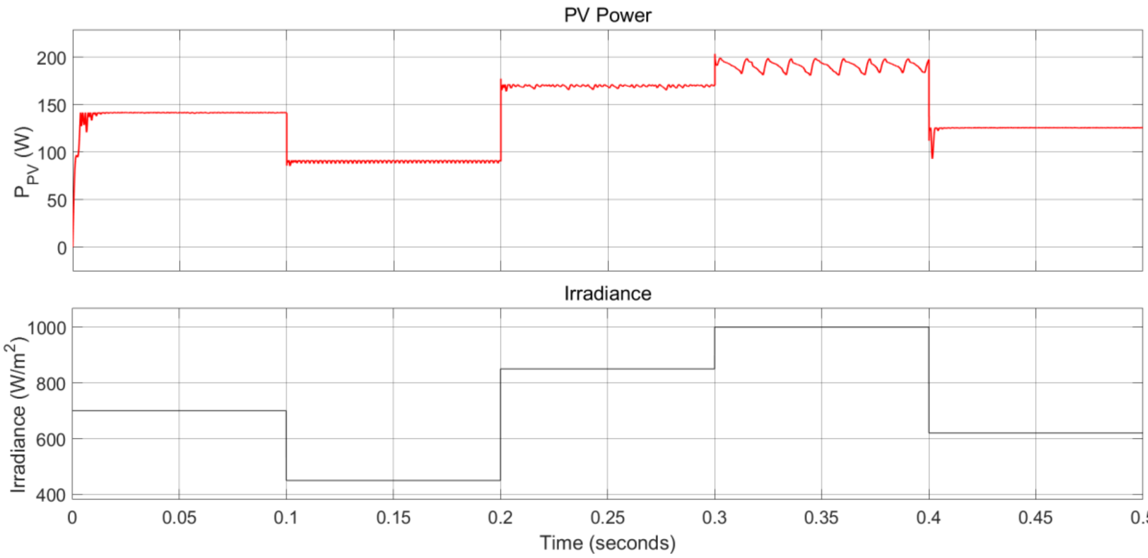

Figure 4.5: P_{pv} output with varying irradiance using P&O algorithm

The output power from the PV array obtained in the first 0.1 seconds for irradiance value of 700W/m^2 oscillates between 141.2W and 138.8W. For the irradiance value of 450W/m^2 in the time interval 0.1 seconds to 0.2 seconds, the output power of solar array oscillates around 91.4W and 88.1W. Furthermore, in the time interval of 0.2 seconds to 0.3 seconds the irradiance input was 850 W/m^2 for which the output of PV array is found to be oscillating around 171W and 166.5W. For the time interval of 0.3 seconds to 0.4 seconds, the irradiance value to the solar array is 1000W/m^2, for which the output power provided by the PV array oscillates in the huge margin between 195.7 and 177.2. And for the last 0.1 seconds, the input irradiance is 620 W/m^2 where the output power of PV array oscillates around 125.8W and 124.6W.

4.4.1.3. Output voltage from PV array for different cell temperature values

Simulation was also carried out by keeping the irradiance constant at 800W/m^2 and changing the cell temperature at an interval of 0.1 seconds. The Figure 4.6 depicts the output voltage of PV array for different cell temperatures.

Similar to the condition where the irradiance was changed and cell temperature was kept constant, in the first 0.1 seconds of the simulation time, the cell temperature value was

25°C for which the output voltage of the PV array is seen to reduce huge oscillations within 0.03 seconds but keeps oscillating around the V_{MPP} for the rest of the time up to 0.1 seconds. For the simulation time interval between 0.1 seconds and 0.2 seconds, the cell temperature of the PV array is increased to 30°C. It can be seen that there is no any significant changes in the PV array output voltage and continues the oscillation when the cell temperature is increased by 5°C.

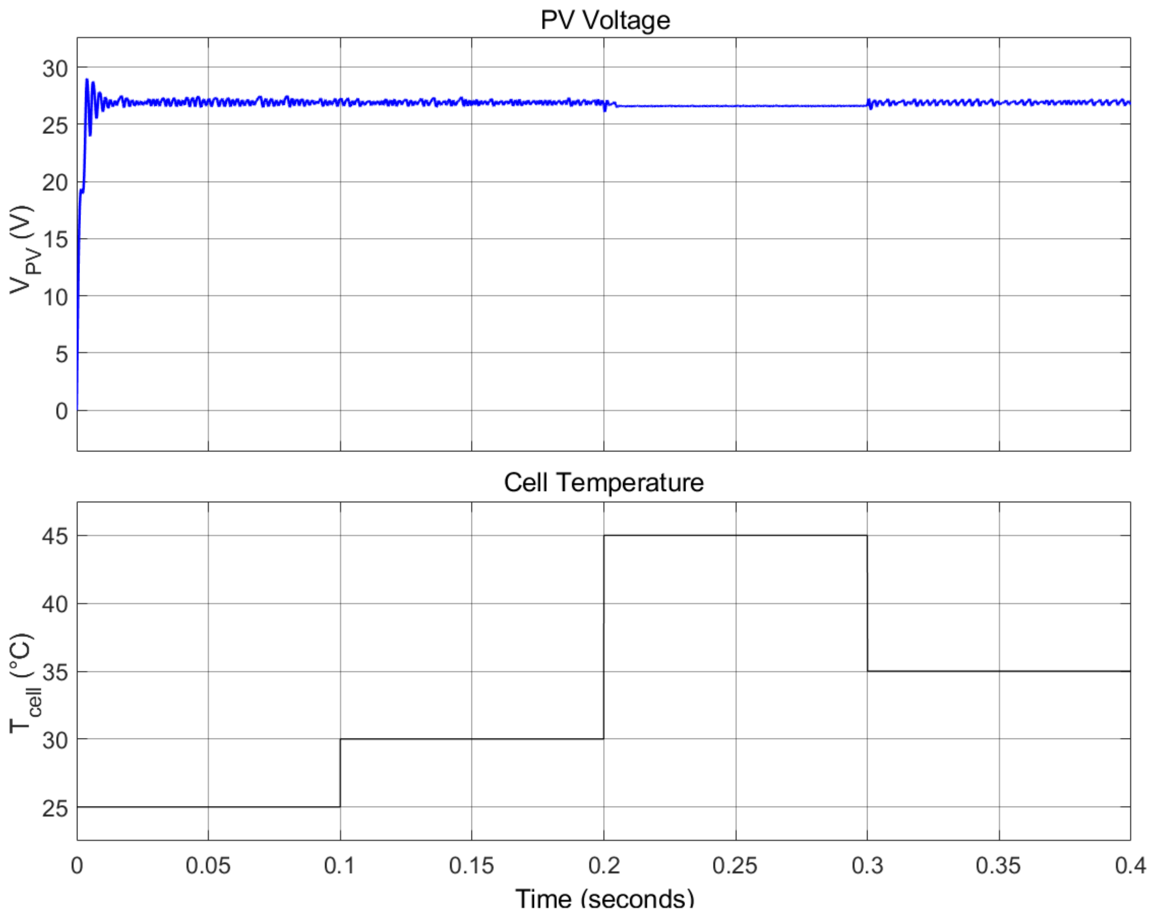

Figure 4.6: V_{pv} output with varying cell temperature using P&O algorithm

The P&O algorithm seems to be facing difficulty in maintaining the V_{MPP} for this cell temperature value as the oscillation around the MPP region is not suppressed. Similarly, for time interval 0.2 seconds to 0.3 seconds, it can be observed that the PV array output voltage has less oscillations around the V_{MPP} when the cell temperature reaches 45°C. The PV array output voltage can be seen stable but there is drastically decrease in the power output which can be seen in the output power plot in the Figure 4.7.

Furthermore, the cell temperature reaches 35°C in the time interval 0.3 seconds to 0.4 seconds for which it maintains the PV array output voltage around the V_{MPP} but a significant amount of oscillation is present as in the other time intervals.

4.4.1.4. Output power from PV array for different cell temperature values

The Figure 4.7 depicts the output power of the PV array for changing cell temperature values at constant irradiance input to the PV array. Similar to the output voltage of the PV array for changing cell temperature, the output power from the PV array keeps oscillating and doesn't attain a constant output power.

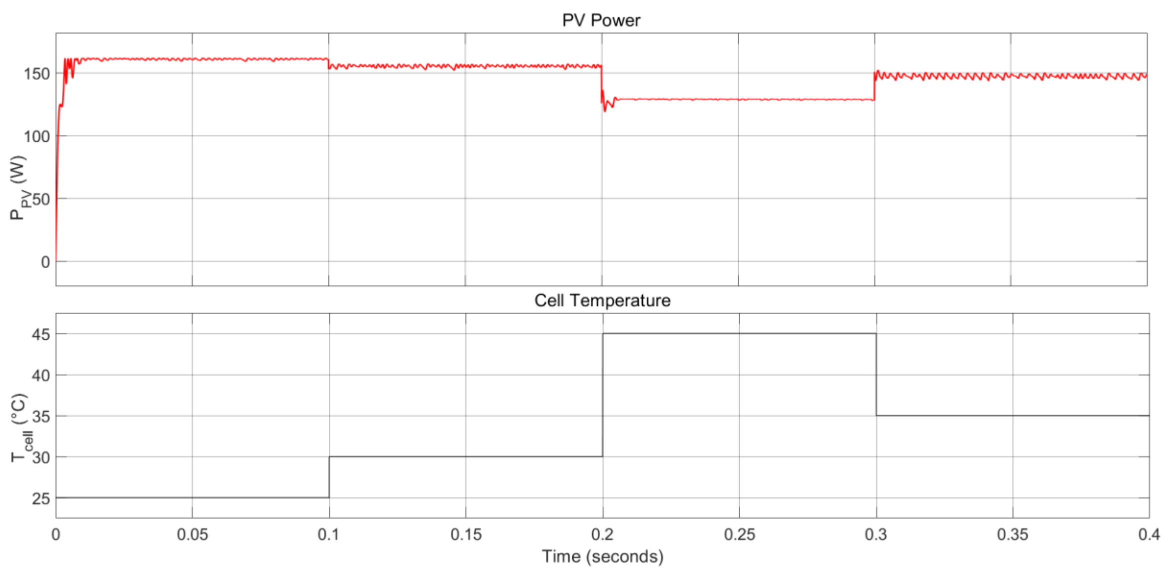

Figure 4.7: P_{pv} output with varying cell temperature using P&O algorithm

The output power from the PV array obtained in the first 0.1 seconds for constant irradiance value of 800W/m^2 with cell temperature of 25°C attains oscillation between 161.4W and 159.2W. When the cell temperature is increased to 30°C in the time interval 0.1 seconds to 0.2 seconds, the output power of solar array decreases and oscillates between 157W and 151.98W. Furthermore, in the time interval of 0.2 seconds up to 0.3 seconds the cell temperature is increased by 10°C and reached 45°C for which the performance of the PV array is greatly decreased. The output of PV array seems to be stable than before but it is found to be slightly oscillating around 129W. And for the last 0.1 seconds, the cell temperature is decreased to 35°C where the oscillation of the output power of PV array is seen increasing and it oscillates between 150.20W and 143.79W.

4.4.2. Results obtained using proposed hybrid MPPT algorithm

4.4.2.1. Output voltage from PV array for different irradiance values

The Figure 4.8 represents the output voltage of the PV array for different irradiance inputs using the proposed hybrid LSTM-P&O MPPT algorithm. Similar to the simulation carried out for the PV system using P&O algorithm, the irradiance values are changed in every 0.1 seconds and the same irradiance values are input to the PV array for the same interval of time as in the simulation of PV system with P&O algorithm.

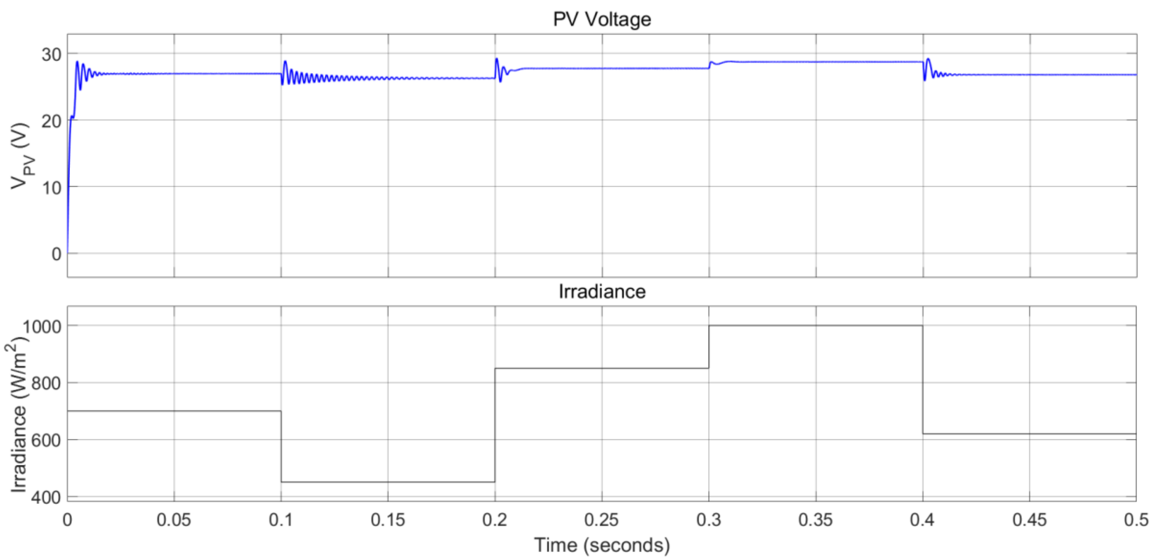

Figure 4.8: V_{pv} output with varying irradiance using proposed hybrid MPPT algorithm

In the first 0.1 seconds of the simulation time, the irradiance input is 700W/m^2 where the output voltage oscillation gradually decreases at 0.02 seconds and almost settles at around 26.9V. After the first 0.1 seconds, the input irradiance is changed to 450W/m^2 where the oscillation is seen due to the change in the irradiance value. But the oscillation gradually decreases and tries to settle around 26.3V. After 0.2 seconds the irradiance value changes to 850W/m^2 which results in oscillation as seen in the figure. The oscillation is settled down at time 0.22 seconds and attains an almost constant value of 27.7V up to time 0.3 seconds. After 0.3 seconds, the irradiance value changes due to which the MPP changes and so does the V_{MPP} to achieve maximum power from the PV system. The irradiance value again changes at time 0.4 seconds which creates an oscillation in the V_{pv} and it settles at 0.33 seconds around 26.8V.

When comparing the output voltage from the PV array at different irradiance level, it can be seen that the output voltage from the PV array with P&O algorithm continues to oscillate with a significant voltage change around the V_{MPP} but in the proposed hybrid LSTM-P&O system, the oscillation due to change in the irradiance level gradually decreases with time and eventually attain almost constant value of the output voltage from the PV array.

4.4.2.2. Output power from PV array for different irradiance values

The Figure 4.9 shown below depicts the output power from the PV array at different irradiance level similar to the PV system with P&O algorithm.

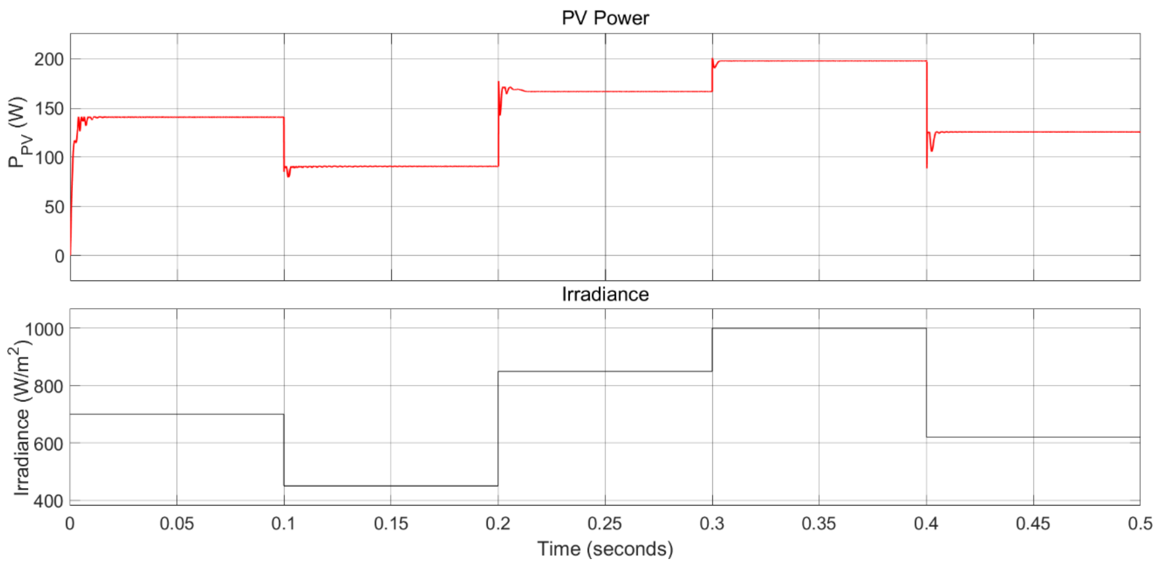

Figure 4.9: P_{pv} output with varying irradiance using proposed hybrid MPPT algorithm

In the first 0.1 seconds of the simulation, the PV array outputs 141.5W power after some oscillations at irradiance level of 700W/m^2. When the irradiance is changed to 450W/m^2 at 0.1 seconds, there seems to be some oscillation which then decreases attaining a almost constant power of around 91.4W. After 0.2 seconds, the irradiance level is changed to 850W/m^2 for which the output power from the PV array after settling down the oscillation is around 169.8W. The irradiance increases to 1000W/m^2 at 0.3 seconds because of which the PV system provides output power nearly equal to the rated power of the solar panel which stables around 196.2W. In the final time interval of 0.1 seconds after 0.4 seconds, the power output from the PV array at irradiance level of 620W/m^2 is found to be almost constant around 125.8W.

Comparing the output power from the PV array with P&O algorithm and the proposed hybrid LSTM-P&O algorithm, it can be seen that the proposed hybrid MPPT system provides almost constant output power and somewhat increased power output from the PV array as the PV system with P&O algorithm oscillates within some significant margin.

4.4.2.3. Output voltage from PV array for different cell temperature values

Similar to the simulation of P&O algorithm, the simulation of proposed hybrid MPPT method was also carried out by keeping the irradiance constant at 800W/m^2 and changing the cell temperature at an interval of 0.1 seconds. The Figure 4.10 shows the output voltage of PV array for different cell temperatures.

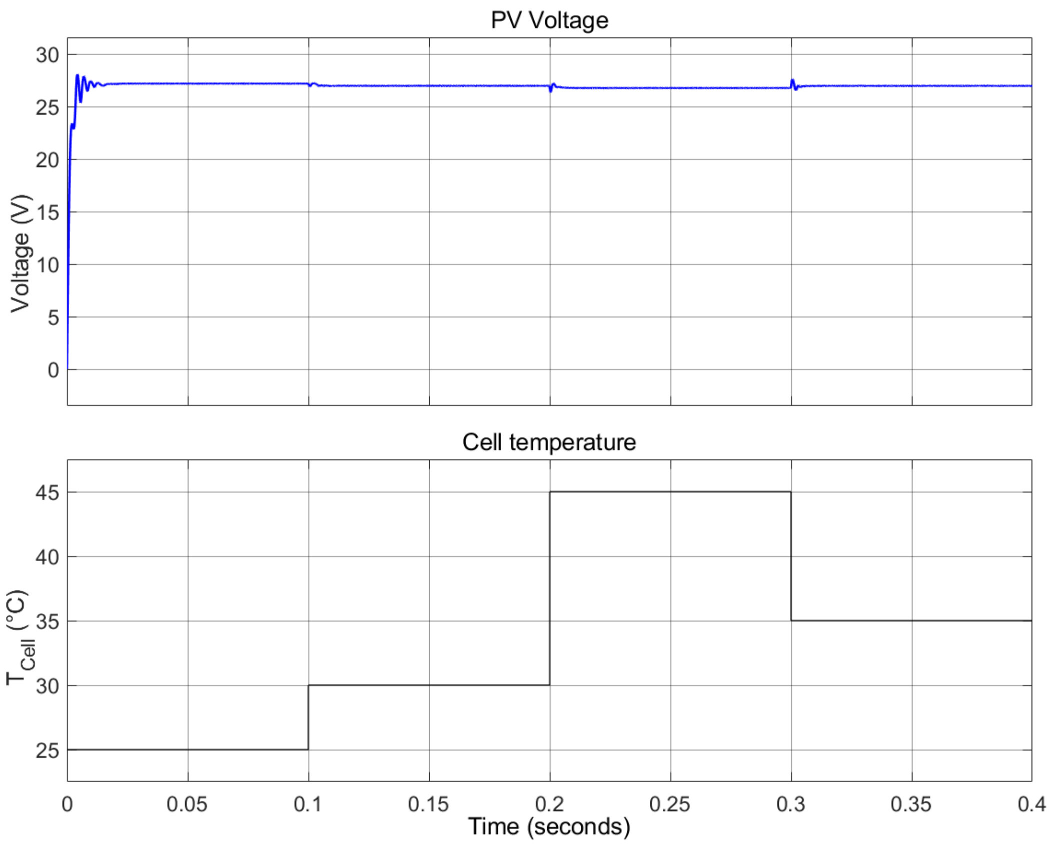

Figure 4.10: V_{pv} output with varying cell temperature using proposed hybrid MPPT algorithm

Similar to the simulation of the system with P&O algorithm, in the first 0.1 seconds of the simulation time, the cell temperature value is kept at 25°C for which the output voltage of the PV array is seen to reduce huge oscillations within 0.02 seconds and attains stable output voltage for the rest of the time up to 0.1 seconds. For the simulation time interval between 0.1 seconds and 0.2 seconds, the cell temperature of the PV array is increased to 30°C where there are some oscillations present at the time of the temperature change. After 0.01 seconds of the temperature change, the oscillations are reduced and the output voltage is seen to be stable throughout this time interval and the voltage value is seen to be slightly decreased as the cell temperature is increased. For the time interval 0.2 seconds to 0.3 seconds, the cell temperature is kept at 45°C where the oscillations are greatly reduced within 0.01 seconds of the change in cell temperature and it attains a stable voltage value but slightly decrease in the value. Finally, for the last 0.1 seconds of the simulation time, the cell temperature decreases and reaches the value of 35°C. In this time interval, the similar pattern of decrement of oscillations reaching a stable value can be seen. The output voltage by the PV array is seen to be increased slightly as the temperature is decreased.

4.4.2.4. Output power from PV array for different cell temperature values

The Figure 4.11 presents the output power of the PV array for changing cell temperature values at constant irradiance of 800W/m^2 input to the PV array.

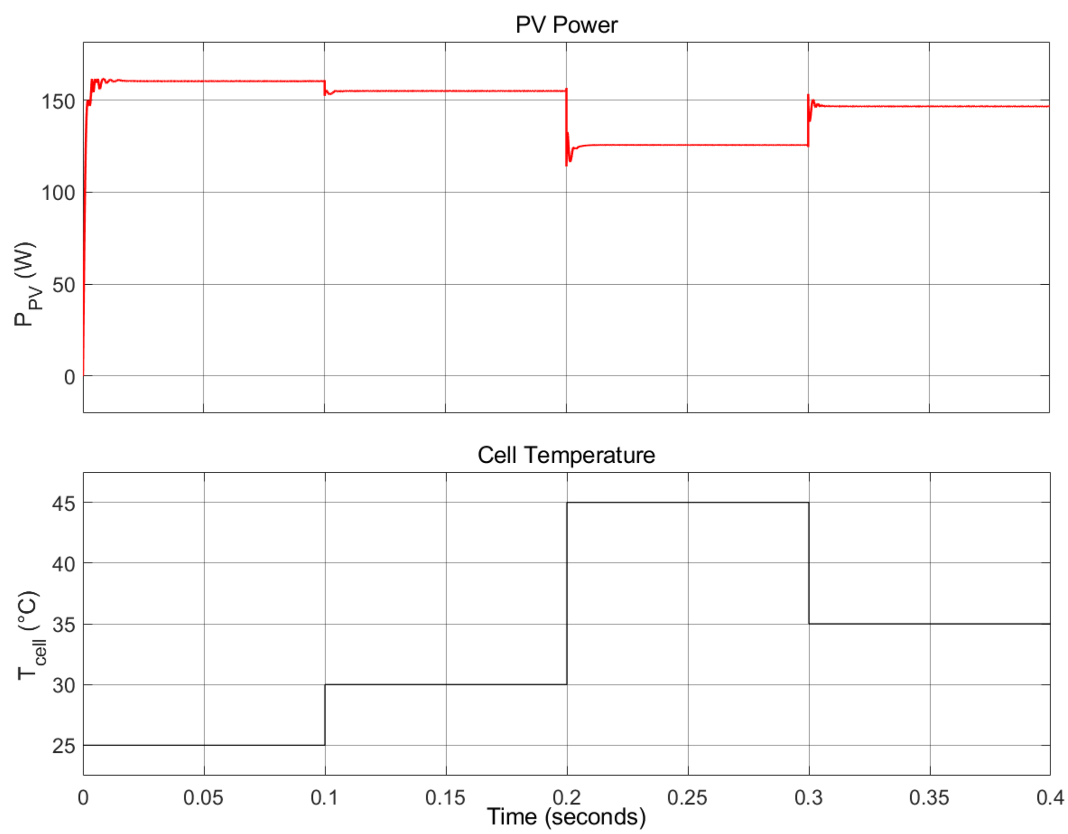

Figure 4.11: P_{pv} output with varying cell temperature using proposed hybrid MPPT algorithm

Similar to the output voltage of the PV array for changing cell temperature, the output power from the PV array reaches a stable value after sudden oscillation at the time of changing the input value, the power output from PV array also follows the same pattern but the power output from the PV array is seen decreasing for the increment in the cell temperature.

The output power from the PV array obtained in the first 0.1 seconds for constant irradiance value of 800W/m^2 with cell temperature of 25°C is seen to be oscillation at first which then decreases and reaches almost stable of 160.3W value within 0.015 seconds. When the cell temperature is increased to 30°C for the time interval between 0.1 seconds to 0.2 seconds, the output power of solar array can be seen to be decreasing and oscillating for around 0.01 seconds after which it attains almost stable value of between 154.98W. Furthermore, in the time interval of 0.2 seconds to 0.3 seconds the cell temperature is increased by 10°C and the cell temperature of 45°C is reached for which the performance of the PV array is greatly decreased as seen from the Figure 4.11. The huge oscillations at the time of cell temperature change are seen to be reduced within 0.01 seconds reaching an almost stable output power of 125.74W. And for the last 0.1 seconds, the cell temperature is decreased to 35°C where the similar pattern of decrement in the oscillation of the output power of PV array is seen attaining an almost stable value of 149.78W.

4.4.3. Results obtained using ANN based MPPT algorithm

An ANN based MPPT algorithm has also been applied for the same system for the validation purpose. The same dataset is used for training the ANN model in the MATALB which is then modeled in Simulink for simulating the PV system. The output obtained for different irradiance and cell temperature are presented in this section.

4.4.3.1. Output voltage from PV array for different irradiance values

The Figure 4.12 represents the output voltage of the PV array for different irradiance inputs using the ANN based MPPT algorithm. Similar to the simulation carried out for the PV system using P&O algorithm and the proposed hybrid MPPT method, the irradiance values are changed in every 0.1 seconds and the same irradiance values are input to the PV array for the same interval of time as in the simulation of PV system with P&O algorithm and the proposed hybrid MPPT algorithm.

In the first 0.1 seconds of the simulation time, the irradiance input is 700W/m^2 where the output voltage oscillation gradually decreases at 0.02 seconds and almost settles at around 28V which is slightly greater than the voltage obtained using the proposed hybrid MPPT method. After the first 0.1 seconds, the input irradiance is changed to 450W/m^2 where the oscillation is seen due to the change in the irradiance value. But the oscillation gradually decreases after 0.04 seconds of the change and tries to settle around 27.1V.

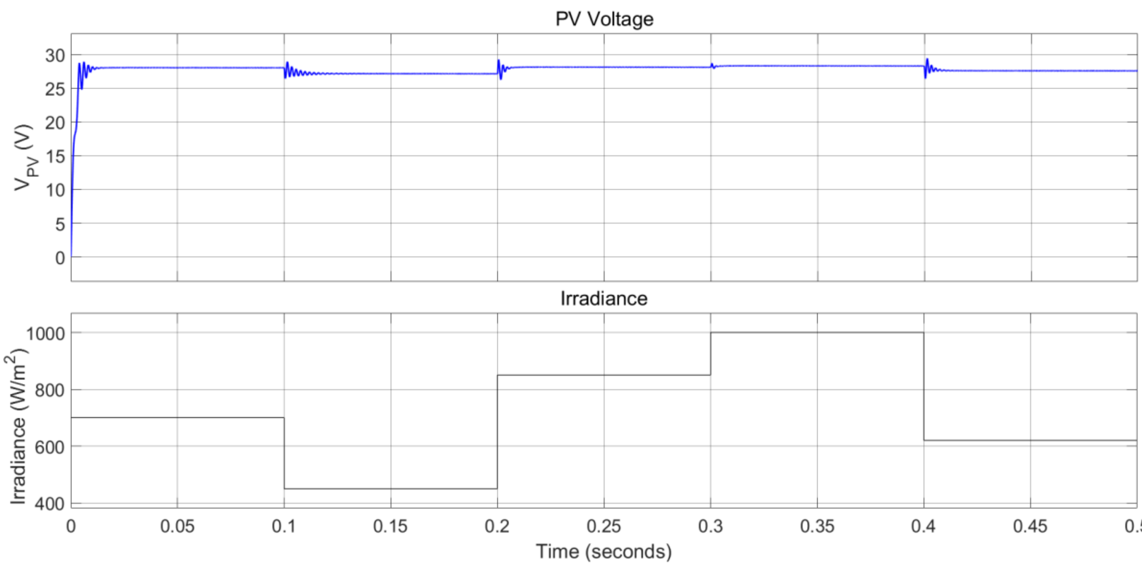

Figure 4.12: V_{pv} output with varying irradiance using ANN based MPPT algorithm

After 0.2 seconds the irradiance value changes to 850W/m^2 which results in oscillation as seen in the figure. The oscillation is settled down at time 0.21 seconds and attains a constant value of 28.1V up to time 0.3 seconds. After 0.3 seconds of the simulation time, the irradiance increases to 1000W/m^2 for which there is small oscillation present which gradually decreases and reaches a stable as shown in the Figure 4.12. The irradiance value again changes at time 0.3 seconds which creates an oscillation in the V_{pv} and it settles at 0.32 seconds at a constant output voltage of 27.6V.

When comparing the output voltage from the PV array at different irradiance level with the proposed hybrid MPPT algorithm, it can be seen that the output voltage from the PV array with proposed hybrid MPPT takes a little more time to reach the stable output voltage than the ANN based MPPT method. However, the voltage value of the proposed hybrid MPPT is closer to the V_{MPP} of the module used for the simulation.

4.4.3.2. Output power from PV array for different irradiance values

The Figure 4.13 shown below presents the output power from the PV array at different irradiance level similar to the PV system with P&O algorithm and proposed hybrid MPPT method.

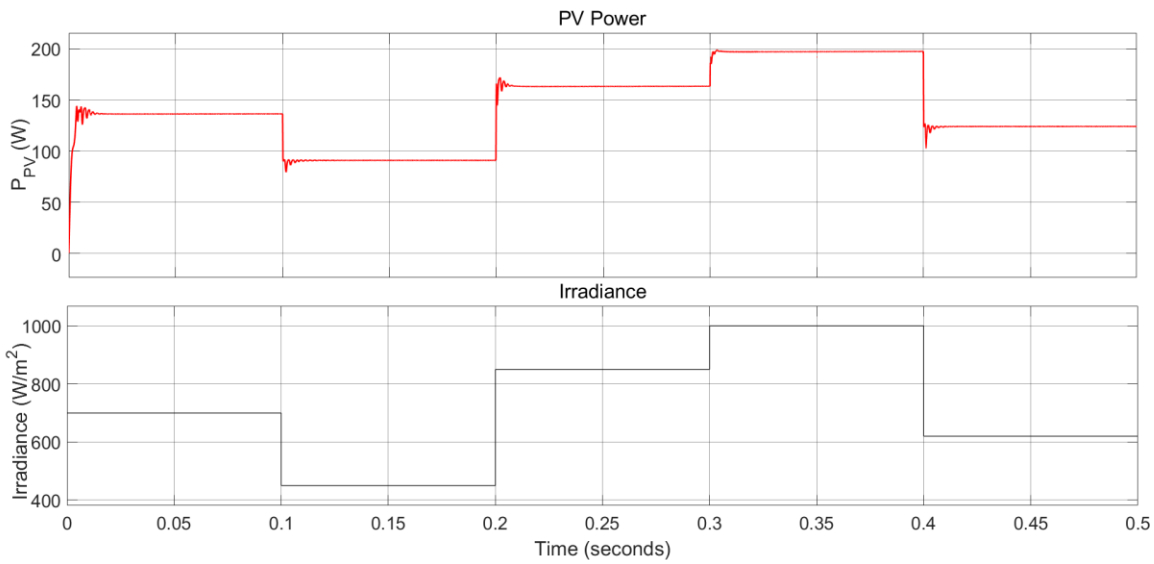

Figure 4.13: P_{pv} output with varying irradiance using ANN based MPPT algorithm

In the first 0.1 seconds of the simulation, the PV array outputs 140.1W power after some oscillations which reduces within 0.02 seconds at irradiance level of 700W/m^2. When the irradiance is changed to 450W/m^2 at 0.1 seconds, there seems to be some oscillation which then decreases attaining a constant power of 90.9W. After 0.2 seconds, the irradiance level is changed to 850W/m^2 for which the output power from the PV array after settling down the oscillation is at 167.3W. At 0.3 seconds, the irradiance reaches 1000W/m^2, and the PV array outputs power near to the rated value but shorts by a certain value because of the losses. The output power provided by the PV array during this interval is found to be 194.4W. In the final time interval of 0.1 seconds after 0.3 seconds, the power output from the PV array at irradiance level of 620W/m^2 is found to be at 124.9W after reducing the oscillations within the time of 0.015 seconds after the change in irradiance value.

Comparing the output power from the PV array with proposed hybrid MPPT algorithm, it can be seen that the oscillations at the time of change in irradiance is reduced faster by the ANN based MPPT method, however the output power provided by the PV array with proposed hybrid MPPT is more for difference irradiance values than the ANN based MPPT method.

4.4.3.3. Output voltage from PV array for different cell temperature values

Similar to the simulation of P&O algorithm and the proposed hybrid MPPT method, the ANN base MPPT method was also carried out by keeping the irradiance constant at 800W/m^2 and changing the cell temperature value at an interval of 0.1 seconds. Figure 4.14 depicts the output voltage of PV array for different values of cell temperatures.

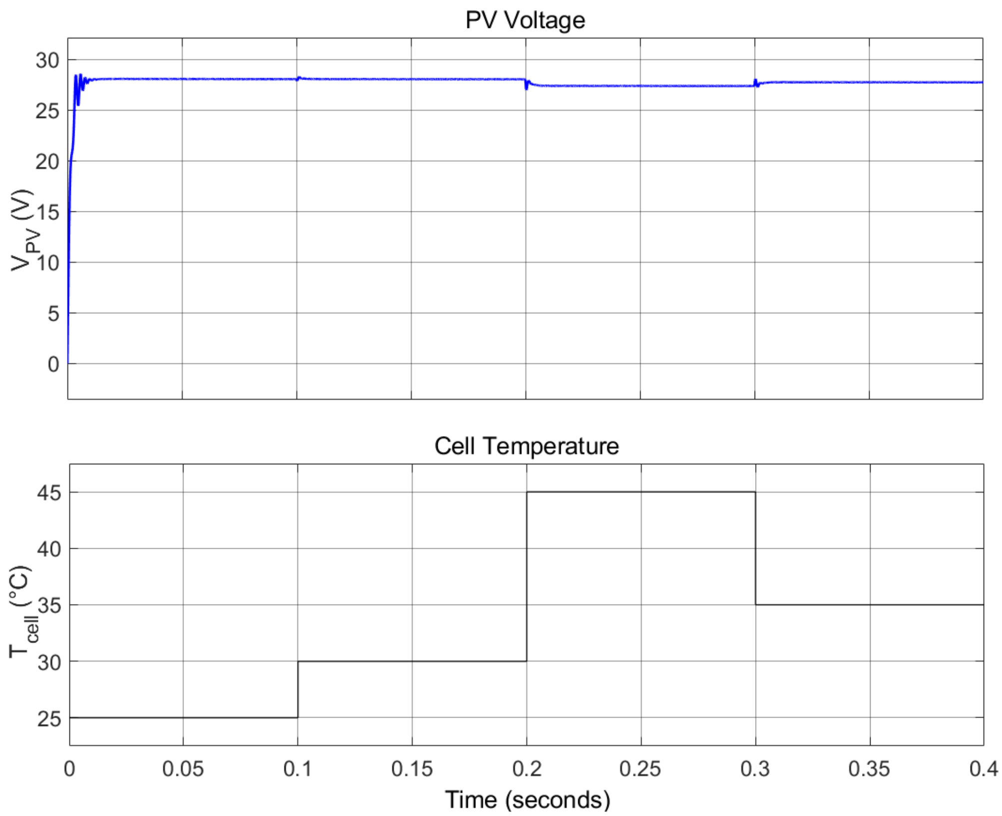

Figure 4.14: V_{pv} output with varying cell temperature using ANN based MPPT algorithm

In the first 0.1 seconds of the simulation time, the cell temperature value is kept at 25°C for which the output voltage of the PV array is seen to reduce huge oscillations within 0.015 seconds and attains stable output voltage of 28V for the rest of the time up to 0.1 seconds. For the simulation time interval between 0.1 seconds and 0.2 seconds, the cell temperature of the PV array is increased to 30°C in which a small oscillation is present at the time of the temperature change. After 0.01 seconds of the change in the cell temperature, the small oscillation is reduced gradually and the output voltage is seen to be stable throughout this time interval. For the time interval 0.2 seconds to 0.3 seconds, the cell temperature is kept at 45°C where a small oscillation is greatly reduced within 0.01 seconds of the change in cell temperature and it attains a stable voltage of 27.3V which is less than the previous voltage value as there is increase in the cell temperature. Finally, for the last 0.1 seconds of the simulation time, the cell temperature decreases and reaches the value of 35°C. In this time interval, the similar pattern of decrement of oscillations reaching a stable value of 27.7V can be seen. The output voltage by the PV array is seen to be increased slightly as the temperature is decreased in similar manner as it was in the proposed hybrid MPPT algorithm.

4.4.3.4. Output power from PV array for different cell temperature values

The Figure 4.15 presents the output power of the PV array for changing cell temperature values at constant irradiance of 800W/m^2 input to the PV array.

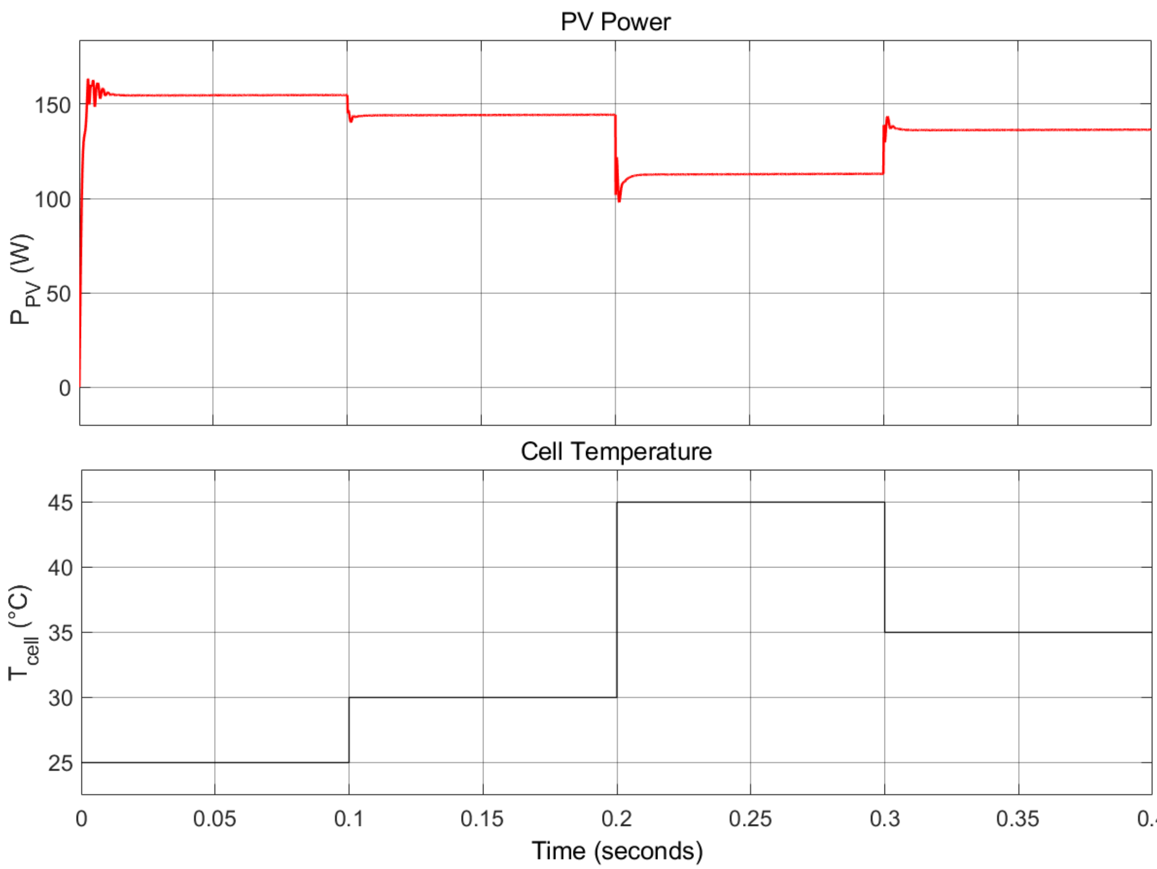

Figure 4.15: P_{pv} output with varying cell temperature using ANN based MPPT algorithm

Similar to the output voltage of the PV array for changing cell temperature, the output power from the PV array reaches a stable value after sudden oscillation at the time of changing the input value, the output power from PV array also follows the same pattern as followed by the output voltage from the PV array, but the output power from the PV array can be seen decreasing when the cell temperature is increased.

The output power from the PV array obtained in the first 0.1 seconds for constant irradiance value of 800W/m^2 with cell temperature of 25°C is seen to be oscillation at first which then decreases and reaches almost stable of 154.7W value within 0.018 seconds. When the cell temperature is increased to 30°C for the time interval between 0.1 seconds to 0.2 seconds, the output power of PV array can be seen to be decreasing and oscillating for around 0.004 seconds after which it attains almost stable value of between 145W. Furthermore, in the time interval of 0.2 seconds to 0.3 seconds the cell temperature is increased by 10°C and the cell temperature of 45°C is reached for which the performance of the PV array is greatly decreased as seen from the Figure 4.15. The huge oscillations at the time of cell temperature change are seen to be reduced within 0.008 seconds reaching an almost stable output power of 112.7W. And for the last 0.1 seconds, the cell temperature is decreased to 35°C where the similar pattern of decrement in the oscillation of the output power of PV array is seen attaining an almost stable value of 136.2W.

4.5 Comparison of P&O, proposed method and ANN based MPPT approach

Table 4.1: Comparison between different MPPT approaches

Time interval (seconds)	**Irradiance (W/m^2)**	**P_{pv} (W) (P&O MPPT)**	**P_{pv} (W) (Hybrid LSTM-P&O MPPT)**	**P_{pv} (W) (ANN based MPPT)**
0.0 – 0.1	700	Oscillates between 141.2 and 138.8	Stables around 141.5	Stables around 140.1
0.1 – 0.2	450	Oscillates between 91.4 and 88.1	Fluctuation at first but stables around 91.4	Stables around 90.9

0.2 – 0.3	850	Oscillates between 171 and 166.5	Stables around 169.8	Stables around 167.3
0.3 – 0.4	1000	Oscillates between 195.7 and 177.2	Stables around 196.2	Stables around 194.4
0.4 – 0.5	620	Oscillates between 125.8 and 124.6	Stables around 125.8	Stables around 124.9

The comparison between the P&O MPPT algorithm, proposed hybrid LSTM-P&O algorithm and ANN based MPPT approach has been shown in the table based on the output power provided from the same PV system with 200W PV array. The comparison has been carried out for the total simulation time of 0.5 seconds. The irradiance value is changed for each 0.1 seconds as discussed in the previous section. The comparison is shown in the Table 4.1.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1. Conclusion

A hybrid LSTM-P&O MPPT algorithm for a 200W PV system was successfully designed and its performance was evaluated under changing environmental conditions. Furthermore, a comparison analysis has been carried out between the proposed method with the widely used traditional method, P&O algorithm. For designing the proposed model, an LSTM model was trained in MATLAB with one year of data which was successfully trained with low RMSE of 0.0975 and a loss of 0.0048.

A 200W PV system was modeled in MATLAB/Simulink where the trained LSTM model was loaded and the simulation of the proposed model was performed. The proposed model generated expected outputs and it was found that the proposed model performed better than the traditional method, P&O. The output voltage from the PV array with P&O algorithm continued to oscillate with a significant voltage change around the V_{MPP} but in the proposed hybrid LSTM-P&O system, the oscillation due to change in the irradiance level gradually decreases with time and eventually attain almost constant value of the output voltage from the PV array. Also, the power output from the PV array with proposed hybrid MPPT is seen to be greater by some margin than the P&O algorithm.

Also, to determine the effectiveness of the proposed hybrid MPPT algorithm, artificial neural network (ANN) based MPPT method was implemented for the comparison. The ANN based MPPT model was used as a benchmark for validating the responsiveness and the accuracy of the proposed hybrid LSTM-P&O MPPT system under changing irradiance and cell temperature. From the simulation results, it is found that the proposed hybrid LSTM-P&O MPPT approach matched closely with the results from ANN based MPPT despite being slower than the ANN based MPPT but provided more output power from the PV array.

5.2. Future Recommendations

Future works for this research can be done on partial shading conditions where the power-voltage curve has multiple peaks. Future works can also be carried out for grid-tied PV system considering the grid voltage fluctuations and control of reactive power can also be carried out for the future research.

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APPENDIX A: MATLAB CODE FOR TRAINING THE LSTM MODEL

```
data = readtable('data.xlsx', 'PreserveVariableNames', true);
data.Date = datetime(data.Date, 'ConvertFrom', 'excel');
data.Date = datetime(data.Date, 'InputFormat', 'dd-mm-yyyy');
data.Time = duration(data.Time * 24, 0, 0);
data.Timestamp = data.Date + data.Time;
data.TimeNum = posixtime(data.Timestamp);
format long g

% Load and Process Data
% Extract relevant features (Irradiance, T_cell)
features = data{:, {'Irradiance', 'T_cell'}};

% Target outputs (Vpv, Ppv)
targets = data{:, {'Vpv', 'Ppv'}};

% Remove NaN values
validIdx = ~any(isnan(targets), 2);
features = features(validIdx, :);
targets = targets(validIdx, :);

% Min-Max Normalization
[features, featureMin, featureMax] = minMaxNormalize(features);
[targets, targetMin, targetMax] = minMaxNormalize(targets);
```

```
% Define Sequence Length
sequenceLength = 288;

% Initialize input (X) and output (Y) arrays
X = {};
Y = [];

% Prepare sequences for LSTM
for i = 1:height(features) - sequenceLength
    % Correct input formatting: numFeatures × sequenceLength
    X = [X; {permute(features(i:i+sequenceLength-1, :)', [1, 2])}];
    Y = [Y; targets(i+sequenceLength, :)];
end

% Ensure X and Y have the same number of sequences
assert(size(X, 1) == size(Y, 1), 'Mismatch in X and Y sequences.');

% Split Data into Training, Validation, and Test Sets
trainRatio = 0.7;
valRatio = 0.15;
testRatio = 0.15;

numTotal = size(X, 1);
```

```
numTrain = floor(numTotal * trainRatio);
numVal = floor(numTotal * valRatio);
numTest = numTotal - numTrain - numVal;

XTrain = X(1:numTrain, :);
YTrain = Y(1:numTrain, :);
XVal = X(numTrain+1:numTrain+numVal, :);
YVal = Y(numTrain+1:numTrain+numVal, :);
XTest = X(numTrain+numVal+1:end, :);
YTest = Y(numTrain+numVal+1:end, :);

% Define LSTM Model
numFeatures = size(features, 2);
numResponses = size(targets, 2);

layers = [
    sequenceInputLayer(numFeatures)
    lstmLayer(128, 'OutputMode', 'sequence')
    lstmLayer(64, 'OutputMode', 'sequence')
    lstmLayer(64, 'OutputMode', 'last')
    fullyConnectedLayer(numResponses)
    reluLayer()
    regressionLayer];
 % Training options
```

```
options = trainingOptions('adam', ...
    'MaxEpochs', 20, ...
    'MiniBatchSize', 256, ...
    'InitialLearnRate', 0.001, ...
    'GradientThreshold', 1, ...
    'ValidationData', {XVal, YVal}, ...
    'Plots', 'training-progress');

% Train the LSTM Model
net = trainNetwork(XTrain, YTrain, layers, options);

% Make Predictions
YPred = predict(net, XTest);

% Denormalize predictions
YPred = minMaxDenormalize(YPred, targetMin, targetMax);
YTest = minMaxDenormalize(YTest, targetMin, targetMax);

% Evaluate Model Performance
rmse = sqrt(mean((YPred - YTest).^2));
fprintf('Test RMSE: %.4f\n', rmse);

% Plot Predictions vs. Actual Values
figure;
```

```
plot(YTest(:,1), 'b'); hold on;
plot(YPred(:,1), 'r--');
legend('Actual Vpv', 'Predicted Vpv');
title('Vpv Prediction');

figure;
plot(YTest(:,2), 'b'); hold on;
plot(YPred(:,2), 'r--');
legend('Actual PPpv', 'Predicted Ppv');
title('Ppv Prediction');

 % Min-Max Normalization
function [normalizedData, minVal, maxVal] = minMaxNormalize(data)
   minVal = min(data, [], 'omitnan');
   maxVal = max(data, [], 'omitnan');
   normalizedData = (data - minVal) ./ (maxVal - minVal);
end

% Min-Max Denormalization
function denormalizedData = minMaxDenormalize(normalizedData, minVal, maxVal)
   denormalizedData = (normalizedData .* (maxVal - minVal)) + minVal;
end
```

APPENDIX B: PUBLICATION

[IOEGC16] Editor Decision

2025-03-28 11:41 PM

Rachhak Shahu, Yuba Raj Adhikari:

We are pleased to inform you that your manuscript titled "Hybrid MPPT for PV Converter Integrating Long Short-Term Memory (LSTM) Networks with Perturb and Observe (P&O) Technique for Real-Time Optimization" submitted to 16th IOE Graduate Conference is **Accepted** for presentation in the Conference as well as inclusion in the Peer-Reviewed Proceedings. Please note that inclusion in hard copy proceedings is contingent upon your timely response to further edits, if any, during the publication process.

With Warm Regards,
IOEGC-16 Editorial Team

Hybrid MPPT for PV Converter: Integrating Long Short-Term Memory (LSTM) Networks with Perturb and Observe (P&O) Technique for Real-Time Optimization

Rachhak Shahu [a], *Yuba Raj Adhikari* [b]

Abstract:

Solar PV generation has significant role in charging the battery, helping in grid tied application and so on. To strengthen the output power of a solar photovoltaic arrangement, it is crucial to obtain the maximum possible energy output from the photovoltaic panel. The research targets an analysis of MPPT control in PV converter systems through the combination of P&O method with LSTM networks for tracking the maximum power points. The hybrid method combines the predictive capability of LSTM networks to handle the sequential data with the simple and stable features of the P&O technique. The aim of this research is to design a hybrid LSTM-P&O MPPT algorithm evaluating its performance in changing environment conditions like fluctuating irradiance and temperature. Performance assessment of the proposed methodology includes training the LSTM model using the historical data and simulation testing of the proposed design for different irradiance conditions. It is found that the proposed hybrid LSTM-P&O MPPT algorithm is able to track the maximum power point efficiently under changing environmental conditions and also performs better than the traditional MPPT method P&O.

Keywords:

LSTM, MPPT, Hybrid MPPT, P&O, Photo Voltaic System, Artificial Intelligence (AI), Machine Learning (ML)

[a, b] *Department of Electrical Engineering, Pulchowk Campus, Institute of Engineering, Tribhuvan University, Nepal*

[a] 079mspde018.rachhak@pcampus.edu.com, [b] yr.adhikari@ioe.edu.np

APPENDIX C: PLAGIARISM REPORT

Rachhak Shahu

Hybrid MPPT for PV Converter Integrating Long Short-Term Memory (LSTM) Networks with Perturb and Obs

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