

Article

Improved Maximum Power Control of Photovoltaic Systems Using Quadratic Boost Converter Based on Deep Recurrent Neural Network

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Abstract

Both temperature and solar radiation cause variations in photovoltaic output power. Nevertheless, each variation has a maximum power point, which represents the photovoltaic output's maximum efficiency. Photovoltaic power must be managed at the highest point in order to achieve optimal efficiency. This can be accomplished by employing a converter to regulate the photovoltaic output voltage at the maximum power. This study proposes a quadratic boost converter (QBC) to control photovoltaic output power by using the Deep Recurrent Neural Network (DRNN) algorithm. The goal of the DRNN is to decrease ripple at the maximum point and speed up the time to reach the maximum power point. The QBC is designed to obtain a higher DC output voltage than a regular boost converter, so it can eliminate the use of a step-up transformer if the photovoltaic is connected to an inverter. The proposed method is applied to a 50 Wp solar panel with an Arduino microcontroller as the controller device. The experimental results demonstrate that the DRNN algorithm-based QBC effectively controls the solar panel output power at the maximum point with a smoother ripple and a faster response. The QBC is also able to produce higher-voltage output according to its characteristics.

Keywords: photovoltaic; maximum power; deep recurrent neural network; quadratic boost converter; Arduino

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1. Introduction

Every country is increasingly promoting renewable energy because fossil fuel supplies are running low. Renewable energy has the potential to eventually replace fossil fuels because it is not only abundant but also environmentally beneficial [1]. As a tropical country, Indonesia has abundant renewable energy sources to utilize. One of them is sunlight, which is available all the time. Solar power plants using photovoltaic modules are starting to develop in Indonesia. The efficiency of the solar module is a priority in order to ensure economical operation of the power plant [2]. The photovoltaic efficiency is determined by the output power, which is influenced by sunlight irradiation and temperature, which always change according to the position of the sun. At each temperature and

irradiation value, there is a maximum power point, which has a different photovoltaic output voltage.

To achieve high efficiency, the photovoltaic output power needs to be controlled at the maximum point, which is also called Maximum Power Point Tracking (MPPT) [3]. To obtain maximum power at all times, the photovoltaic voltage needs to be controlled to remain at the maximum point by using a DC–DC converter. Several types of DC–DC converters that have been used include buck converters [4,5], boost converters [6], switched-capacitor boost converters [7], Sepic converters [8], Cuk converters [9] and Quadratic Boost Converters (QBCs) [10]. The type of converter is determined by the purpose of the solar panel. Home-scale solar panels generally have a low output voltage of around 20–36 Volts, while consumers require a load voltage of 220 Volts. This is generally overcome by using an inverter equipped with a step-up transformer. In this paper, a QBC is proposed for the MPPT system with the aim of obtaining a higher output voltage, so that the step-up transformer in the inverter can be eliminated. This can be obtained because the QBC has a quadratic output voltage ratio from its input [11].

Photovoltaic voltage control through the converter can be done by adjusting the switch converter modulation pulse through PWM duty cycle control. Conventional PWM will reduce efficiency, while the pulse density (PDM) in PWM causes quite large current and voltage ripples [12]. In the MPPT system, this duty cycle setting is done using the MPPT algorithm. Several MPPT algorithms have been applied to solar panels, ranging from conventional algorithms to artificial intelligence (AI)-based algorithms. Several conventional algorithms that have been developed include the Incremental Conductance (IC) algorithm [13], the Perturbation and Observation (PO) algorithm [14–17], the sliding mode algorithm [18], and the Fractional Open Circuit algorithm [19–21]. Each MPPT algorithm has its advantages and disadvantages. The PO algorithm has the advantage of being easy to implement, but its performance is determined by the step value in finding the maximum power point. A good MPPT algorithm is an algorithm that can provide a fast response to reach the maximum point, so that it is robust to changes in irradiation and temperature. Fast response to reach the maximum power point in the P&O algorithm can be obtained by increasing the step value, but it has a negative effect on the power ripple at the maximum point. The power ripple will be low if the step value is small, but this will slow down the response to reach the maximum point. Therefore, choosing a suitable step value is a disadvantage of the P&O algorithm. To overcome this, an algorithm has been developed with a varying step value [15,22], so that it can accelerate the response to reach the maximum power point while reducing the power ripple at the maximum point.

To improve the performance of the MPPT algorithm, AI-based MPPT algorithms have also been developed, including an Artificial Neural Network (ANN) [23], a Fuzzy Logic Controller [24,25] and an Adaptive Neuro Fuzzy Inference System (ANFIS) [26,27]. Rapid technological developments have also helped these AI algorithms develop rapidly. One of the AI algorithms that is widely used today is deep learning, which involves the development of an ANN with more hidden layers, making it more accurate than an ordinary ANN [28]. Several deep learning methods have been applied to MPPT algorithms, such as deep reinforcement learning [29] and deep Q networks [30]. This paper proposes another deep learning method, namely the Deep Recurrent Neural Network (DRNN), that developed from the Recurrent Neural Network (RNN) with more hidden layers, so it is expected to be more accurate than the conventional RNN [31]. There are several DRNN models that have been developed, such as Gated Recurrent Unit (GRU), vanilla RNN and Long Short-Term Memory (LSTM) [32]. This paper proposes an LSTM model for the MPPT algorithm that was developed from the PO algorithm. The constant step in the PO is developed into a varying step using LSTM. The LSTM model is created using the Matlab deep learning toolbox implemented with an Arduino microcontroller. The proposed

method is implemented on a 50 WP photovoltaic module. To validate the proposed method, the results will be compared with the conventional PO algorithm.

2. Materials and Methods

The proposed maximum power control improvement of the photovoltaic system uses the DRNN algorithm with a QBC as a power converter to obtain an output voltage level that matches the consumer's voltage value. The design is implemented on a 50 WP solar panel with an Arduino Mega 2560 microcontroller (Arduino S.r.l., Ivrea, Italy) as the central controller. Figure 1 shows a schematic of the proposed system, which consists of a photovoltaic module, a QBC, and a DRNN-based MPPT algorithm processed in Arduino.

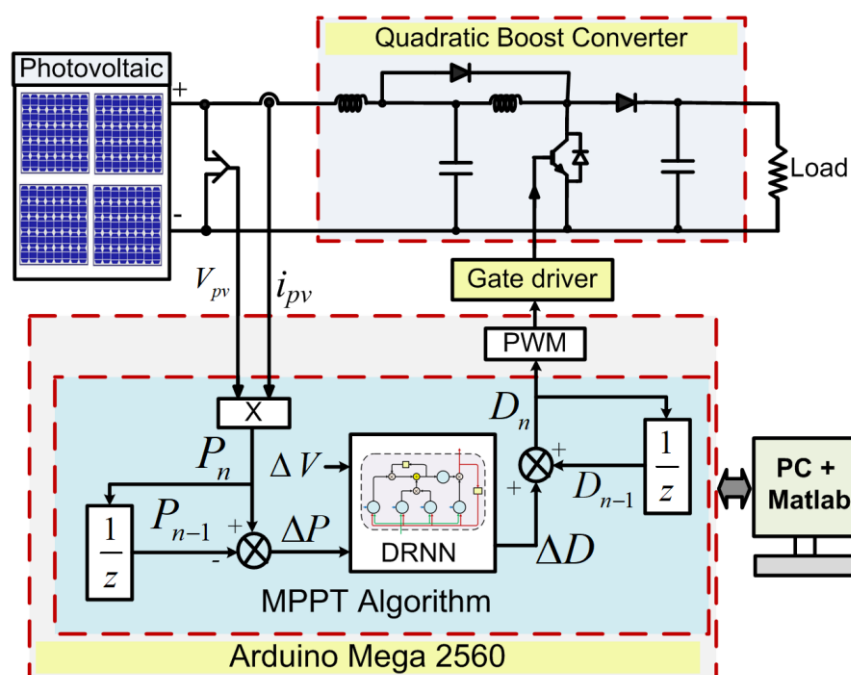


Figure 1. Proposed MPPT scheme of photovoltaic system using a QBC.

2.1. Photovoltaic System

Solar panels are made up of many solar cells that use the photovoltaic effect to transform solar energy into electrical power. Solar cells consist of PN junction semiconductor material that will produce electron movement when the solar cell receives energy from photons when the surface of the solar cell is exposed to sunlight. The movement of electrons will produce an electric current if the solar cell module is connected in a closed circuit with a load. The solar cell model is illustrated with an equivalent circuit in Figure 2.

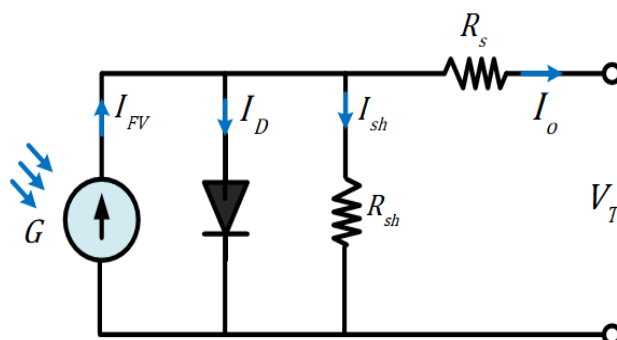


Figure 2. Equivalent circuit of solar cell.

The current produced by a solar cell is determined by the irradiation G and temperature T that affect it and the load resistance R_s , which is formulated as:

$$I_o = \left[I_{pv} + K_c (T_e - T) \frac{G_e}{G} \right] - I_k \left(\frac{T}{T_e} \right)^3 \exp \left[\frac{Qe_g}{\alpha K_b} \left(\frac{1}{T} - \frac{1}{T_e} \right) \right] \left[\exp \left(\frac{V_T R_s I_o Q}{n_i K_b T_e \alpha} \right) - 1 \right] - \frac{R_s I_o V_T}{R_{sh}} \quad (1)$$

where Q is electric charge value of the photovoltaics, K_b is the Boltzmann constant, I_k is the inverse saturation current at a normal condition, e_g is the gap energy of the semiconductor, α is the ideal coefficient of the solar cell, T_e and G_e are the ambient temperature and the ambient nominal irradiation intensity, and n_i , K_c , and I_{pv} are the cell numbers in series, the current coefficient, and the nominal current generated by the cell, respectively. V_T is the photovoltaic voltage at the output terminal, which is formulated as:

$$V_T = V_o - R_s I_o \quad \text{with} \quad V_o = \frac{z T_e K_b}{Q} \ln \left(1 + \frac{I_{pv}}{I_D} \right) \quad (2)$$

where V_o is the photovoltaic voltage at the open circuit. I_{pv} is the photocurrent produced when a solar cell receives energy from photons in the presence of sunshine. I_D is the saturation current of the diode and z is the diode ideality factor value. The power produced by photovoltaics can be written as follows:

$$P_o = I_o V_T \quad (3)$$

The photovoltaic voltage and current vary according to changes in sunlight irradiation, as illustrated by Figure 3a. If the irradiation increases, the voltage and current also increase, so the output power of the solar panel also increases. This makes the photovoltaic power always change according to changes in irradiation. At each irradiation value, there is a maximum power point P_{max} . This maximum power point is at a different voltage value. The voltage value at the maximum power point is also called V_{mpp} . Therefore, to obtain maximum photovoltaic power at each change in irradiation, the photovoltaic voltage must be controlled at the maximum power point. Photovoltaic performance is also impacted by temperature variations. Photovoltaic voltage fluctuates according to temperature variation, as shown in Figure 3b. The temperature value and the voltage value have an inverse relationship. The voltage will decrease as the temperature rises. This will also reduce the power produced by the photovoltaic. Thus, maintaining high photovoltaic efficiency also involves keeping the photovoltaic temperature low.

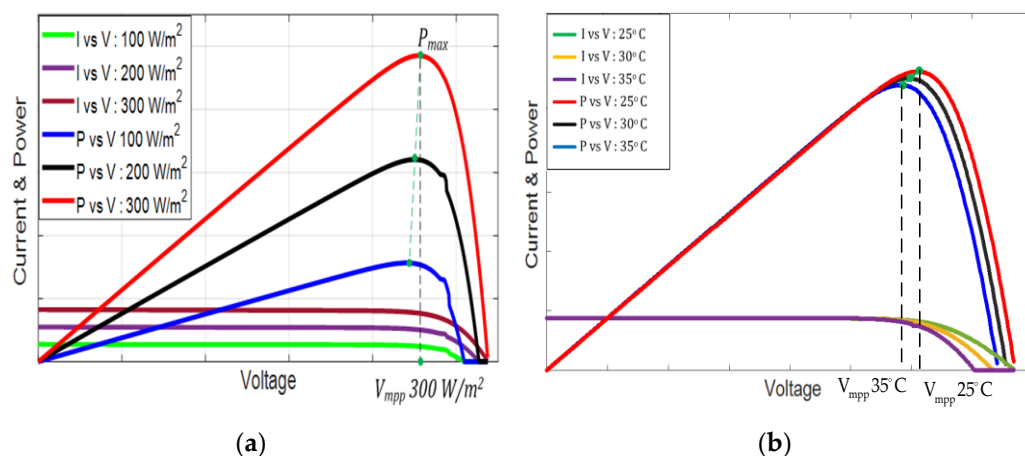


Figure 3. Photovoltaic characteristic curve: (a) I vs. V and P vs. V curves when irradiance varies and temperature is constant; (b) I vs. V and P vs. V curves when irradiance is constant and temperature varies.

2.2. Quadratic Boost Converter (QBC)

A QBC is a variant of a DC–DC converter whose output voltage is higher than the input voltage. Unlike conventional boost converters, a QBC can produce a quadratic output voltage from the input voltage. The increase in the output voltage ratio is obtained by adding storage capacitor and inductor components. A conventional boost converter has the components of a diode, a capacitor, an inductor and one semiconductor switch. Several QBC structures have been discussed to increase the output voltage level by combining the number of diodes, inductors and semiconductor switches [33,34]. In this paper, the QBC structure used for the solar panel MPPT control system consists of two inductors, two capacitors, three diodes and one semiconductor switch, as illustrated in Figure 4.

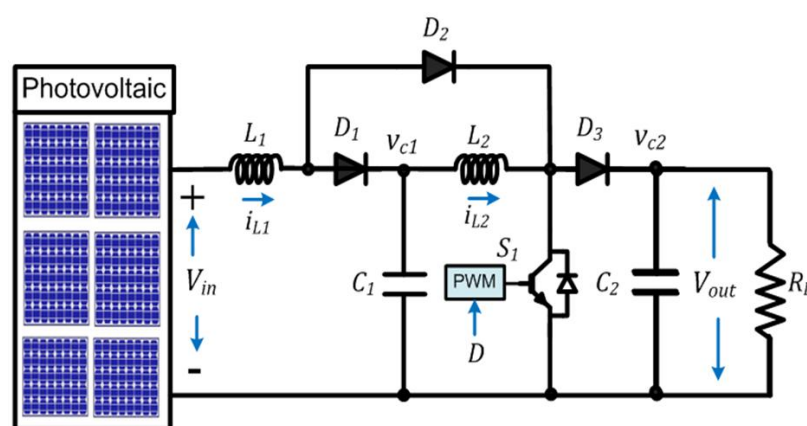


Figure 4. Proposed QBC.

The parameters of the QBC illustrated in Figure 4 can be written as follows:

$$\frac{di_{L1}}{dt} = -\frac{1}{L_1}(1-D)v_{C1} + \frac{1}{L_1}V_{in} \quad (4)$$

$$\frac{di_{L2}}{dt} = -\frac{1}{L_2}(1-D)v_{C2} + \frac{1}{L_2}V_{C1} \quad (5)$$

$$\frac{dv_{C1}}{dt} = -\frac{1}{C_1}(1-D)i_{L1} - \frac{1}{C_1}i_{L2} \quad (6)$$

$$\frac{dv_{C2}}{dt} = -\frac{1}{C_2}(1-D)i_{L2} - \frac{1}{C_2R_L}v_{C2} \quad (7)$$

where v_{C1} and v_{C2} are voltage of capacitors C_1 and C_2 , respectively. i_{L1} and i_{L2} are the currents of inductors L_1 and L_2 , respectively. D is the duty cycle of the modulation pulse for switch S_1 . Based on the duty cycle value, the output voltage can be written as:

$$V_{out} = \frac{V_{in}}{(1-D)^2} \quad (8)$$

where V_{in} is the input voltage of the QBC. To obtain the appropriate output voltage ratio, the capacitor and inductor values must be determined using the following equations:

$$L_1 = D \frac{V_{in_min}}{2 f_{sw} \Delta i_{L1}} \quad \text{and} \quad L_2 = D \frac{V_{in_min}}{2 f_{sw} \Delta i_{L2}} \quad (9)$$

$$C_1 = D \frac{I_{out}}{f_{sw} \Delta v_{C1} (1-D)} \quad \text{and} \quad C_2 = D \frac{I_{out}}{f_{sw} \Delta v_{C2}} \quad (10)$$

$$\Delta i_{L1} = \frac{I_{out}}{(1-D)^2} \quad \text{and} \quad \Delta i_{L2} = \frac{I_{out}}{1-D} \quad (11)$$

$$v_{C1} = \frac{V_{in}}{1-D} \quad \text{and} \quad v_{C2} = \frac{V_{C1}}{1-D} \quad (12)$$

where f_{sw} is the switching frequency of the QBC switch. The QBC is used to control the photovoltaic output voltage at the maximum power point. This is carried out by adjusting the duty cycle value D of the QBC switch. The setting of the duty cycle value D is done using the DRNN algorithm.

2.3. MPPT Algorithm

The maximum power of a photovoltaic system can be achieved by regulating its voltage at the maximum power point. Because photovoltaics produce direct voltage, voltage regulation can be done using a DC–DC converter. In this study, a QBC was chosen to regulate the photovoltaic voltage at the maximum power point. Photovoltaic voltage regulation with a QBC can be done by adjusting the duty cycle value, which will regulate the width of the switch converter modulation pulse. In the MPPT system, the duty cycle value for maximum power is sought using the MPPT algorithm, as illustrated by Figure 5.

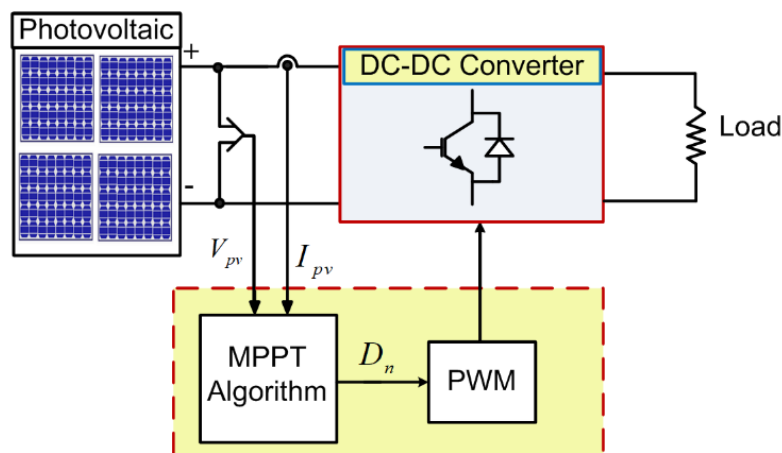


Figure 5. MPPT of a photovoltaic system.

2.3.1. Perturbation and Observation (PO) Algorithm

Among the traditional MPPT methods, the Perturbation and Observation (PO) algorithm has been used extensively. This algorithm uses voltage and photovoltaic power variations to obtain the duty cycle D_n value. Figure 6 shows the working principle of the PO algorithm. In line with the QBC output voltage's properties, which dictate that it is directly proportional to D_n , the solar panel's output power is regulated at its maximum point by varying the D_n value through an algorithm step that alters the duty cycle (ΔD) according to the power and voltage changes. The value of D_n in the PO algorithm is:

$$D_n = \begin{cases} D_{n-1} + \Delta D & \text{if } \Delta P / \Delta V > 0 \\ D_{n-1} & \text{if } \Delta P / \Delta V = 0 \\ D_{n-1} - \Delta D & \text{if } \Delta P / \Delta V < 0 \end{cases} \quad (13)$$

$$\Delta P = (I_{pv(n)} V_{pv(n)}) - (I_{pv(n-1)} V_{pv(n-1)}) \quad (14)$$

$$\Delta V = V_{pv(n)} - V_{pv(n-1)} \quad (15)$$

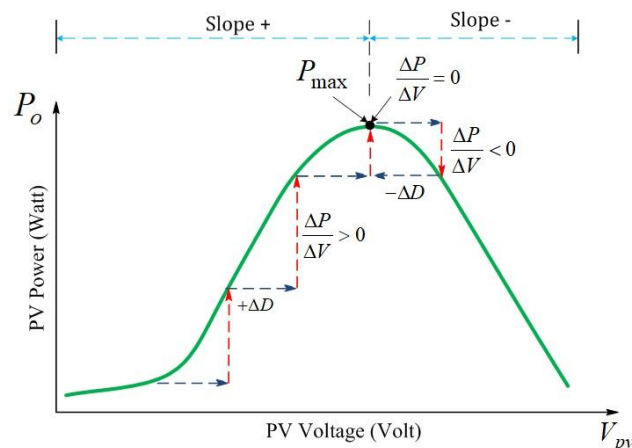


Figure 6. The working principle of the PO algorithm.

The value of the duty cycle change ΔD determines the PO algorithm's performance. In addition to minimizing power ripple at the maximum power point, an effective MPPT algorithm must be able to respond quickly to reach the maximum power point. Using traditional PO algorithms to accomplish this is challenging. A high ΔD value is necessary to rapidly reach the maximum power point, although doing so will result in significant power ripples at that point. A small ΔD is needed to limit the power ripple at the maximum point. Consequently, the MPPT algorithm needs a variable ΔD value in order to accomplish both objectives. This cannot be obtained in the conventional PO algorithm, because it has a constant ΔD value. Therefore, it is proposed to develop the PO algorithm to obtain varying ΔD values using the Deep Recurrent Neural Network (DRNN).

2.3.2. Deep Recurrent Neural Network (DRNN)

The Deep Recurrent Neural Network (DRNN) is a development of the Conventional Recurrent Neural Network (RNN) that has an internal memory feature. This allows information from the previous step to be carried over to the next step, making it suitable for sequential data training and so on. The DRNN has more hidden layers than the conventional RNN, so it can provide more valid results. The internal memory of the RNN allows each RNN neuron to receive input data from the previous layer and also receive data from the previous step through the hidden state. This allows the RNN to have a short-term memory of what has been processed. The RNN structure consists of an input layer X , a hidden layer h and an output layer y , as shown in Figure 7.

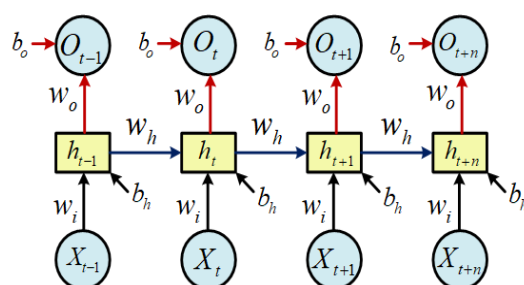


Figure 7. RNN Structure.

The current RNN output O_t is calculated based on the current hidden layer value h_t , weighting between the hidden layer and the output layer w_o and the bias value on the output layer b_o , while the current hidden layer output value h_t is determined by the previous hidden layer value stored in memory h_{t-1} , the current input value X_t , the weights connecting the input layer to the hidden layer w_i , the weights of the hidden layer w_h and the bias b_h . The output O_t and hidden layer h_t are calculated by:

$$O_t = \sigma(w_o h_t + b_o) \quad \text{with} \quad h_t = \sigma(w_i X_t + w_h h_{t-1} + b_h) \quad (16)$$

where σ is an activation function which can be a tanh or sigmoid function. Equation (16) shows that the output value of the RNN is determined by the input value and the hidden layer value of the previous step stored in memory. This gives the RNN short-term memory in the data training process, thus providing more valid results. Figure 7 shows that the RNN data training process is carried out sequentially. This makes the training time longer than the feedforward neural network. In addition, the internal memory in the RNN structure can cause gradient shrinkage or explosion in long data sequences. To overcome this, two types of DRNN have been developed, namely Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), which can have more hidden layers, so they can provide more valid results than a conventional RNN [35]. To obtain variable ΔD in the MPPT algorithm, the LSTM is proposed. The LSTM structure can be seen in Figure 8.

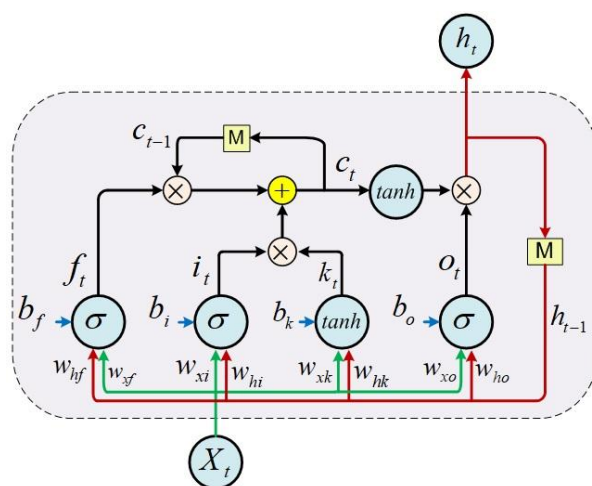


Figure 8. LSTM structure.

The LSTM structure illustrated in Figure 8 consists of output gate o_t , cell state c_t , forget gate f_t , cell input layer k_t and input gate i_t . Each part is represented by the following equations:

$$o_t = \sigma(w_{xo} X_t + w_{ho} h_{t-1} + b_o) \quad (17)$$

$$c_t = f_t c_{t-1} + i_t k_t \quad (18)$$

$$f_t = \sigma(w_{xf} X_t + w_{hf} h_{t-1} + b_f) \quad (19)$$

$$k_t = \tanh(w_{xk} X_t + w_{hk} h_{t-1} + b_k) \quad (20)$$

$$i_t = \sigma(w_{xi} X_t + w_{hi} h_{t-1} + b_i) \quad (21)$$

$$h_t = o_t \tanh(c_t) \quad (22)$$

Based on Equations (17)–(22), the hidden layer output h_t is determined by the cell state c_t , which stores the memory of the cell. The c_t value is updated by the forget gate f_t , input gate i_t and cell input layer k_t . A forget gate f_t uses a sigmoidal function to decide which data from earlier cell stages should be retained or forgotten. The cell input layer k_t has the same flow as the gate input with a tanh activation function. The output k_t is determined by the weighting values w_{xk} and w_{hk} , as well as the bias b_k . At the input gate i_t , data is selected to enter the cell using the sigmoid function. The output i_t will be one if information is allowed to pass into the cell or zero if data is blocked from entering the cell.

LSTM is used as an MPPT algorithm to determine the ΔD based on the value of ΔP and ΔV . The ΔD value of the LSTM output will determine the current duty cycle value D_n , which will control the photovoltaic voltage through the QBC switch at the maximum power point. LSTM is used to obtain varying ΔD , so it can overcome the shortcomings of constant steps in conventional PO algorithms. The proposed photovoltaic MPPT system based on the DRNN algorithm using BQC is illustrated in Figure 1. The proposed MPPT system based on DRNN is implemented with the Arduino Mega 2560 microcontroller.

3. Results

The proposed DRNN-based photovoltaic MPPT system was tested and verified through laboratory experiments. The proposed MPPT system was implemented on a 50 WP solar panel with an Arduino Mega 2560 microcontroller. The solar panel has an open-circuit voltage rating of 22.5 Volts and a maximum power rating of 17.6 Volts. In the test, the solar panel was illuminated with a spotlight whose radiation can be adjusted by adjusting the spotlight voltage using an autotransformer. The solar panel was equipped with radiation sensor PYR20, K-type thermocouple temperature sensors, current sensor ACS712 and a voltage sensor using a voltage divider. The QBC was modulated with a 31 KHz switching frequency and a sample time of 0.05 s. The MPPT algorithm was designed using MATLAB/Simulink R2022b (The MathWorks, Inc., Natick, MA, USA). Figure 9 shows the hardware setup for the experiment.

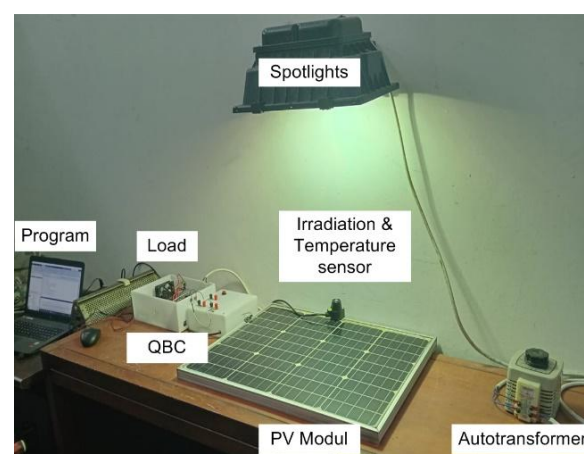


Figure 9. Hardware setup for experiment.

The first step in the experiment was to create a DRNN model for the MPPT algorithm using the deep learning toolbox in Matlab. The DRNN model was trained in the form of an LSTM with a two-input and one-output system with 100 hidden layers. The LSTM model was trained using 50 data samples and 500 epochs. Figure 10 shows the results of LSTM training. The ΔD value as the LSTM output is made to vary from -0.35 to 0.35 . LSTM performance is evaluated based on overfitting analysis. Figure 10a shows that the training error reached 0.005 at epoch 100. This result has provided a model that can produce output values according to the target, as shown in Figure 10b.

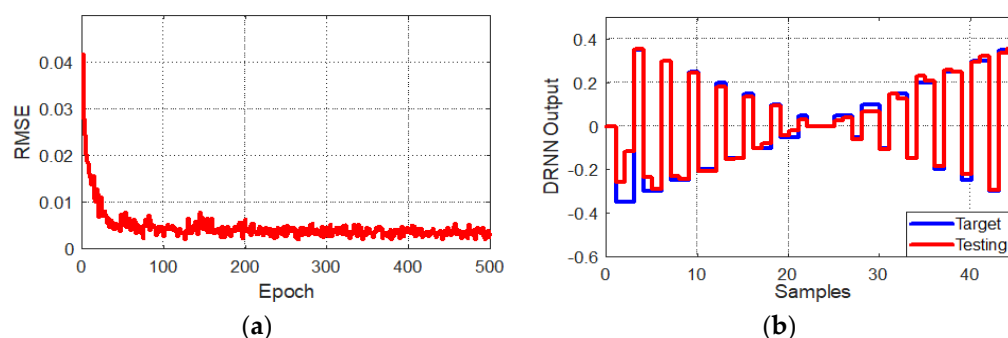


Figure 10. Result of LSTM training. (a) Training error; (b) DRNN output.

Based on the results of the DRNN model using the training data shown in Figure 10b, it can be concluded that the DRNN model is valid for use as an MPPT algorithm. Next, the DRNN model is implemented in the MPPT system created in Matlab Simulink. After the MPPT system program was declared valid, several experiments were conducted to test the proposed MPPT system.

The first experiment was conducted with constant irradiance at the maximum radiation produced by the spotlight. Figure 11 shows the irradiance and temperature values from the sensor in the first experiment. Figure 11a shows that the light irradiation from the spotlight hitting the surface of the solar panel is around 630 Wb/m^2 , while the temperature of the solar panel at that time is 31° Celsius , as illustrated in Figure 11b.

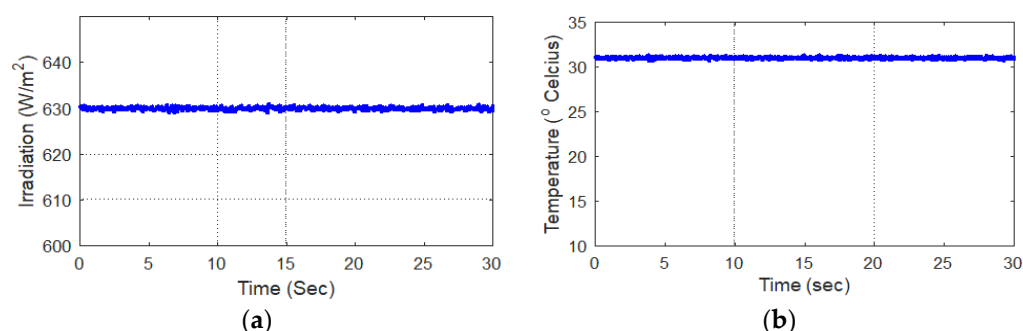


Figure 11. Treatment in the first experiment. (a) Irradiation; (b) temperature.

The first experiment was conducted with three MPPT methods, namely the high-step PO with a step of 0.1, the low-step PO with a step of 0.001 and the DRNN method with varying steps. The output power of the photovoltaic system from the three MPPT techniques is displayed in Figure 12a, while the zoomed power spectra in transient condition are displayed in Figure 12b. The high-step PO-based MPPT method provides a fast response, reaching the maximum power point within 0.6 s, but produces large power ripples at steady state. Low power ripples can be obtained with the low-step PO method, but it is too slow to reach the maximum power point, namely 15 s. This shows the weakness of the PO method, namely that it is difficult to determine the appropriate step size to achieve a fast response to reach the maximum point and it also has low power ripple.

The proposed DRNN-based MPPT technique provides a good response. The varying step size generated by DRNN successfully accelerated the power response to reach the maximum point within 0.7 s and also successfully minimized the power ripple at a steady state. Additionally, Figure 12a demonstrates that the solar panel's maximum output power was effectively managed by all three MPPT techniques. The maximum solar panel power generated by all three MPPT techniques was 19.5 watts. Table 1 presents a performance comparison of the three MPPT techniques.

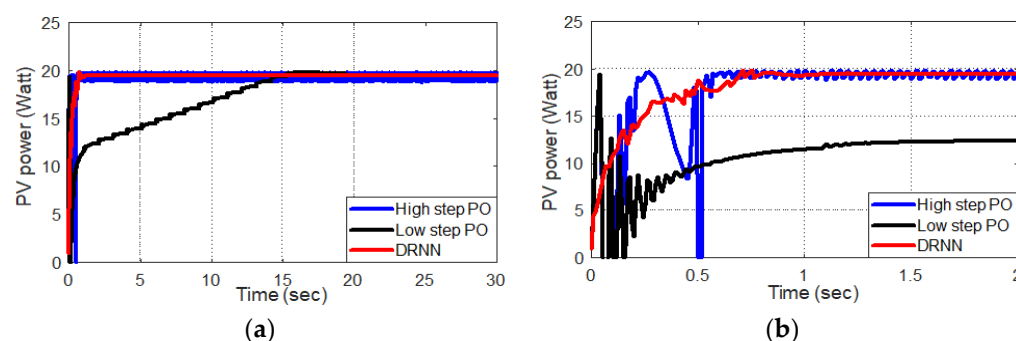


Figure 12. PV power in the first experiment. (a) Power; (b) zoomed power.

Table 1. The first experimental results.

MPPT Method	Max Power (Watt)	Power Ripple (Watt)	Settling Time (s)
High-step PO	19.5	± 0.5	0.6
Low-step PO	19.5	± 0.1	15
DRNN	19.5	± 0.1	0.7

Figure 13a shows the power graph of the QBC output with a value of 15 Watts at a steady state. These results indicate that the QBC output power is lower than the photovoltaic output power. This is due to power losses in the converter. These results indicate that the QBC's efficiency is approximately 76%. This value can be considered good for QBC performance. The QBC is designed to achieve a higher output voltage than conventional boost converters. The QBC developed in this study was able to produce an output voltage of 180 Volts, as illustrated in Figure 13b, with an input voltage from the solar panel of 17.5 Volts, as illustrated in Figure 13c. These results indicate that the proposed QBC has worked according to its characteristics. Figure 13c shows that the solar panel output voltage decreases from an open-circuit voltage (V_o) of 19.7 Volts to a maximum power point (V_{mpp}) voltage of 17.5 Volts. This data indicates that the MPPT algorithm works to control the solar panel's output power by regulating the solar panel's voltage to remain at V_{mpp} . The step size produced by each MPPT algorithm determines how quickly the voltage response reaches the V_{mpp} point. The MPPT algorithm based on DRNN with high-step PO offers a quick voltage response that reaches V_{mpp} . High-step PO causes significant ripple in the voltage at steady state because of its big step value. DRNN may generate a quick response that reaches V_{mpp} and has minimal ripple in steady state, in contrast to DRNN, which has a changeable step value. One of the weaknesses of the PO algorithm is that it is difficult to determine an appropriate step size. A high step will produce high ripple, while a low step will result in a slow response to reach the set point. In contrast to the voltage characteristics, the QBC has a lower output current than the input. Figure 13d shows that the QBC produces an output current of approximately 0.08 Amperes at steady state with an input current from the solar panel of 1.15 Amperes, as illustrated by Figure 13e. The performance of the QBC is determined by the duty cycle D generated by the three MPPT algorithms. Figure 13f illustrates the duty cycle generated by the three MPPT algorithms. The D value produced by high-step PO produces high ripple at steady-state conditions, thus also producing high ripple in the solar panel's output power. This contrasts with the D value generated by the DRNN and low-step PO, which have minimal ripple under steady-state conditions. However, it takes too long for the low-step PO with constant value to achieve a steady state. A DRNN with variable step provides a better response. The DRNN can quickly reach maximum power with low ripple under steady-state conditions.

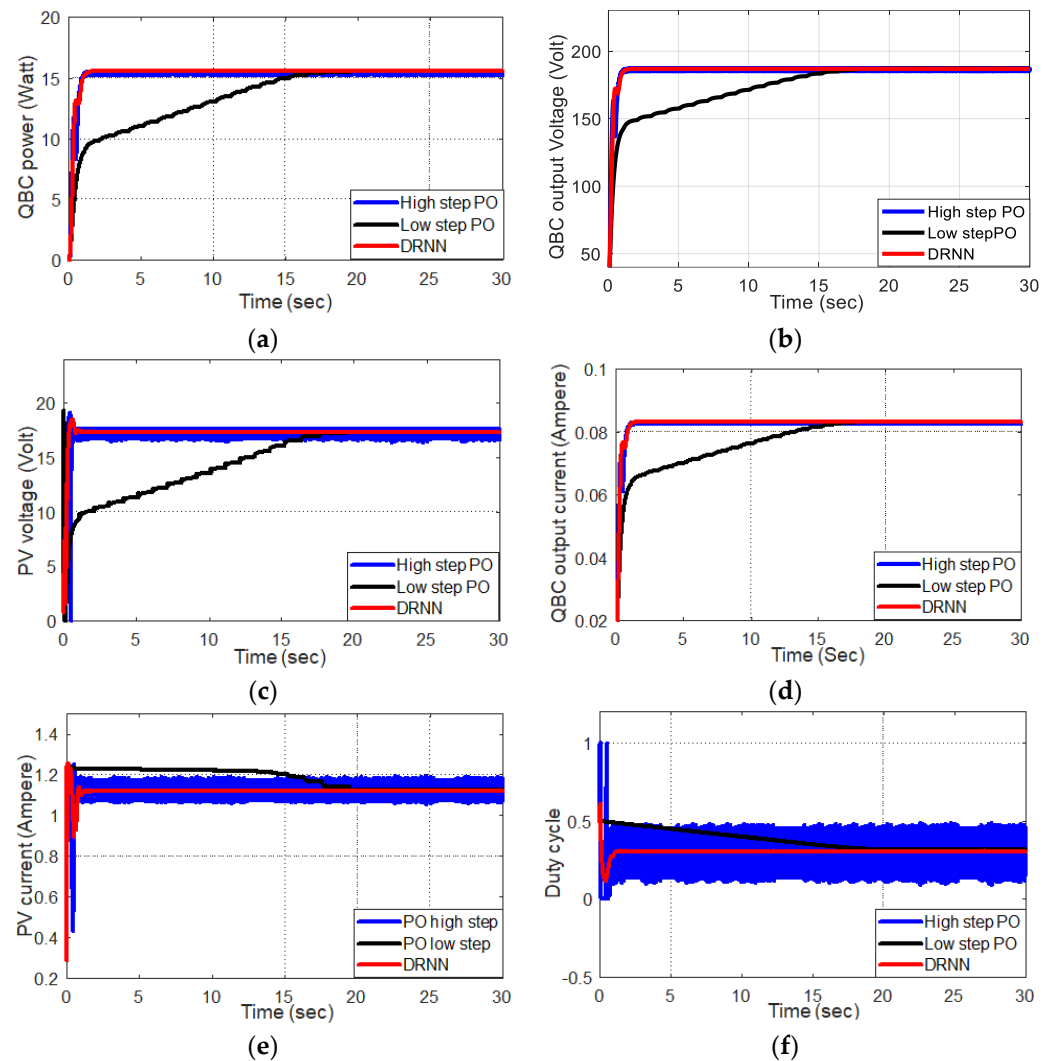


Figure 13. The QBC's performance in the first experiment. (a) Output power; (b) output voltage; (c) input voltage; (d) output current; (e) input current; (f) duty cycle.

After the DRNN-based MPPT algorithm was declared better than the PO algorithm, the DRNN-based MPPT algorithm was then verified through a second experiment with varying irradiance. The irradiance variation was achieved by adjusting the spotlight voltage through an autotransformer. Figure 14 displays the outcomes of the second experiment. Figure 14a shows a graph of the irradiance hitting the photovoltaic surface, and Figure 14b shows a graph of the photovoltaic temperature during the test. The maximum irradiance was 630 Wb/m^2 when the lamp was at maximum voltage, then reduced to 400 Wb/m^2 and finally to 310 Wb/m^2 . At the start of the test, the temperature rose from 31° Celsius to 33° Celsius , then slowed down as the irradiance was reduced.

The QBC produces varying voltages with a maximum value of 180 Volts when the maximum irradiation is 630 Wb/m^2 , 150 Volts when the irradiation is 400 Wb/m^2 and 135 Volts when the irradiation is 310 Wb/m^2 . The output voltage variation is influenced by the varying input voltage as well as by variations in irradiation and temperature. The output voltage generated by the QBC is far above the input voltage. This is in accordance with the characteristics of the QBC, where the output voltage value is the quadratic of the input voltage, as illustrated in Figure 14c. The duty cycle value D produced by the DRNN algorithm determines the QBC's output voltage value. As seen in Figure 14d, the DRNN algorithm generates a D value that fluctuates in accordance with the D value for the maximum power point for each variation in irradiation and temperature. According to the features of the

QBC, the D value generated by the DRNN increases with the amount of spotlight irradiation that strikes the solar panel's surface, resulting in a higher output voltage. This is in accordance with the QBC output voltage equation formulated in (8), where the output voltage value is the quadratic of the input voltage. The QBC output current also varies according to changes in irradiation and temperature affecting the solar panel surface, as shown in Figure 14e. The QBC's input current is approximately 1.15 Amperes when the maximum irradiation is 630 Wb/m^2 with an output current of 0.085 Amperes. This is consistent with the characteristics of the QBC, which has a greater input current than output current. Solar panel output power also varies with variations in irradiation and temperature. The solar panel produces 19.5 Watts of power when the maximum irradiation is 630 Wb/m^2 , then it drops to 13 Watts when the irradiation drops to 400 Wb/m^2 . When the minimum irradiation is 310 Wb/m^2 , the solar panel only produces 10 Watts of power, as illustrated by Figure 14f. The power produced by this solar panel is the power at the maximum point, where the value varies according to variations in irradiation and temperature that affect the solar panel. This maximum power is also at varying V_{mpp} , as shown by the graph of the solar panel output voltage in Figure 14c.

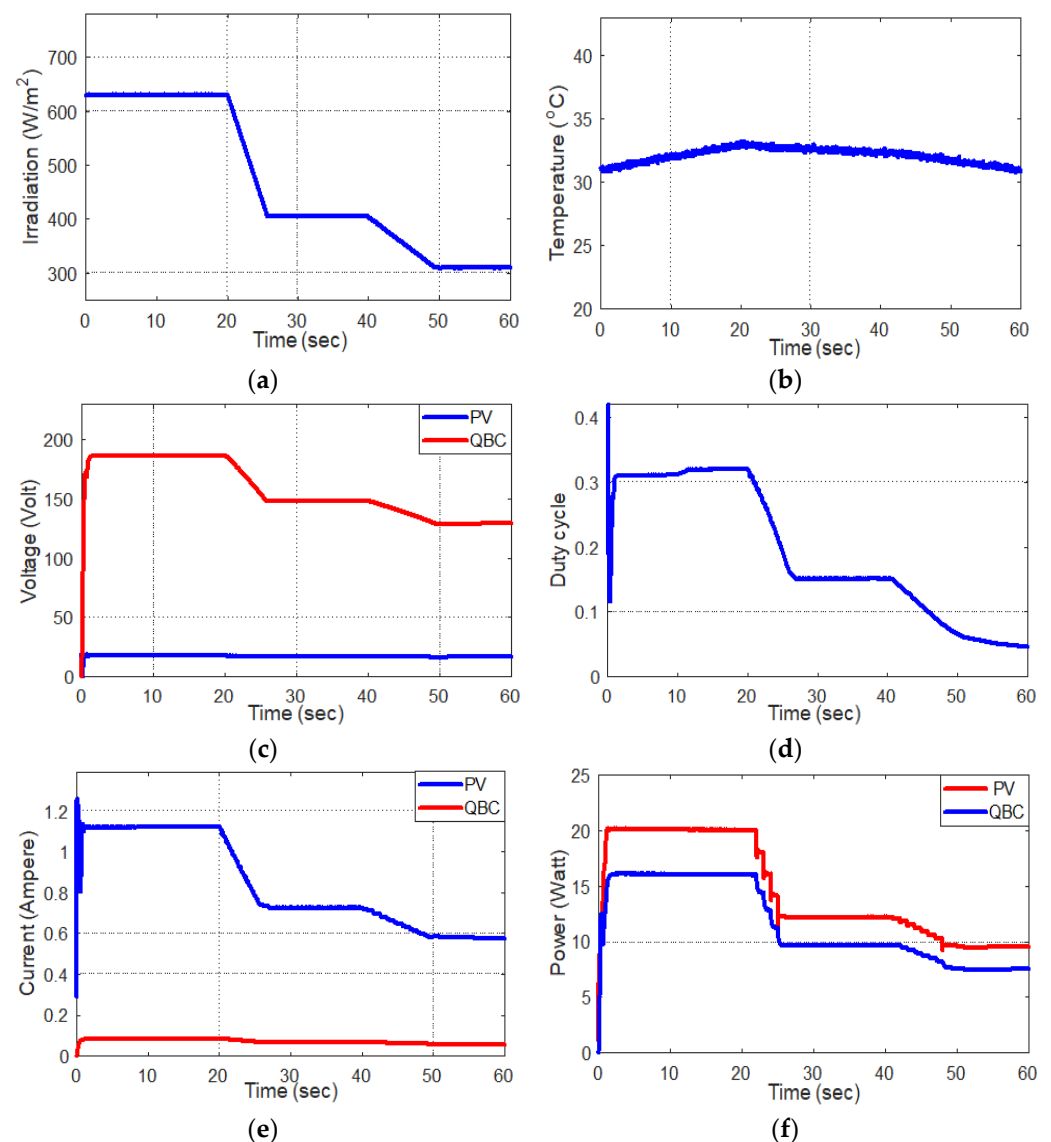


Figure 14. Results of the second experiment. (a) Irradiation; (b) temperature; (c) voltage; (d) duty cycle; (e) current; (f) power.

4. Discussion

A DRNN-based MPPT method is proposed to improve the response time to reach the maximum power point and also to reduce the power ripple at steady state at the maximum power point. The performance of the conventional PO algorithm is determined by the step value ΔD . Conventional PO algorithms have a constant ΔD value, making it very difficult to achieve excellent MPPT system performance. This is because a high ΔD value is required to accelerate the response to the maximum power point, while a low ΔD value is required to minimize power ripple. The DRNN is proposed to obtain varying ΔD values, so it is expected to accelerate the response to reach the maximum power point and also minimize power ripple at the maximum point. The proposed DRNN algorithm is verified by comparing it with two PO algorithms, namely, high-step PO and low-step PO. A comparison of the three MPPT methods is outlined in Table 2.

Table 2. Performance comparison of MPPT methods.

MPPT Method	Step Size (ΔD)	Power Ripple	Time Response
High-step PO	0.1	High	Fast
Low-step PO	0.001	Low	Slow
DRNN	−0.35 to 0.35	Low	Fast

Table 2 shows that high-step PO has a constant ΔD value of 0.1 and low-step PO has a constant ΔD value of 0.001, while DRNN has a ΔD value varying from −0.35 to 0.35. Experimental results show that high-step PO has the advantage of a fast response to reach the maximum power point but has the disadvantage of producing high power ripple. High-step PO can reach the maximum power point in 6 s with a power ripple of ± 0.5 Watts, as shown in Table 1 and Figure 12. In contrast, low-step PO has the advantage of producing low-ripple power but has the disadvantage of slow response to reach the maximum power point. Low-step PO takes up to 15 s to reach the maximum power point, but the resulting ripple power is only ± 0.1 Watts at steady state. The DRNN algorithm, which has varying ΔD , can provide advantages in both time response and power ripple. The DRNN-based MPPT system can reach the maximum power point in a fast time, namely 7 s, and can also produce a low ripple power of only ± 0.1 Watt. Based on the comparison of these three MPPT methods, it can be concluded that the proposed DRNN-based MPPT system has been able to produce a fast response and has also succeeded in minimizing power ripple, so it is better than conventional PO algorithms.

The use of a QBC to obtain a larger output voltage compared to a conventional boost converter has also been achieved in this study. The proposed QBC has been able to produce an output voltage of 180 Volts with an input voltage from the solar panel of 17.5 Volts. This shows that the proposed QBC has a DC gain of 10.28. The performance of the proposed QBC is verified by comparing it with several types of DC–DC boost converters, as described in Table 3.

Table 3. Performance comparison of power converters for MPPT in photovoltaic systems.

Converter Type	Switch	Diode	Capacitor	Inductor	Transformer	DC Gain
Boost [6]	1	1	2	1	-	2
Switched-capacitor boost [7]	1	6	6	3	-	60
Three-level QBC [10]	2	4	3	2	-	2.4
QBC with transformer [11]	1	5	4	1	1	22
Modified QBC [33]	1	7	5	3	-	45
Proposed QBC	1	3	2	2	-	10.28

Table 3 shows that the conventional boost converter proposed in [6] only has a maximum DC gain of 2. The DC gain of a boost converter is determined by the number of switch components, inductors, capacitors and diodes used in the circuit. Table 3 describes that the highest DC gain is obtained in the switched-capacitor boost converter discussed in [7]. This converter uses more inductors and capacitors than the proposed QBC. However, the DC gain is designed according to the requirements. In this paper, a converter that can increase the voltage from 17.5 to 200 Volts is required. This has been achieved by the proposed QBC with fewer components than the QBCs discussed in [10,11,33].

5. Conclusions

The performance enhancement of the maximum power control of a photovoltaic system is proposed by using a QBC based on the DRNN algorithm. The purpose of using a QBC is to obtain a higher output voltage ratio, while the DRNN method is proposed as an MPPT algorithm to increase the response to reach the maximum power point and reduce the power ripple at the maximum point. The proposed method is implemented on a 50 WP solar panel module using an Arduino Mega 2560 microcontroller as its control device. The design of the maximum power control system based on the DRNN and QBC is evaluated and compared with the conventional P&O MPPT algorithm. The results of laboratory experiments show that the proposed DRNN-based MPPT algorithm has successfully accelerated the response to reach the maximum power point and has also successfully reduced the power ripple at the maximum point. The use of QBC has been able to produce high output voltages in accordance with the objectives. QBC can produce an output voltage of 180 Volts when the input voltage of the solar panel converter is 17.5 Volts. All of these results indicate that the design of the maximum power control based on the DRNN and QBC was in accordance with the objectives.

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Abbreviations

D	Duty cycle
DRNN	Deep Recurrent Neural Network
GRU	Gated Recurrent Units
LSTM	Long Short-Term Memory
MPPT	Maximum Power Point Tracking
QBC	Quadratic Boost Converter
PO	Perturbation and Observation

Symbol

σ	The sigmoid function
ΔD	Duty cycle changes
ΔP	Power changes
ΔV	Voltage changes
b_k	Bias at the gate forget
b_o	Bias value at the gate output
c_t	Cell state of LSTM
f_t	Forget gate of LSTM
i_t	Input gate of LSTM
k_t	Cell input layer of LSTM
o_t	Output gate of LSTM
W_{hf}	Weights between the hidden layer and forget gates
W_{ho}	Weights between the hidden layer and output gates
W_{xf}	Weights between the input and forget gates
W_{xo}	Weights between the input and output gates

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