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(Research Article)

Optimization of solar energy using recurrent neural network controller with dc-dc boost, Cuk, and single-ended primary inductor converter (SEPIC) Converters

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Abstract

The pressing issue of the greenhouse effect demands strategies to reduce carbon dioxide (CO2) emissions, a detrimental gas with widespread adverse effects. The sun, as the ultimate renewable energy source, generates energy without CO2 emissions. Harnessing solar power necessitates a photovoltaic (PV) system equipped with a Maximum Power Point Tracker (MPPT) to optimize energy output. The MPPT adapts to changing environmental conditions and communicates through a Pulse Width Modulator (PWM) to an Insulated Gate Bipolar Transistor (IGBT), which alters its duty cycle to align system resistance with the load. Traditional Perturbation and Observation (P&O) algorithms struggled with environmental variations, but advanced AI-based Recurrent Neural Network (RNN) controllers enhance efficiency. This research compares RNN controllers using three data sets of 104, 201, and 1001 entries with three DC-DC converters: Boost, Cuk, and Single-Ended Primary Inductor Converter (SEPIC).

Keywords: Dc-DC boost converter; DC-DC cuk converter; DC-DC single-ended primary inductor converter; Maximum power point tracking; Photovoltaic system; Recurrent neural network

1. Introduction

The primary challenge in combating today's greenhouse effect is reducing CO_2 emissions, a gas that significantly raises global temperatures. Recently, solutions have focused on renewable energy sources to mitigate this harmful gas. Solar energy, harnessed from the sun, is a clean energy source. However, solar energy production requires a solar system with various components. The initial challenge is maintaining similar resistance between the solar system and the connected load. If the solar system is directly connected to a load with different resistance values, energy production is minimized. To match the resistance values of the solar system and the load, a DC-DC converter is necessary. This converter ensures maximum energy production when properly utilized [1].

Our solar system design includes a Maximum Power Point Tracker (MPPT), consisting of mathematical equations and logical rules, to adjust based on changes in temperature (T) and irradiance (G). When correctly attuned, these equations and rules ensure high power conversion. The MPPT sends an output signal to the Pulse Width Modulator (PWM), which modulates the signal and sends it to the gate of the Insulated Gate Bipolar Transistor (IGBT). This process adjusts the duty cycle, changing the solar system's resistance to match that of the load, thereby maximizing system efficiency [2].

The MPPT requires a controller to manage the output signal before it reaches the PWM. An older method, the Perturbation and Observation (P&O) algorithm, is widely used but weak when facing significant changes in T or G values, such as those caused by passing clouds or sudden temperature shifts. These changes are nonlinear, necessitating an AI-based controller with nonlinear calculations and predictions [3]. A Recurrent Neural Network (RNN) controller, designed for this purpose, requires training on data samples. In this work, the RNN controller is compared with three

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DC-DC converters: Boost, Cuk, Single-Ended Primary Inductance Converter (SEPIC) converters to determine the highest efficiency [4].

A DC-DC converter is essential in our proposed solar system before connecting it to a load. This ensures maximum efficiency in power production by matching the resistance of the solar system with the load. Changes in T and G values are nonlinear, and the RNN controller, which relies on nonlinear calculations and predictions, is used to address these changes.

This paper is sectioned as:

Section 2: Material and methods

PV System Description and Modeling

- Detailed analysis of the 213.15-Watt photovoltaic array design.
- Breakdown of the essential block model for PV arrays.
- Exploration of the solar cell architecture and operation, emphasizing p-n semiconductor junctions.
- Description of the model's inputs (irradiance and temperature) and output (voltage).
- Methods used to simulate and evaluate the PV system's performance in various conditions.
- Design and modeling of the DC-DC Boost Converter.
- Design and modeling of the DC-DC Cuk Converter.
- Design and modeling of the DC-DC Single-Ended Primary Inductance Converter (SEPIC).

Methodology of RNN Controller with DC-DC converters

- Overview of AI-driven control systems.
- In-depth discussion of the applied Recurrent Neural Network (RNN) model.
- Exploration of the AI RNN controller's application in improving photovoltaic system performance, focusing on its ability to handle non-linear and dynamic inputs like irradiance (G) and temperature (T).

Section 3: Results and Discussion

- Presentation of the results obtained with the RNN controller.
- Assessment of the RNN's effectiveness in enhancing photovoltaic systems.
- Examination of the benefits and drawbacks of the RNN controller approach.
- Analysis of the results regarding the optimization efficiency and effectiveness of PV systems.
- RNN controller design and modeling with a DC-DC Boost Converter.
- RNN controller design and modeling with a DC-DC Cuk Converter.
- RNN controller design and modeling with a DC-DC Single-Ended Primary Inductance Converter (SEPIC).
- Comparison of all RNN controllers used with DC-DC Boost, Cuk, and SEPIC converters.

Section 4: Conclusion

- Summary of the key findings from the research.
- Highlights of the progress made in renewable energy and photovoltaic system optimization.
- Recommendations for future research areas.
- Final reflections on the potential advantages of using AI controllers to enhance PV system efficiency.

2. Material and methods

2.1. PV System Model

The model designed here includes a solar array system with two inputs, temperature (T) and irradiance (G), and one output, voltage (V). The inputs (T and G) sent to the solar array generate instantaneous output (V), this value is also sent to the RNN controller, which is a two-input, one-output device. The solar array produces a corresponding voltage based on T and G values. The RNN controller then calculates and predicts a voltage signal, which is sent to the MPPT [5]. This signal adjusts the MPPT, which uses its mathematical and logical module to generate an unmodulated duty signal. This signal is then sent to a Pulse Width Modulator (PWM), which modulates the signal before sending it to the gate of the IGBT in the designed DC-DC converter subsystem, resulting in the output voltage (V_{out}). The RNN algorithm calculates and predicts the output voltage based on training data sets with samples of 104, 201, and 1001. Figure 1 shows the block diagrams for the proposed solar system, including the DC-DC converter, load, and RNN controller model [6].

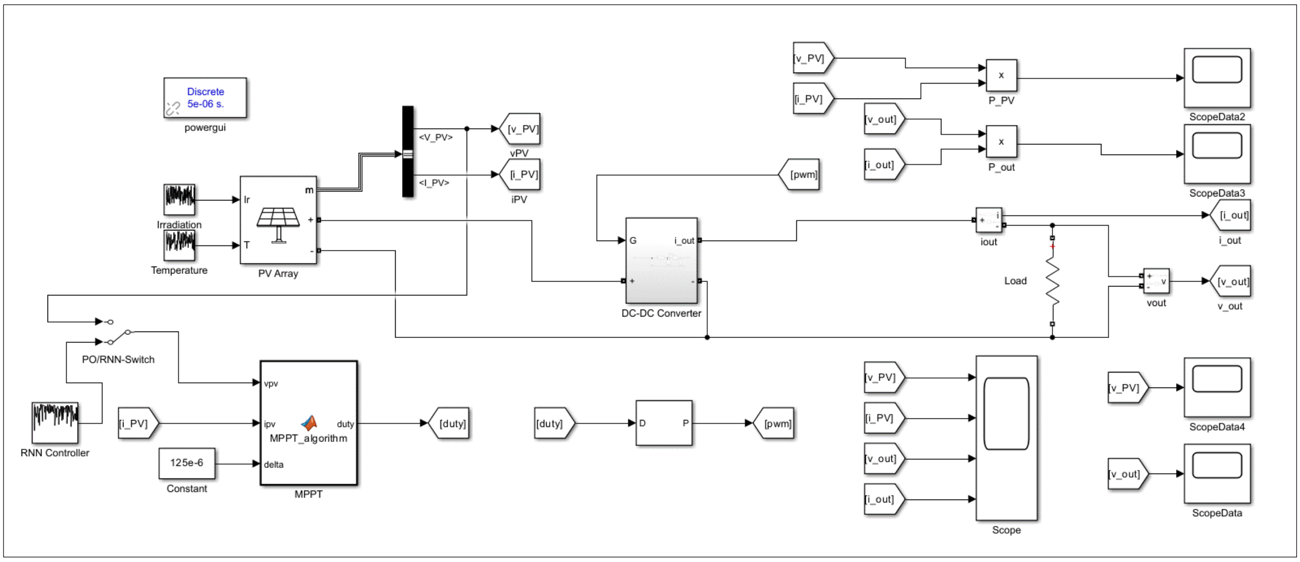

Figure 1 Block Diagram for The Proposed Model

2.2. DC-DC Converter Model

The block diagrams for the proposed solar system, including the DC-DC subsystem and load with the RNN model, Scopes are used to monitor changes in voltages, currents, and power of the PV array and system output at various calculated and predicted values [7].

2.2.1. DC-DC Boost Converter Model

The resistance of the PV system differs from that of the load, requiring a method to adjust the solar system's resistance to match the loads. A DC-DC Boost converter model is essential for this purpose, as it alters the voltage at the solar system's terminal to achieve resistance matching, thereby maximizing efficiency. The output voltage of a DC-DC Boost converter exceeds its input voltage, while the output current is lower than at the input terminals. Figure 2 illustrates the use of a capacitor to filter out any observed ripple, ensuring a steady output voltage [8, 9].

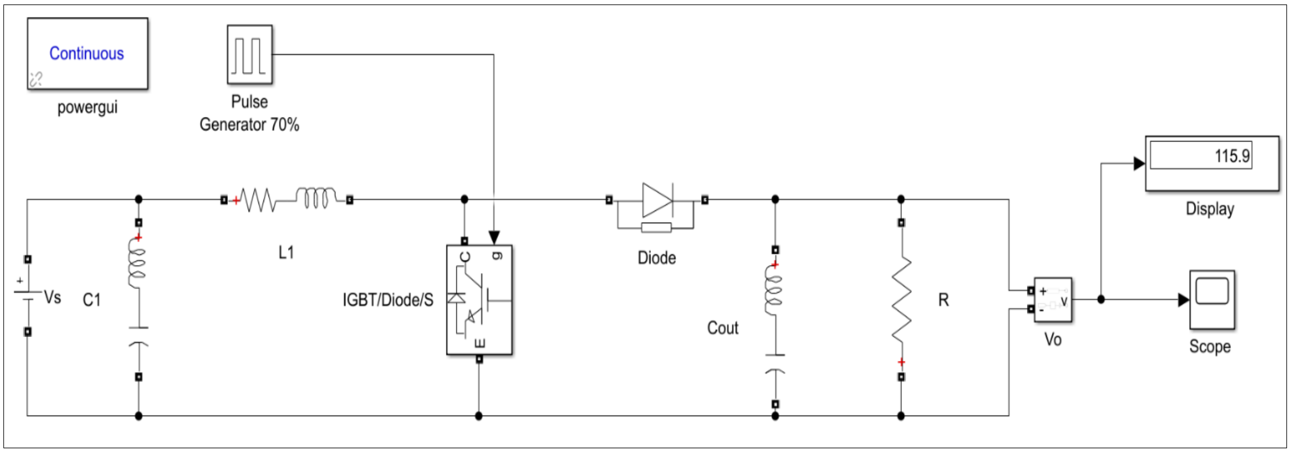

Figure 2 PV Circuit Diagram of a DC-DC Boost Converter Using an IGBT

The output voltage of a DC-DC Boost converter is ensured to exceed that of its input. Therefore, the conversion ratio of a DC-DC Boost converter can be calculated using the following equation:

$$\frac{V_O}{V_S} = \frac{I_{in}}{I_o} = \frac{1}{1-D} \text{ ....(1)}$$

The output voltage is directly influenced by the duty cycle, with the choice of inductor posing a significant challenge. It's crucial to note that inductance is inversely proportional to current ripple [10, 11]. To minimize ripples, a larger inductor is required in the converter.

2.2.2. DC-DC Cuk Converter Model

Small to medium DC sources such as DC generators with moderate voltages, lithium-based batteries, and PV solar systems can effectively power a Cuk converter. The concept of a DC-DC converter involves changing DC voltage from one level to another. A Cuk converter adjusts input voltage either upward or downward by controlling the gate open time of the IGBT [12, 13]. It functions as a versatile step-up and step-down converter, altering the source voltage through modulation of the duty cycle. A DC-DC Cuk converter employing a gated diode is particularly suitable for applications requiring low to medium voltage control. The gated diode offers robust handling capabilities for high voltages and powers. In this study, a MATLAB Simulink model is developed for a DC-DC Cuk converter utilizing a gated diode, and the circuit diagram is illustrated in Figure 3 [14, 15].

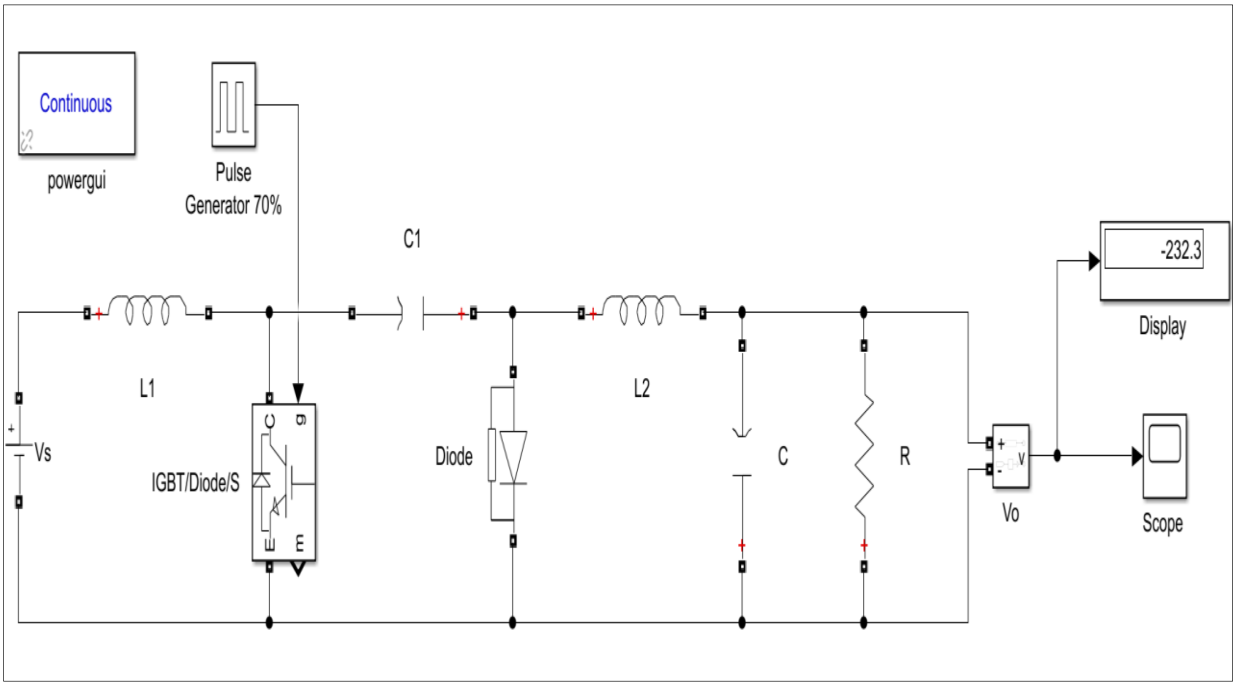

Figure 3 PV Circuit Diagram of a DC-DC Cuk Converter Using an IGBT

We can calculate the DC voltage transfer function or the duty cycle of a DC – DC Cuk converter by the following equation:

$$\frac{V_O}{V_S} = \frac{D}{1-D} \quad \text{.................}(2)$$

2.2.3. DC-DC Single Ended Primary Inductance Converter Model (SEPIC)

Power for the SEPIC converter can be sourced from various DC sources like DC generators, batteries, solar panels, and rectifiers [16, 17]. The process of converting one DC voltage to another is known as DC-DC conversion. Typically, a SEPIC converter adjusts DC voltages to be either higher or lower than the source voltage. It is often referred to as a step-up-step-down converter because it can increase or decrease the source voltage accordingly [18, 19]. In SEPIC converters, the output voltage can be either higher or lower than the input voltage, thus the name "SEPIC," without reversing polarity. A DC-DC SEPIC converter employing a power MOSFET is suitable for applications requiring low to medium current handling and control. For applications needing to manage very high voltages and powers, a DC-DC SEPIC converter utilizing an IGBT is designed using MATLAB Simulink, with the circuit diagram depicted in Figure 4 [20, 21].

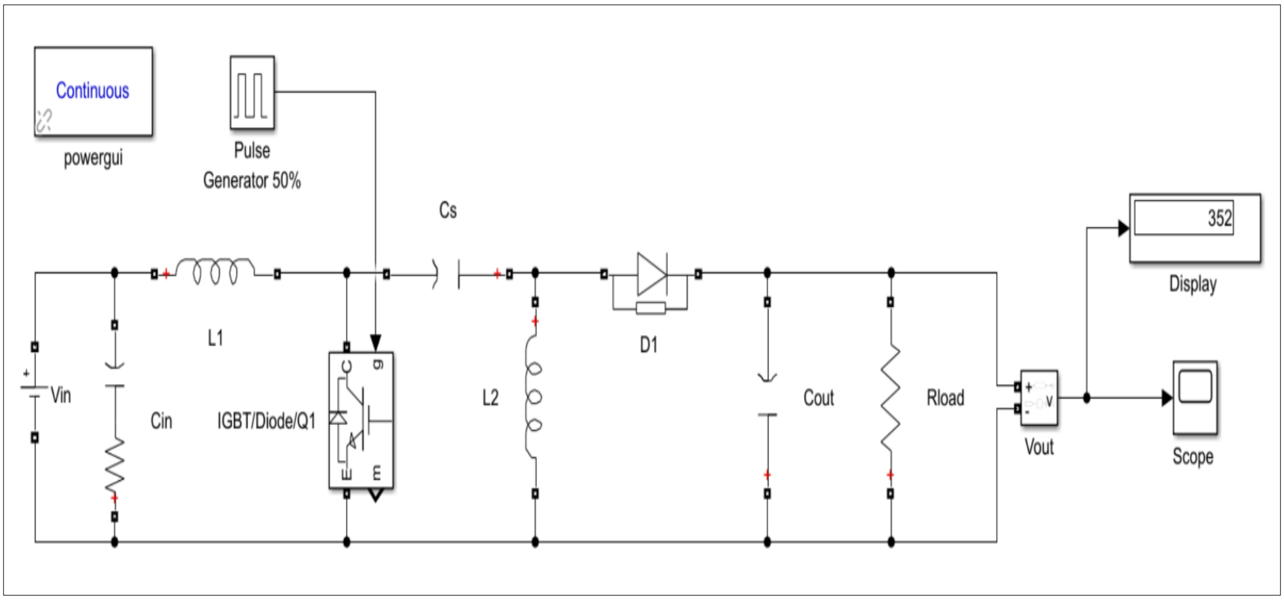

Figure 4 PV Circuit Diagram of a DC-DC SEPIC Converter Using an IGBT

We can calculate the DC voltage transfer function or the duty cycle of a DC – DC SEPIC converter by the following equation:

$$D = \frac{V_{out}+V_D}{V_{in}+V_{out}+V_D} = \frac{V_{out}}{V_{out}+V_{in}} \quad \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

2.3. Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) resembles a standard Artificial Neural Network (ANN) in structure but differs in that it includes connections among hidden layers that involve time-delayed feedback [22, 23]. These connections allow the model to retain information from previous inputs, helping it uncover temporal relationships between events spaced apart in the data [24, 25].

2.3.1. Selecting the Network Structure

The irrigation (G) and temperature (T) inputs are linked to the hidden layer via weighted connections, where they influence the calculation and prediction of the output voltage (V). The effectiveness and control of this process hinge on the configuration of the hidden layers and the number of neurons within each layer [26, 27]. Training the RNN typically involves a trial-and-error approach. In this setup, there is an input layer with two neurons (representing G and T), an output layer with one neuron (outputting V), and hidden layers, illustrated in Figure 5 with a 90-degree tilt [28, 29].

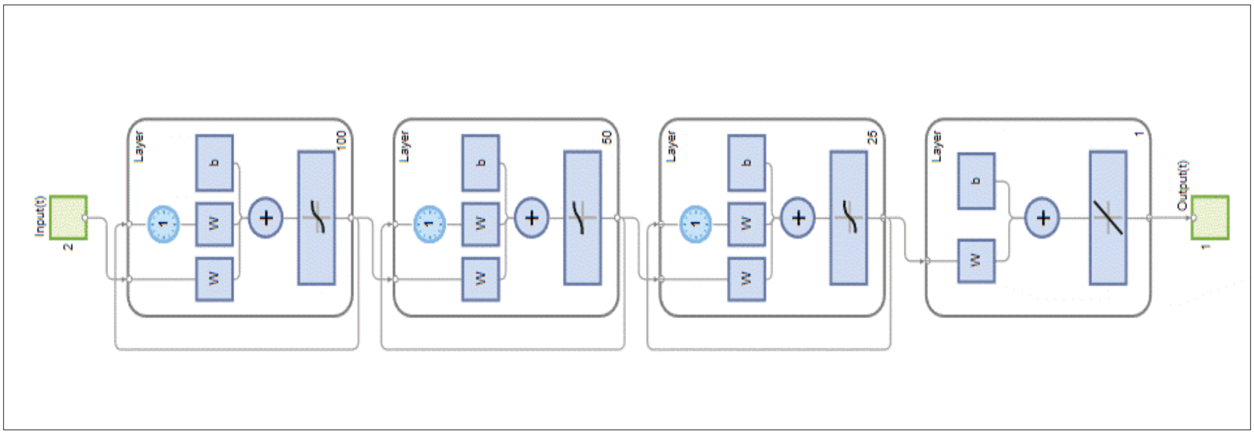

Figure 5 For MPPT Proposed RNN Structure

2.4. DC-DC Converters with RNN controller

The suggested DC-DC converter incorporates a Recurrent Neural Network (RNN) controller model with a photovoltaic (PV) array, taking irradiance (G) and temperature (T) as inputs and generating voltage (V) as an output [30, 31]. Both G and T are supplied to the PV array and the RNN controller. The PV array generates a corresponding voltage, while the RNN controller calculates a voltage signal for maximum power point tracking (MPPT). The MPPT then generates a duty cycle signal sent to a pulse-width modulation (PWM) controller for controlling an IGBT in a DC-DC converter, thereby regulating the output voltage (V_o). This V_o, as predicted by the RNN algorithm, powers a connected load [32, 33].

2.4.1. DC-DC Boost Converter with RNN Controller

The proposed Boost Controller with an RNN model integrates a PV array that takes inputs from G (irradiance) and T (temperature), generating output V (voltage). G and T values are fed into both the PV array and the RNN controller. The PV array produces a corresponding voltage output, while simultaneously the RNN controller calculates a voltage signal sent to the MPPT for adjustment [34, 35]. The MPPT then generates a Duty signal, which is passed through a Pulse Width Modulator (PWM) to modulate a signal sent to the IGBT in the DC-DC Boost converter, ensuring the output voltage (V_o). This voltage output is predicted and controlled by the RNN algorithm and is ultimately supplied to a load. The block diagram illustrating this model is depicted in Figure 6 [36, 37].

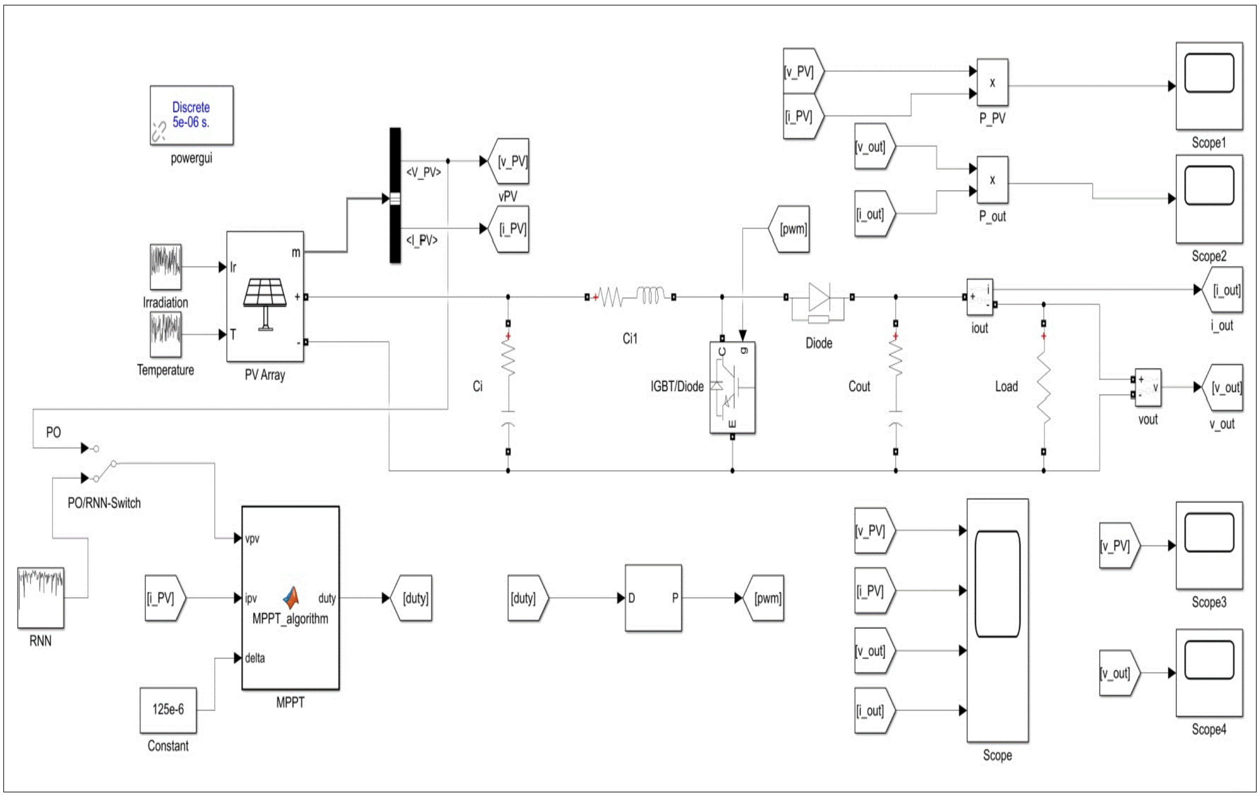

Figure 6 Proposed PV System with a DC-DC Boost Converter with an RNN Controller

2.4.2. DC-DC Cuk Converter with an RNN Controller

The proposed Cuk Controller with an RNN model integrates a PV array that takes inputs from G (irradiance) and T (temperature), generating output V (voltage). G and T values are input into both the PV array and the RNN controller [38, 39]. The PV array produces a corresponding voltage output, while simultaneously the RNN controller calculates a voltage signal sent to the MPPT for adjustment. The MPPT then generates a Duty signal, which is passed through a Pulse Width Modulator (PWM) to modulate a signal directed to the IGBT in the DC-DC Cuk converter, ensuring the output voltage (V_o) [40]. This voltage output is predicted and controlled by the RNN algorithm and is connected to a load. The block diagram illustrating this model is depicted in Figure 7 [41, 42].

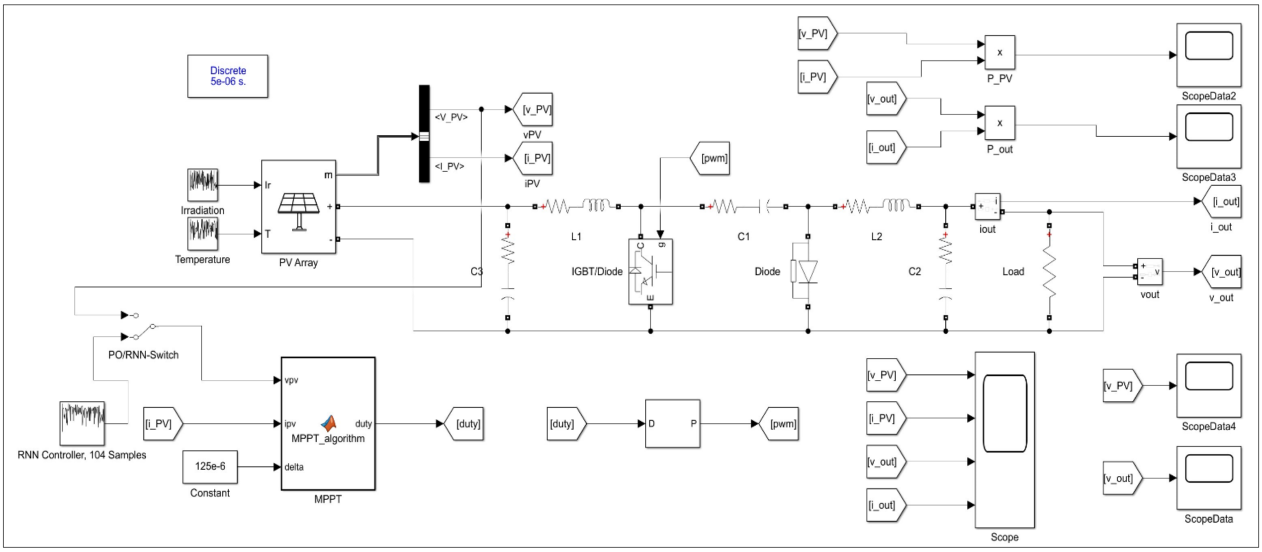

Figure 7 Proposed PV System with a DC-DC Cuk Converter with an RNN Controller

2.4.3. DC-DC Single Ended Primary Inductance Converter (SEPIC) with an RNN Controller

The proposed SEPIC Controller with an RNN model integrates a PV array with inputs G (irradiance) and T (temperature), resulting in output V (voltage). G and T values are input into both the PV array and the RNN controller. The PV array generates a corresponding voltage, while simultaneously the RNN controller calculates a voltage signal sent to the MPPT to achieve maximum power point tracking [43]. The MPPT generates a Duty signal, which is fed into a Pulse Width Modulator (PWM) to modulate a signal directed to the IGBT in the DC-DC SEPIC converter, thus determining the output voltage (V_o). This output voltage is predicted and controlled by the RNN algorithm and is connected to a load. The block diagram illustrating this model is depicted in Figure 8 [44, 45].

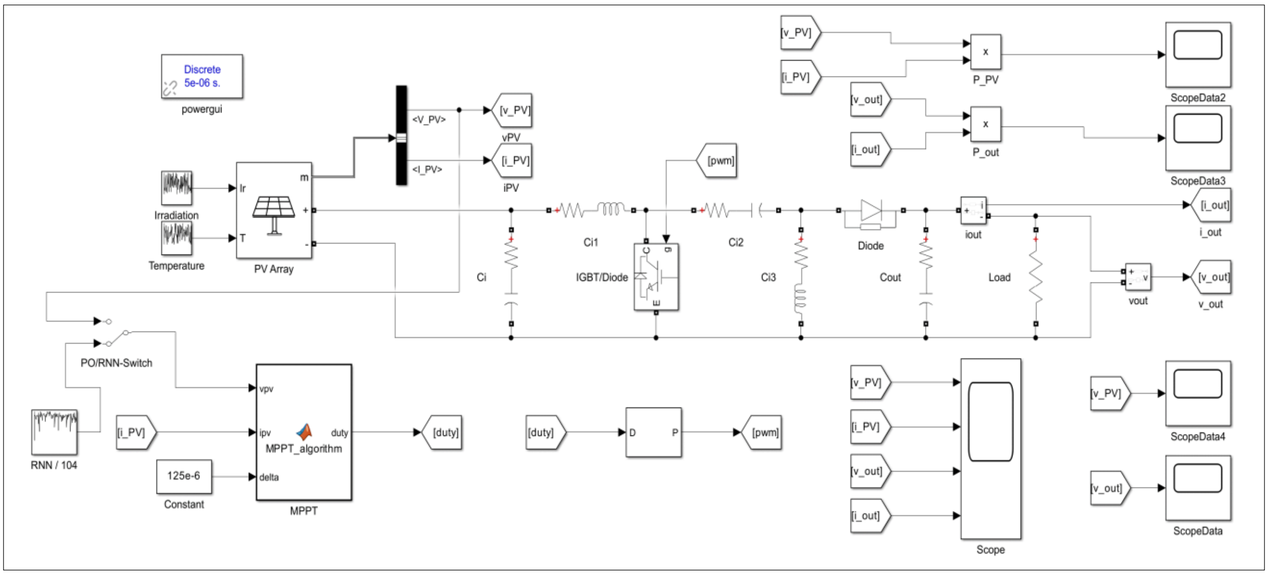

Figure 8 Proposed PV System with a DC-DC SEPIC Converter with an RNN Controller

After training the RNN controller using 104, 201, and 1001 data samples, a comparison was conducted across all three converters to determine the optimal dataset for achieving maximum efficiency [46, 47]. Consequently, two alternative datasets were selected: 102 samples and 1001 samples, in addition to the existing 104 samples. Using these datasets, the RNN controller was comprehensively trained, and its performance was evaluated against PV efficiency [48]. The RNN controller with the lowest error output was chosen for further testing, performance metrics in PV systems for the three converters is seen in Table 1.

Table 1 Performance Metric in PV Systems

Metric	Boost Converter with RNN	Cuk Converter with RNN	SEPIC Converter with RNN
Efficiency	Superior in boost configuration	Outstanding in boost and buck configurations	Exceptional in both step-up and step-down modes
Response Time	Swift due to RNN's responsive adaptation	Rapid adjustment to changing conditions	Quick response to input variations
Stability	Enhanced performance under dynamic states	Superior management of intricate configurations	Increased stability across broad input spectrum
MPP Tracking	Efficient tracking, particularly in low-voltage situations	Accurate tracking in both high and low voltage scenarios	Superior tracking over a broad input voltage range
Ripple	Average ripple in the output voltage	Minimal ripple owing to dual-inductor structure	Minimal ripple in both input and output currents
Versatility	Restricted to boost functions	Adaptable for both boost and buck applications	Extremely adaptable to different input voltages

3. Results and Discussion

3.1. RNN Controller with a DC-DC Boost Converter

We compared the performance of PV panels under different control conditions: with a P&O controller, with an RNN controller using 104 samples, with an RNN controller using 201 samples, and with an RNN controller using 1001 samples [49, 50]. Introducing a P&O controller improved efficiency to 94.3388%. Implementing an RNN controller with 104 samples decreased efficiency to approximately 92.8430%, while using an RNN controller with 201 samples raised efficiency to about 94.4294%. The highest efficiency among the RNN controllers was achieved with 1001 samples, reaching 97.2852%, as shown in Table 2, 1001 samples is higher than that of all other samples used [51, 52]. This significant increase in efficiency highlights the potential of using a larger dataset with RNN controllers for optimizing PV system performance. Moreover, the comparison emphasizes the importance of advanced control strategies in enhancing the overall efficiency of photovoltaic systems.

Table 2 Comparison of All Used RNN Controllers with A DC – DC Boost Converter

No.	Controller Type	Efficiency
1	P&O	94.3388%
2	RNN using 104 samples	92.8430%
3	RNN using 201 samples	94.4294%
4	RNN using 1001 samples	97.2852%

3.2. RNN Controller with a DC-DC Cuk Converter

We conducted a comparison of PV panels under various control conditions: with a P&O controller, with an RNN controller using 104 random samples, with an RNN controller using 201 random samples, and with an RNN controller using 1001 random samples. Introducing a P&O controller resulted in an efficiency of 93.8339%. Implementing an RNN controller with 104 samples decreased the efficiency to approximately 92.2337%, while using 201 samples further improved it to about 93.8021% [53]. The highest efficiency among the RNN controllers was observed with 1001 samples, reaching 94.2270%, as indicated in Table 3. This demonstrates that the RNN controller with 1001 samples outperforms all other configurations in terms of efficiency [54, 55]. This significant increase in efficiency underscores the advantage of utilizing a larger dataset with RNN controllers for optimizing PV system performance. Additionally, the comparison highlights the critical role of advanced control strategies in enhancing the overall efficiency of photovoltaic systems.

Table 3 Comparison of All Used RNN Controllers with A DC – DC Cuk Converter

No.	Controller Type	Efficiency
1	P&O	93.8339%
2	RNN using 104 samples	92.2337%
3	RNN using 201 samples	93.8021%
4	RNN using 1001 samples	94.2270%

3.3. RNN Controller with a DC-DC SEPIC Converter

We conducted a comparative study of PV panels using various control setups: with a P&O controller, an RNN controller with 104 random samples, an RNN controller with 201 random samples, and an RNN controller with 1001 random samples. Introducing a P&O controller reached an efficiency of 94.0032% [56, 57]. The efficiency decreased to approximately 92.5903% with the RNN controller using 104 samples, and further improved to about 94.0345% with 201 samples. Remarkably, the RNN controller utilizing 1001 samples achieved the highest efficiency at 95.3488%, as documented in Table 4. This underscores the superior performance of the RNN controller with 1001 samples compared to all other configurations in maximizing efficiency [58, 59].

Table 4 Comparison of All Used RNN Controllers with A DC – DC SEPIC Converter

No.	Controller Type	Efficiency
1	P&O	94.0032%
2	RNN using 104 samples	92.5903%
3	RNN using 201samples	94.0345%
4	RNN using 1001 samples	95.3488%

3.4. Comparison of All Used RNN Controllers with DC-DC Boost, Cuk, and SEPIC Converters

Figure 9 illustrates the efficiency comparison of various RNN controllers paired with DC-DC Boost, Cuk, and SEPIC converters. The bars depict the efficiency of each converter under different controllers, facilitating a straightforward visual assessment of their performance [60].

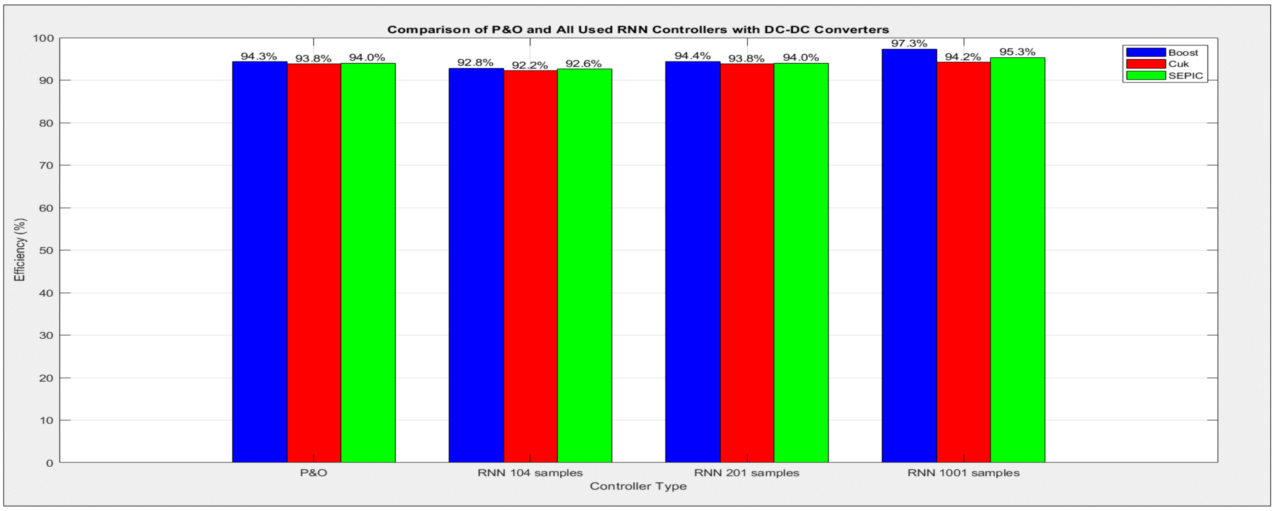

Figure 9 Comparison of All Used RNN Controllers with DC-DC Converters

The RNN controllers using 1001 random samples consistently show the highest efficiency across all three types of DC-DC converters (Boost, Cuk, and SEPIC). These controllers using 1001 samples outperform the P&O method in terms of efficiency, demonstrating the effectiveness of RNNs when trained with enough data.

- The **Boost Converter** typically achieves the highest efficiency with RNN controllers when utilizing 1001 samples.
- The **Cuk Converter** while slightly less efficient than the Boost Converter, still demonstrates improvements with the use of RNN controllers.
- The **SEPIC Converter** displays varying levels of efficiency, with RNN controllers markedly enhancing performance compared to scenarios without a controller or with a P&O controller.

4. Conclusion

The proposed RNN control algorithm, when compared to the Perturb and Observe (P&O) algorithm, demonstrates higher efficiency and superior prediction capabilities for output voltages. This indicates that integrating an RNN controller for MPPT in PV arrays enhances the efficiency of the solar PV system and maximizes output power. Utilizing 1001 samples yielded the highest efficiency, reaching 97.2852% for the RNN controller with a DC-DC Boost Converter, significantly enhancing the capability to extract maximum power from any PV system. Although using more than 1001 samples might seem advantageous for achieving higher efficiency, our findings show that feeding more samples to the RNN controller for the DC-DC Converters resulted in poor training status and suboptimal efficiency. This study concludes that 1001 samples with a DC-DC Boost Converter offer the optimal conditions for ensuring the RNN controller operates with maximum efficiency.

Compliance with ethical standards

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Disclosure of conflicts of interest

The authors declare that no conflicts of interest exists between them.

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