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Review Article

Deep learning based maximum power point prediction for Arduino controlled solar water pumping systems

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Abstract

Solar water pumps are bringing environmental and socio-economic benefits for remote areas where agriculture plays a vital role in the livelihoods of people. Maximum power point tracking (MPPT) solar charge controller known as smart DC-DC converter is necessary for all solar photovoltaic (PV) power system to extract maximum available power from PV module MPPT controller forces PV module to operate at voltage close to a maximum power point which improves the efficiency of the solar PV system. The prior knowledge of MPP is necessary to start any conventional MPP algorithm. As the MPPT algorithms have no prior knowledge of the MPP at the start of the perturbation, these algorithms take a long time to reach the MPP. In this work, a deep learning-based long short term memory (LSTM) network is used to provide the prior knowledge on MPP which minimizes the tracking time and maximizes the efficiency of the PV system. The cascaded buck-boost converter is utilized to minimize the input and output side ripples. The dataset needed to train the LSTM is collected from a 33 kWp PV plant installed in PSR Engineering College, India. The PV system along with an Arduino UNO based MPP controller is simulated using Proteus software. The proposed algorithm is found to be far better by its statistical analysis and also this initial value makes the MPP algorithm superior in both accuracy and response, i.e., 0.05 seconds prior. To validate the proposed algorithm hardware prototype with proportional parameters is developed.

Keywords: deep learning, LSTM network, prediction, incremental conductance MPPT, Proteus, python, Arduino UNO

1. Introduction

The increasing energy demand, the fast decline in existing sources of fossil fuels and the growing alarm regarding environmental pollution, have pushed mankind to discover new non-conventional, renewable energy resources such as solar, wind energy, and others for the production of electrical energy (Geoffrey, Dieu, Pierre, Pierre, & Aimable, 2015). A photovoltaic power generation is an effective approach for using solar energy. One of the applications of this technology is in irrigation systems for farming (Babaa *et al*., 2020). Photovoltaic pumping systems (PVPs) are easy to be installed in any place and they require less maintenance. The solar-powered irrigation system can be an appropriate alternative for farmers in the present state of the energy crisis in India and other countries. A PV converts light energy (solar irradiance) into electricity (Al-Mashakbeh, 2017). The electric power produced by a PV to run a pumping water system depends on meteorological parameters which are variable in time. The overall efficiency of the photovoltaic water pumping system was improved by better system design and load matching (Nisha & Sheela 2020; Verma, *et al*., 2021).

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Errouha, Derouich, Motahhir, & Zamzoum (2020) investigated the steady-state performance of a PV powered DC motor driving an isolated three-phase self-excited induction generator (SEIG) and found that SEIG is a perfect load match for a PV powered DC motor with the PV generator for maximum utilization of efficiency. The electrical characteristic of the panel is non-linear and has a specific point called "maximum power point" (MPP) for which the panel operates at its maximum power, this point is sensitive to the climatic conditions (solar irradiance and ambient temperature) (Alkarrami, Iqbal, Pope, & Rideout, 2020) which makes the position of the MPP variable in time and therefore difficult to locate. To extract the maximum power provided by a PV whenever temperature or irradiation variation occurs, different maximum power point tracking (MPPT) techniques, such as: Perturb and observe (P&O), incremental conductance (IC), and others, have been proposed (Khader & Daud, 2013). The MPPT algorithms are implemented through a DC-DC converter. These conventional MPPT algorithms take more time to reach the maximum power point (MPP) (Kamran *et al*., 2018; Ramli, Twaha, Ishaque & Al-Turki, 2017; Srikumar & Saibabu, 2020) as they have no prior knowledge of the MPP at the start of the perturbation. Generally, the starting value of perturbation is obtained from the linear equation which relates the physical values of PV panels such as open-circuit voltage or short circuit current or both (Ji, *et al*., 2011). This approach needs manual tuning. Also, this increases the computation burden, thus making real-time implementation more difficult. Existing literature covers comparison of classification and performance between 6 major AI-based MPPT techniques have been made which intend to provide new insights into the choice of optimal AI-based MPPT techniques (Yap, Sarimuthu, & Lim, 2020). Providing prior knowledge of MPP can make the existing MPPT algorithms to more effectively.

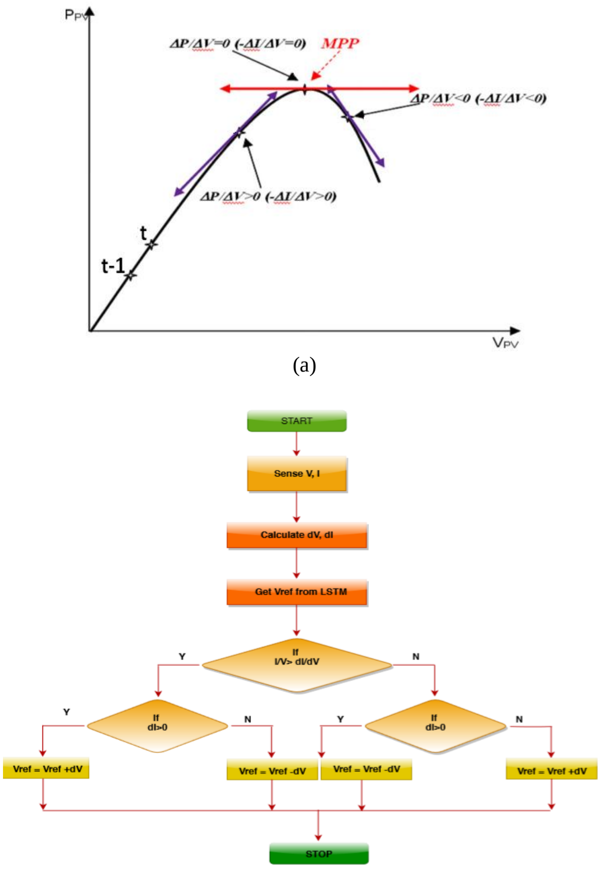
Since the solar PV system exhibits non-linear characteristics, volatility, intermittent and randomness, many researchers have proposed solar forecasting as an effective measure which is vital for mitigating related uncertainties and is helpful to the planning, management and real-time control and operation of power generation systems (Khodayar *et al*., 2020). However, accurate solar energy forecasting remains a challenging task due to the intermittent, chaotic and variable nature of solar irradiation and temperature caused by moving clouds. Various algorithms such as auto-regressive integrated moving average (ARIMA), genetic programming (GP) (Russo, Leotta, Pugliatti, & Gigliucci, 2014), artificial neural network (ANN) (Reikard, 2009), and support vector machine (SVM) (Rana, Koprinska & Agelidis, 2016) have been reported in the literature to provide accurate renewable energy predictions for the next few minutes to the next few days. Deep learning is considered to be the most promising branch of machine learning and is capable to discover most non-linear features and big-data training has been reported in the literature makes to rethink the solar forecasting based on deep learning network (Wang *et al*., 2019). Also, deep convolution neural network (Wang *et al*., 2017), deep recurrent neural network (Rahman, Srikumar, & Smith, 2018), time-series statistical (Hua, Qin, Hao & Cao, 2019) and stacked extreme learning machine (Srivastava & Lessmann, 2018) have also been frequently reported for renewable energy forecasting. In Ref. (Ahmad, Murtaza, & Sher, 2019), LSTM deep neural networks are evaluated for irradiance forecasting. Nevertheless, so far, the utilization of solar energy forecasting for providing a prior value of perturbation to MPP algorithm from the perspective of deep learning has not yet been investigated. Therefore, this paper aims to fill this gap. In this work, deep learning-based LSTM (long short term memory) network- prediction approach for MPP is proposed to provide the starting value of perturbation on-line for the IC MPPT method implemented in Arduino UNO microcontroller for solar PV based water pumping system.

The main contribution of this work is to provide the initial value of perturbation to the conventional IC MPPT algorithm using the LSTM network to increase perturbation response and tracking speed. The paper is organized as follows: Section 2 presents the concepts behind MPPT and its validation, section 3 describes the deep Learning-based LSTM network development for prediction, section 4 analyses the results and conclusions are presented in the last section.

2. Concepts Behind Solar PV MPP Algorithm

The maximum power point tracking (MPPT) method is an essential part of any PV system, because of the nonlinear characteristics of the PV array. The power at maximum power point is expressed as $P_{max}=V_{max} \times I_{max}$. The commonly used MPPT techniques like P&O, incremental conductance (IC), and others, are perturbation algorithms and are implemented through a DC-DC converter. These algorithms are initiated from some random low value of MPP or duty ratio of the DC-DC converter and progress through successive perturbations to reach MPP. By increasing the perturbation interval, the algorithm can be made faster, but it tends oscillations around MPP and the optimum point is never reached (Ishaque, & Salam, 2013; Nadeem, Sher & Murtaza, 2020). If instead the interval is made smaller, then it results in slow response and often fails to track the shift in the operating point (Connor, Martin & Atlas, 1994; Husain, Jain, Tariq, & Iqbal, 2019). In general, these perturbation MPPTs require long convergence time to reach the Maximum Power Point (MPP) (Husain, *et al*., 2019; Kamran *et al*., 2018; Ramli, *et al*., 2017; Srikumar, & Saibabu, 2018), as they have no initial knowledge of the MPP at the start of the perturbation. The effective way to utilize a conventional MPPT algorithm is to have prior knowledge of perturbation value. Compared to P&O MPPT method, IC MPPT is widely used as an MPPT method due to its simplicity, high accuracy, good efficiency, less oscillation and also adaptability in fast-changing conditions. In this method, instantaneous conductance (I_{pv}/V_{pv}) is compared with incremental conductance ($\Delta I_{pv}/\Delta V_{pv}$) by which MPP is tracked. The principle of the IC MPPT is shown in Figure 1. a. The flowchart of the IC MPPT algorithm is shown in Figure 1.b.

However, the speed and accuracy of IC MPPT highly depend on the initial value and its increment size. To overcome this issue, accurate predicted or forecasted value is utilized for initial or reference value for perturbation. This work utilizes deep learning-based LSTM network for forecasting or prediction of MPP and is further used as a starting value of perturbation in IC MPPT. The data required to generate the LSTM model are obtained from the solar PV cell under different irradiation and temperature conditions. Using this Vref value IC algorithm can find the global MPP.



(a)

(b)

Figure 1. Modified IC MPPT algorithm, with (a) principle and (b) flowchart

Because the collected real time data spanned over a full calendar year, all four seasons data were represented, as well as data that varied uniformly shaded and non-uniformly shaded data, and partially shaded information due to clouds also included.

3. Deep Learning-based LSTM network development for prediction

Deep learning is one of the promising methods in machine learning techniques due to its self-extracting relevant features from data sets and network automatic connection. Even though deep learning methods like recurrent neural networks (RNN) is proved good at data processing and excellent in time-series prediction, it has a drawback of forgetting and gradient exploding problems which lead to the large training time (Hochreiter, & Schmidhuber, 1997). To overcome this problem, long short-term memory (LSTM) is designed. LSTM is a type of recurrent neural network (RNN) capable of remembering the past information and while predicting the future values, it takes this past information into account. This is a special neuron for memorizing long-term dependencies. LSTM contains an internal state variable which is passed from one cell to the other and modified by operation gates. The structure of the LSTM network consists of an input gate, forget gate, control gate and output gate to protect and control the cell states. All LSTM networks are formed by the chain of repeating modules of the different structure as shown in Figure 2.

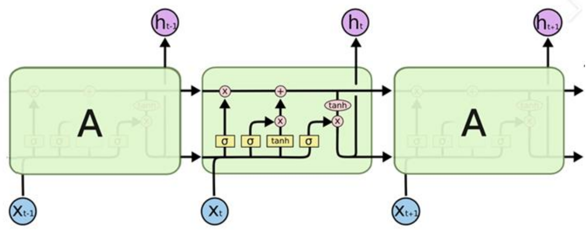


Figure 2. Four different structures in repeating modules of LSTM network

Each LSTM module in the series consists of four structure or layer. The first layer in the LSTM is to decide what information is going to forget from the previous states (h_{t-1} and X_t) which are decided by sigmoid layer or forget gate layer depends on previous output C_{t-1}. If C_{t-1} is 1, represents "completely keep" else "completely get rid of" given in equation (1).

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{1}$$

The next step is to decide what new information is going to be stored in the state. This has another two layers whose function is given by the equations (2) and (3).

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C.[h_{t-1}, x_t] + b_C) \tag{3}$$

The first layer is called a sigmoid layer or an input gate layer that decides which value will be updated. Next *tanh* layer creates a vector of new values which will be added to the state shown in equation (4).

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

The third layer consists of a combination of these two to create and update to the state. The final or fourth state is to update the old state C_{t-1}, into new states C_t. At last multiply the old state by O_t. The equation (4) is the new value decided to update each state value. Now the output will be based on cell state of a filtered version. Here is a sigmoid layer which decides parts of the state going to be output. Then, to put the state through *tanh* (to push the values to be between −1 and 1) and multiply it by the output of the sigmoid gate, so that the only output the parts decided to is given in equation (5) and (6).

$$O_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = O_t * \tanh(C_t) \tag{6}$$

In equation (6), to scale the values into range −1 to 1 *tanh* is used, σ is the sigmoid activation function and W are the weight matrices.

In this work, LSTM is proposed to predict MPP voltage for IC MPPT initial perturbation value. The network is trained using the day-wise database 365 numbers collected from real solar PV system of 33 kWp in PSR Engineering College, Sivakasi. The steps involved in time series forecasting using deep learning-based LSTM network are sequence data loading, data preprocessing, predictors and responses preparing, developing LSTM network training, testing and prediction. In data preprocessing stage, dependent variable as many days from 25th September 2018 to 25th September 2019 (365 counts) collected from the data logger. This data set is split into two; one for training and another one for testing purpose. Training is done using the first 78% of the data and testing is based on the remaining 22%. To prevent the training and testing data from diverging and fitting, standardizing the data is needed.

4. Results

4.1 Simulated system result

First, the performance of the proposed algorithm is evaluated through simulation in Proteus software. Figure 3 depicts the simulated circuit diagram. It consists of Proteus ISIS model of Cascaded (Cascaded Buck & boost) DC-DC converter with 300 Wp PV array, Arduino controller for IC MPPT, blocking diode and resistive loads. The specifications of the simulated solar PV array are given in Table 1. The simulation has been done with the resistive load of 1,000 Ω, the inductor values are chosen as 564 μH and 0.78 H, and output capacitor value is taken as 22 μF *and* 220 μF. Arduino Uno controller which implements IC MPPT gets the starting value of perturbation from the predicted value of the LSTM network. LSTM network is developed in python language.

4.1.1 Discussion of LSTM network development

In this section, time series analysis is performed using long-short term memory (LSTM) network, to predict maximum voltage (V_{max}). The data required to develop the LSTM network is collected from 33 kWp solar PV system in P S R Engineering College, Sivakasi. The actual 33 kWp solar PV system and its data logger is depicted in Figure 4. The data from 29th September 2018 to 29th September 2019 is collected to develop the network. For training, MPP data (78%) from 29th September 2018 to 29th July 2019 is used. For prediction, MPP data (22%) from 1st August 2019 to 29th September 2019 is used. The database contains ten columns: Date, time, voltage, Ampere, kWh, PF, kW, P_{max}, V_{max} and hours. The predicted value is V_{max}, therefore no need to give any importance to the rest of the items.

Table 1. PV array specification

PV parameters specification	Rating
Maximum power (P_{max})	300 W
Open circuit voltage (V_{ocn})	44.6 V
Short circuit current (I_{scn})	8.87 A
Voltage at maximum power point (V_{pm})	36.1 V
Current at maximum power point (I_{mp})	8.3 A
Arduino specifications	**Uno (Atmega328/P)**
Pin Count	28/32
Flash (Bytes)	32 K
SRAM (Bytes)	2 K
EEPROM (Bytes)	1 K
General Purpose I/O Lines	23
SPI	2
TWI (I2C)	1
USART	1
ADC 10-bit	15 KSPS
ADC Channels	8
8-bit Timer/Counters	2
16-bit Timer/Counters	1
Cascaded buck-boost converter design specification	**Theoretical values**
Input voltage $V_{in}(avg)$	9.5 V
Efficiency of the converter (η)	99%
Buck Inductor (L_1)	0.78 H
Boost_Inductor (L_2)	564 µH
Buck_Capacitor (C_1)	220 µF
Boost_Capacitor (C_2)	22 µF
Switching frequency (F_S)	25 kHz
Buck_Duty cycle ($D1$)	42.10%

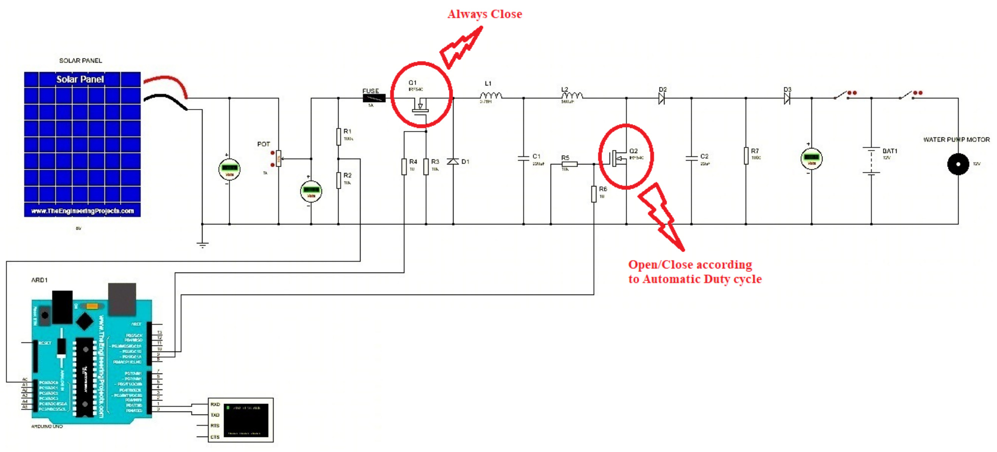


Figure 3. Overall system developed in proteus software.

Figure 4. 33 kW real solar PV system, its data logger and Recorded value of P_{max} and V_{max} for 365 days

Figure 4 also show the recorded value of P_{max} and V_{max} respectively collected from data logger of real solar 33 kWp PV system for the past one year. From the figures, it is found to be highly non-linear and it is very difficult to capture the trend using this information. Hence, LSTM is utilized in this work. The steps involved in LSTM network development in Python is the same as any other machine learning algorithm. The first step is to import the required libraries such as numpy, matplotlib, and pandas. The second step is to import dataset and normalize/scale the data between 0 and 1 using MinMaxScaler. The third step is to split the data into training and testing data. Among 364 data first 285 data (78%) is taken as training data and the remaining 80 (22%) as testing data. The fourth step is to create LSTM model by importing sequential, dense, LSTM, and dropout classes from the library. LSTM layer is added to our model using add method, additional layers, the number of time steps and dropout can be included using their corresponding parameters. To make the model robust, dense layer is added at the end of the model with many parameters to be predicted. Then compile method is used to compile the model and mean square error as loss function and Adam as optimizer in this work. Then to train the algorithm fit method is called. The next the steps involved is to import (80 data) training data, normalized it in between 0-1 and then execute and plot. In the output, the blue line represents the actual V_{max} (scaled) value for July and August 2019, while the red line represents the predicted V_{max} value. Figure 5 shows 50 days ahead of predicted or future value of P_{max} *and* V_{max}.

A comparison is made between the recorded P_{max} and V_{max} from data logger and LSTM algorithm predicted values and is tabulated in Table 2. It is also observed that the error percentage in both cases is very less with the proposed LSTM algorithm.

4.1.2 Discussion of utilization of predicted value in IC MPPT

In the IC-based method, MPP is obtained by comparing the instantaneous conductance (I/V) to the incremental conductance $\Delta I/\Delta V$. Based on that voltage reference (V_{ref}) is increased or decreased by a small value at which the PV array is forced to operate. The most appropriate way to enhance the performance of conventional IC MPPT method is to have prior knowledge of V_{ref} value, which will reduce the tracking time of the algorithm. For that, we can make use of the estimated value of V_{mpp} from LSTM network as the initial value. Figure 1.b depicts the flowchart of IC MPPT which utilizes day-wise LSTM predicted V_{mpp} as V_{ref}. Figure 6 show that the IC MPPT with LSTM predicted initial value attains its maximum voltage faster than the other one, i.e. 0.05 sec prior and also has fewer oscillations.

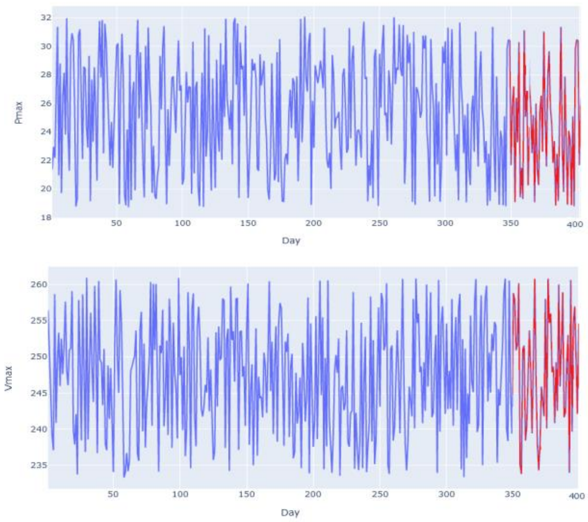


Figure 5. Predicted value of P_{max} for 50 days and V_{max} for 50 days

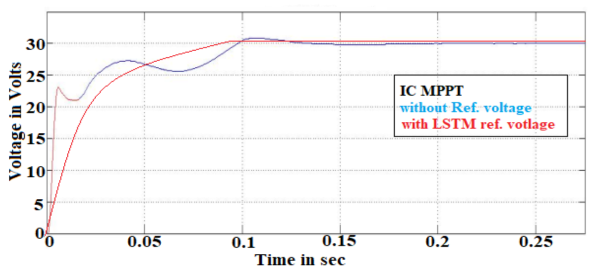


Figure 6. Converter output voltage with and without the utilization of LSTM V_{ref} value in IC MPPT

Table 2. Comparison of recorded and predicted P_{max} and predicted V_{max}

Day	Date	Recorded value		Predicted value		Error percentage (%)	
		P_{max}	V_{max}	P_{max}	V_{max}	P_{max}	V_{max}
351th	29.07.2019	30.00149	248.8033	31.7	246.03	-5.66142	1.114656
352th	30.07.2019	31.5281	246.0425	30.9	246.21	1.992191	-0.06808
353th	31.07.2019	31.32706	248.078	31.01	250.13	1.012096	-0.82716
354th	01.08.2019	27.3262	247.0213	25.03	249.53	8.402925	-1.01558
355th	02.08.2010	25.31183	242.8388	24.8	241.96	2.022098	0.361886
356th	03.08.2019	26.3232	241.2563	26.3	239.7	0.088135	0.645082
357th	04.08.2019	27.72407	258.0024	28.0	256.51	-0.99527	0.578444

4.2 Hardware realization of proposed MPPT controller

Arduino UNO ATMEGA 328P is utilized in this work to implement IC MPPT whose initial start of the reference voltage is provided by deep learning-based LSTM network predicted to result in online. Arduino is an open-source electronics platform based on easy-to-use hardware and software. All Arduino boards are completely open-source, empowering users to build them independently and eventually adapt them to their particular needs. The software, also, is open-source, and it is growing through the contributions of users worldwide. The specifications of Arduino UNO are presented in Table1. The overall hardware setup is given in Figure 7. It consists of a solar PV panel (V_{oc}=14.5 V, I_{sc}= 1.21 A, P_{mpp}= 10 W, V_{mpp}=9.5 V, and I_{mpp}=1 A), a voltage sensing circuit, Cascaded buck-boost converter, Arduino controller, battery sets and pneumatic diaphragm water pump motor R365. Solar PV panel voltage and current are given to the Arduino controller via the voltage sensing circuit. LSTM network predicted the value of the start of iteration is given to the Arduino controller in offline as a reference value. IC MPPT implemented in the Arduino controller then tracks the maximum voltage and corresponding duty cycle and thus PWM waveform is generated for DC-DC cascaded buck-boost converter. The PWM signal and converter output voltage are shown in Figure 8. The cascaded buck-boost converter design specification is tabulated in Table 1 itself.

It is also observed that the maximum voltage in the proposed method is obtained faster, and has lesser oscillations in case of both 8 V and 12 V.

5. Conclusions

This paper has presented a modified IC MPPT algorithm whose initial perturbation or reference value is provided by LSTM network to increase its tracking speed and response. Day wise maximum power and voltage of 365 days are collected from 33 kWp solar PV system to predict maximum voltage which is utilized as a reference voltage or initial perturbation value for IC MPPT controller implemented on Arduino UNO controller. Because the collected data spanned over a full calendar year, all four seasons' data were represented, as well as data that varied uniformly and non-uniformly data, and partially shaded information due to clouds. In spite of the verity of data, the proposed system delivers good results. The statistical error is calculated to evaluate the effectiveness of prediction of LSTM network. It is found that LSTM has predicted the Vmpp accurately. Also, it is inferred from the results that the proposed IC MPPT provides a good response with less tracking time (0.05 sec lesser) and fewer oscillations around the MPP value.

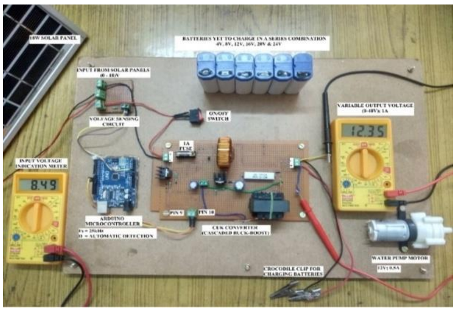
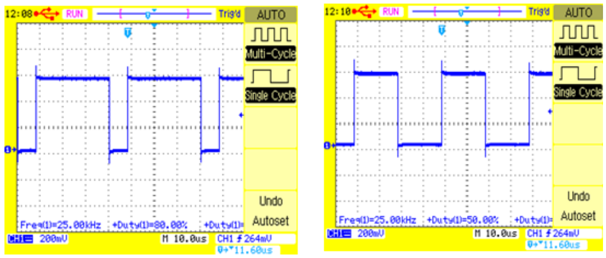
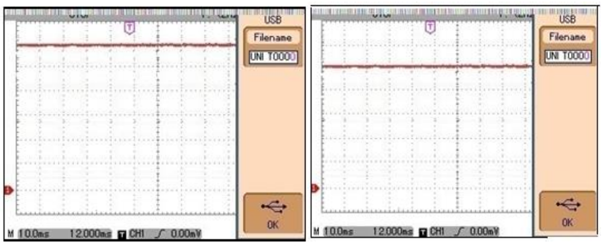


Figure 7. Overall hardware setup



(a)



(b)

Figure 8. Cascaded buck-boost converter with (a) duty cycle (80%) and duty cycle (50%), and (b) maximum output voltage (8 V and 12V)

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