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Optimization of solar energy using artificial neural network vs recurrent neural network controller with ultra lift Luo converter

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Abstract

In today's society, the demand for clean energy is essential. Traditionally, renewable sources such as hydropower, wind, and solar have provided sustainable solutions. Photovoltaic (PV) systems generate electricity from sunlight using semiconductor PV cells, which have been effective for over 30 years. The efficiency of PV cells depends on irradiance (solar photon intensity) and temperature. Higher irradiance boosts efficiency, while higher temperatures reduce it. Despite their low voltage outputs, PV systems can be optimized with DC-DC Ultra Lift Luo converters to meet load requirements, improving system efficiency. The Ultra Lift Luo converter, a type of DC-DC converter, offers a higher voltage conversion gain than conventional boost converters. This converter belongs to the Luo converter family, which uses advanced techniques to achieve high voltage gain and efficiency. Solar irradiance fluctuates throughout the day, impacting PV cell output. Maximum Power Point Trackers (MPPTs) adjust the system's operating point to sustain peak efficiency. This study aims to design AI controllers for MPPT management. We will evaluate the performance of Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) with three datasets to determine the most efficient AI controller for optimizing solar energy systems.

Keywords: Artificial neural network; DC-DC Ultra lift luo converter; Maximum power point tracking; Photovoltaic system; Recurrent neural network

1. Introduction

Traditionally, energy generation predominantly relied on the combustion of fossil fuels such as coal, oil, and natural gas. This method transformed the chemical energy contained in these fuels into heat, subsequently used to produce electricity through different techniques. However, the dependence on fossil fuels has considerably amplified the emission of greenhouse gases, especially carbon dioxide, over the past seven decades, exacerbating global climate change. To mitigate these adverse environmental effects, there is an increasing shift towards cleaner and more efficient energy conversion technologies, with a particular focus on photovoltaic (PV) systems [1].

Photovoltaic (PV) systems generate electricity directly from sunlight through PV cells. However, the electrical output from these cells typically has a low voltage, necessitating the use of DC-DC converters to elevate the voltage levels. The Ultra Lift Luo converter plays a pivotal role in this scenario [2]. This converter not only enhances the voltage output but also aligns the impedance between the PV system and its connected load, effectively tackling a major obstacle in maximizing the efficiency of PV systems [3].

Solar irradiance, which quantifies the strength of sunlight photons, fluctuates throughout the day. Concurrently, ambient temperature shifts due to environmental factors, influencing the performance of PV systems. To optimize energy capture and efficiency, a Maximum Power Point Tracker (MPPT) is employed [4]. The MPPT dynamically adjusts

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the operating point of the PV system in real-time to ensure it functions at its maximum power point (MPP), where output power is maximized. This real-time adjustment is crucial as it corresponds to the varying maximum voltage curve of the PV cells over the course of the day. The MPPT signal directs the DC-DC Ultra Lift Luo converter, which incorporates components such as Insulated Gate Bipolar Transistor (IGBT) to manage its duty cycle. By modulating the duty cycle, the converter effectively adjusts the output voltage to meet the load requirements [5].

Due to the non-linear and ever-changing characteristics of solar irradiance (G) and temperature (T), conventional time-domain controllers often struggle to manage these fluctuations effectively. As a result, artificial intelligence (AI) controllers present a superior alternative. This research explores two AI control strategies: Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN). These AI controllers are adept at managing non-linear variations in input values from PV cells, thereby optimizing control efficiency and improving the overall performance of the system [6].

Shifting from fossil fuels to renewable energy sources like photovoltaic (PV) systems is a vital step towards achieving sustainability. By leveraging cutting-edge technologies such as Maximum Power Point Trackers (MPPTs), DC-DC converters, and AI-based controllers, we can efficiently utilize solar energy, enhance system performance, and lower the environmental footprint.

This paper is sectioned as:

Section 2: PV System Description and Modelling

- Detailed Outline of the 213.15-Watt Photovoltaic (PV) Array Model.
- Summary of the Basic Block Diagram of PV Arrays.
- Examination of Solar Cell Design and Operation Using p-n Semiconductor Junctions.
- Evaluation of the Inputs (Irradiance and Temperature) and Outputs (Voltage and Power) of the PV Array Model.
- Techniques employed for simulating and assessing the PV system under various conditions.
- Design and Modeling of the DC-DC Ultra Lift Luo Converter.

Section 3: Methodology of ANN Controller

- Overview of AI-based control systems.
- Detailed outline of the Artificial Neural Network (ANN) model applied.
- Discussion on the deployment of this AI ANN controller for optimizing the PV system, with a focus on its efficiency in managing non-linear and variable inputs, specifically irradiance (G) and temperature (T).

Section 4: Methodology of RNN Controller

- Overview of artificial intelligence (AI) controllers.
- Detailed description of the Recurrent Neural Network (RNN) model employed.
- Discussion on the implementation of this AI RNN controller for enhancing the performance of the PV system, with an emphasis on its capability to manage non-linear and dynamic inputs such as irradiance (G) and temperature (T).

Section 5: Results and Discussion

- Evaluation of ANN and RNN performance in enhancing PV system optimization.
- Examination of the advantages and disadvantages of each AI control technique.
- Analysis of results concerning the efficiency and effectiveness of PV system optimization.

Section 6: Conclusion

- Overview of the Major Results of the Study.
- Advancements to the Field of Renewable Energy and Optimization of PV Systems.
- Suggestions for Future Research Paths.
- Final Thoughts on the Influence of AI Controllers in Improving PV System Efficiency.

2. PV System Description and Modelling

We present a comprehensive description of the PV system model, detailing its components and the integration of ANN and RNN controllers. Block diagrams are included to illustrate the proposed models. The PV array model receives inputs of Solar Irradiance (G) and Temperature (T) and has two outputs for the ANN controller: Output Voltage and Output

Power, and one output for the RNN controller: Output Voltage [7]. A DC-DC Ultra Lift Luo Converter is employed, with the MPPT playing a crucial role in maximizing power output by adjusting the operating point. The reference voltage (Vpv) is generated based on calculations and predictions from ANN or RNN algorithms. The PV system is directly connected to a fixed load [8]. The block diagrams in Figure 1, and Figure 2, visually clarify the system's architecture and control flow [9].

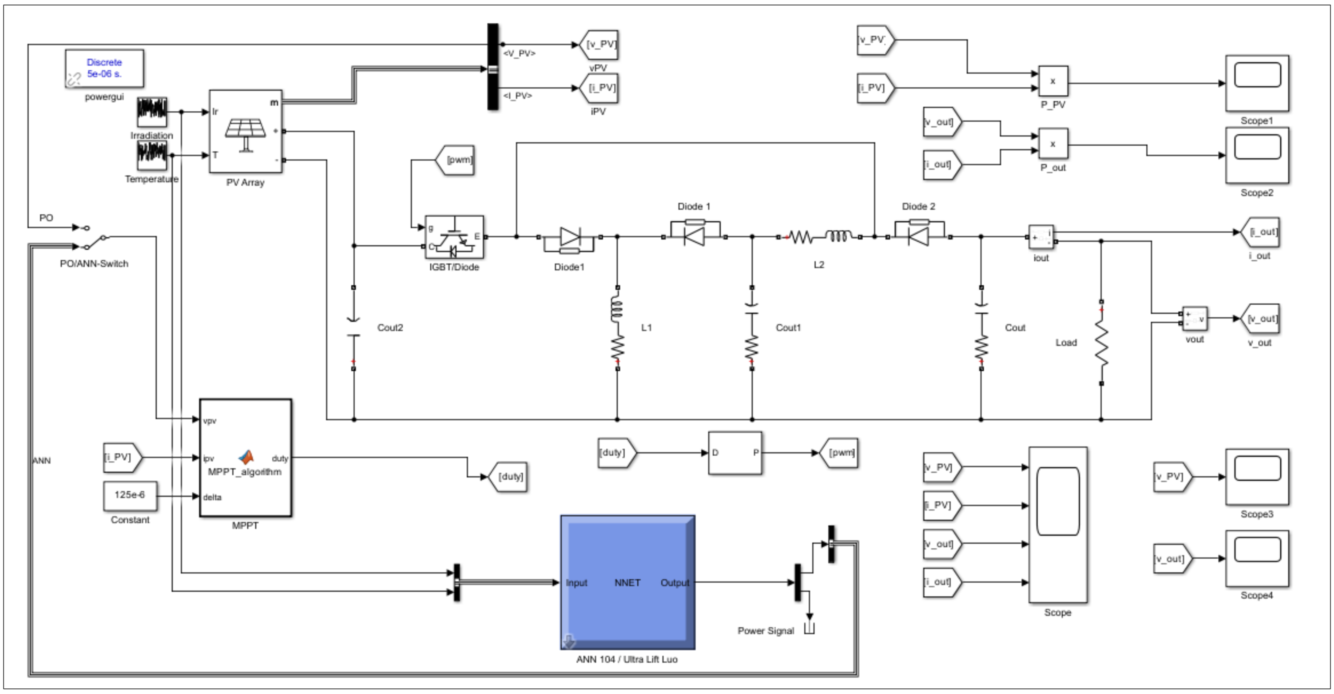

Figure 1 Block Diagram for The Proposed Designed ANN Model

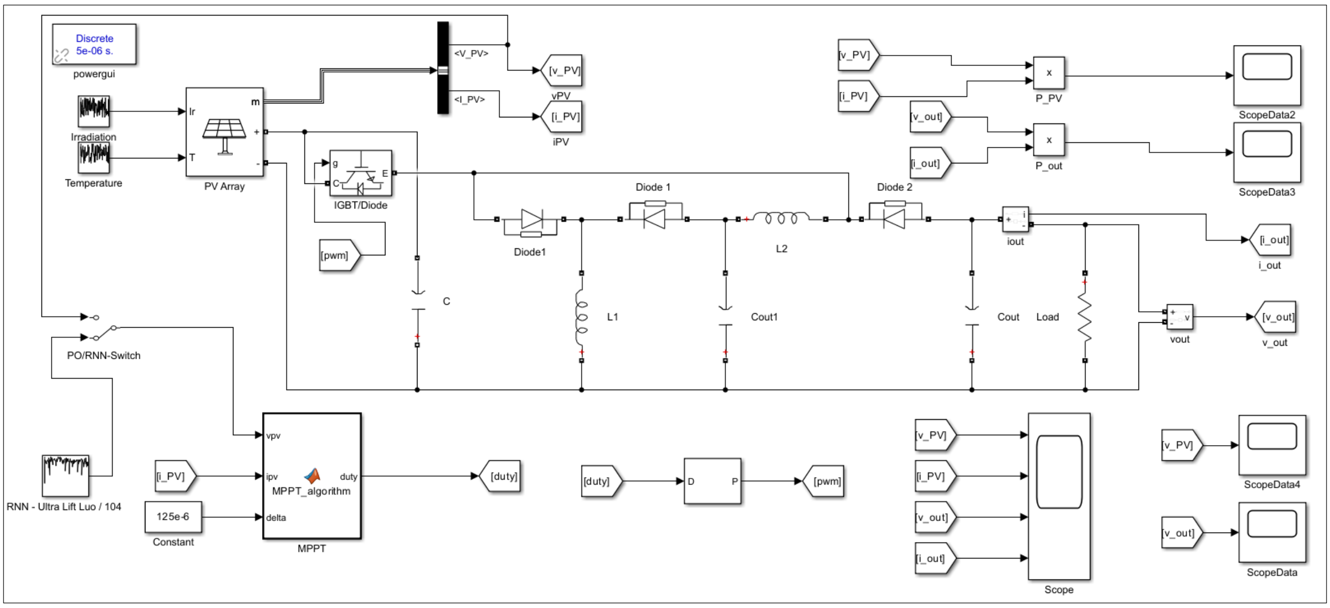

Figure 2 Block Diagram for The Proposed Designed RNN Model

2.1. Mathematical Solar Array Modeling

The single-diode model is commonly used for simulating photovoltaic (PV) cells. This model includes the following components:

- Photo-current source (I_{ph}): Represents the current generated by the solar cell when exposed to sunlight.
- Diode (D): Models the p-n junction of the solar cell, providing a path for the recombination of charge carriers.
- Series Resistance (R_s): Represents the resistive losses within the cell.
- Shunt Resistance (R_{sh}): Represents leakage currents within the cell.

The equivalent circuit of a PV cell using the single-diode model can be represented as:

$$I = I_{ph} - I_D - I_{sh} \quad \text{……………………………………………………………………………….. (1)}$$

Where:
I is the output current of the PV cell.
I_{ph} is the photo-generated current.
I_D is the current through the diode.
I_{sh} is the shunt leakage current.

In this research, we concentrate on the design and modeling of a 213.15-Watt photovoltaic (PV) array, a critical component for solar energy systems. The PV array is made up of interconnected solar cells that convert sunlight directly into electricity. The main inputs for the array are solar irradiance (G) and temperature (T) [10]. Solar irradiance, which measures the intensity of sunlight falling on the PV array in watts per square meter (W/m^2), leads to higher photo-generated current with increased irradiance. Temperature, measured in degrees Celsius (°C), represents the surrounding ambient temperature and impacts the efficiency and output of the PV cells, with higher temperatures typically reducing efficiency [11]. The key outputs of the PV array include the voltage output (V), representing the electrical voltage produced and influenced by both irradiance and temperature, and the power output (P) for the ANN controller, indicating the total electrical power generated by the PV array, calculated as the product of the voltage and current produced by the PV cells [12].

Understanding how the PV array operates across different levels of solar irradiance and temperature is essential to gauge its performance capabilities. Through simulating the PV array model in diverse environmental scenarios, we can anticipate its responses and refine its design to achieve optimal efficiency [13].

This research centers on intricately modeling a 213.15-Watt PV array, highlighting its fabrication using p-n semiconductor junctions and its responsiveness to solar irradiance and temperature changes. The voltage and power outputs serve as key indicators of the PV array's operational efficiency, pivotal for its integration into renewable energy setups [14]. Precise modeling facilitates AI-driven predictions and improvements in the PV array's performance across diverse environmental settings [15].

2.2. Modelling and Simulation of 213.15W PV array

The photovoltaic (PV) array used in the designed PV system was carefully selected from the MATLAB/Simulink toolbox for simulation purposes. This selection provides detailed information about the array's electrical properties and includes visual aids demonstrating its performance under different temperature and irradiance conditions [16]. Figure 3 displays a graphical representation of the chosen PV array model from MATLAB/Simulink, illustrating its response to varying environmental factors. Additionally, Table 1, outlines specific electrical parameters that characterize the PV array, offering a clear understanding of its capabilities and performance metrics under diverse operational scenarios [17].

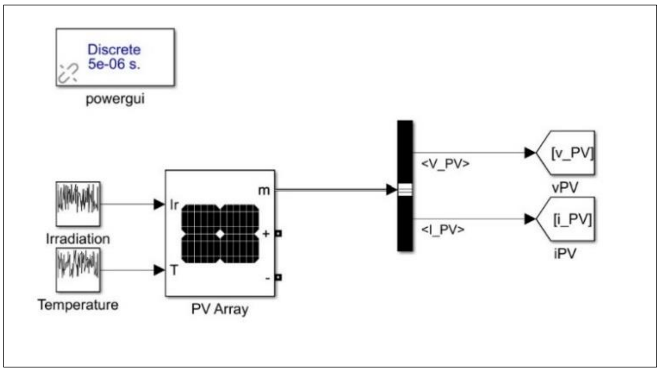

Figure 3 Block Diagram for The Proposed Designed PV Array Model

Table 1 Electrical Characteristics of The PV Module

Description	User-defined
Maximum power	312.15 W
Voltage at Pmax (Vmax)	29.00V
Current at Pmax (I_m)	7.35 A
Short Circuit current (I_{sc})	7.84 A
Open circuit voltage	36.30 V
Temperature coefficient Ki	0.102 A/°C

The Voltage-Current (V-I) characteristics curve demonstrates how the voltage and current output of the PV array relate to each other under specified conditions, shown in Figure 4. At a temperature of 25 °C and 45 °C, this curve indicates that the current output remains stable until the voltage approaches a certain threshold (close to the open circuit voltage), beyond which the current decreases significantly [18].

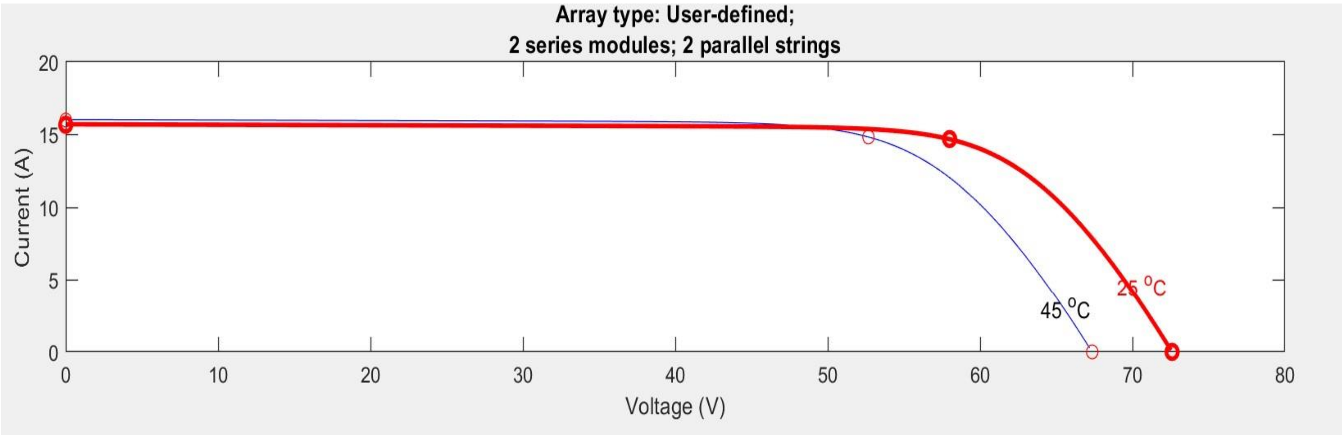

Figure 4 Voltage-Current (V-I) Characteristics curve at a Temperature of 25 °C and 45 °C

The Voltage Power (V-P) characteristics curve illustrates how the power output of the PV array changes with varying voltage levels, specifically at temperatures of 25 °C and 45 °C, as depicted in Figure 5. Typically, this curve exhibits a peak that signifies the maximum power point (MPP), where the PV array operates most efficiently [19]. Beyond this point, the power output declines as the voltage continues to increase [20].

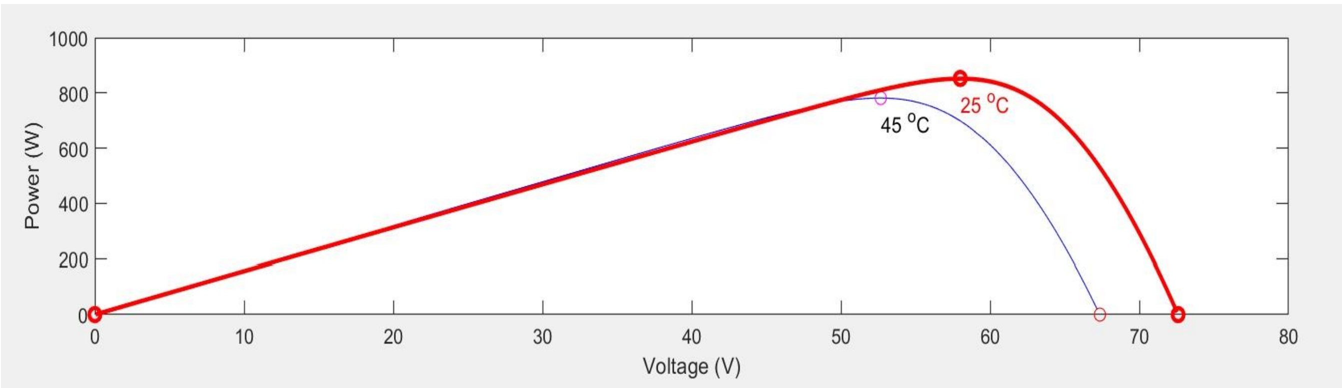

Figure 5 Voltage Power (V-P) Characteristics curve at Temperatures of 25 °C and 45 °C

The Voltage Current (V-I) characteristics curve, depicted in Figure 6, illustrates how the output current of the PV array changes with varying voltages under different levels of sunlight intensity. Higher levels of irradiance generally result in increased current outputs, while the overall shape of the curve remains consistent across varying irradiance levels [21].

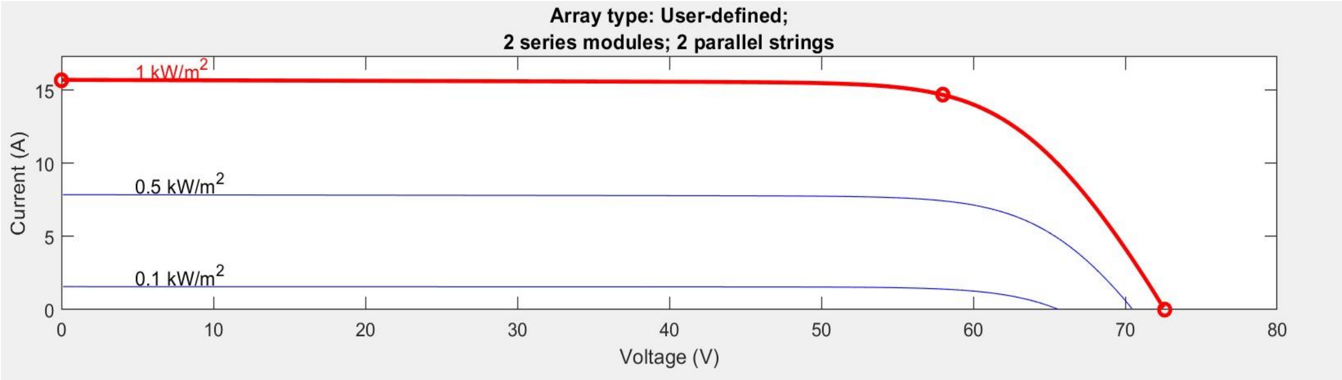

Figure 6 Voltage Current (V-I) Characteristics Curve Under Different Levels of Sunlight Intensity

The Voltage Power (V-P) characteristics curve for specified irradiance levels illustrates how the power output changes with voltage under varying sunlight intensities. Like the temperature-dependent V-P curve shown in Figure 7, the curve influenced by irradiance also exhibits a peak at the maximum power point. Higher irradiance levels lead to higher peak power values, highlighting the direct relationship between sunlight intensity and PV array performance in generating electrical power [22].

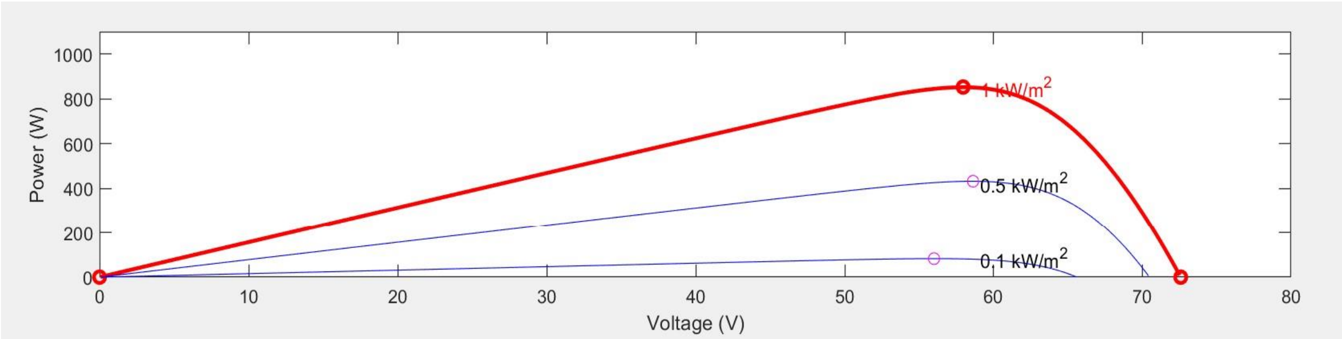

Figure 7 Voltage Power (V-P) Characteristics Curve Under Varying Sunlight Intensities

2.3. DC-DC Ultra Lift Luo Converter Model

2.3.1. DC-DC Ultra Lift Luo Converter Model

The DC-DC Ultra Lift Luo converter represents a sophisticated power electronics component engineered to effectively convert and control voltage levels. It is specifically tailored for applications in photovoltaic (PV) systems, where there is a requirement to elevate the typically low and unregulated output voltage to a level that is suitable for practical use [23].

2.3.2. *Voltage Lift Technique*

Arithmetic Progression: In basic voltage boosting designs, the output voltage incrementally increases through sequential steps, adhering to a systematic arithmetic pattern. This method ensures a gradual and predictable rise in voltage levels, typically in straightforward voltage conversion and regulation mechanisms [24].

Geometric Progression: The Ultra Lift Luo converter enhances voltage amplification by utilizing geometric progression. This method results in greater and more efficient increases in output voltage, making the process significantly more effective [25].

2.3.3. *Components and Circuit Design*

The converter employs inductors, capacitors, diodes, and an IGBT switch arranged strategically to achieve precise voltage alteration according to operational needs. This configuration ensures efficient transformation of electrical energy, maintaining stability and reliability throughout the conversion process, crucial for achieving the intended voltage output reliably and effectively [26].

The converter's function is based on switching processes that regulate how energy is stored and released in its inductors and capacitors. This controlled energy management leads to a gradual increase in output voltage, which follows a systematic and incremental pattern, akin to an arithmetic progression [27].

2.3.4. Advantages Over Traditional Converters

Higher Voltage Gain

Traditional converters such as Boost, Cuk, and SEPIC are often constrained by their limited ability to increase voltage. In contrast, the Ultra Lift Luo converter stands out for its capability to achieve significantly higher voltage spans, leveraging a geometric progression mechanism that enhances its efficiency and performance in voltage transformation applications [28].

Reduced Harmonics

Excessive harmonics are problematic as they can interfere with operations and decrease power system efficiency [29]. The Ultra Lift Luo converter effectively mitigates harmonics, resulting in a cleaner and more efficient power output that enhances overall system performance.

Improved Power Factor

Conventional converters often struggle with undesirable high-power factors, which can result in inefficiencies within the system. In contrast, the Ultra Luo converter is specifically engineered to optimize and maintain a more favorable power factor. This design enhancement ensures that the converter operates more efficiently, minimizing energy losses and improving the overall performance and reliability of the power system [30].

Higher Efficiency

The converter enhances efficiency through effective reduction of current ripples, resulting in decreased energy losses and improved overall system performance. By ensuring smoother and more stable current flow, the converter minimizes heat generation and switching losses, optimizing energy usage [31]. This enhanced efficiency not only conserves energy but also enhances the reliability and longevity of connected equipment. Reduced current ripples also contribute to maintaining high power quality, ensuring consistent and reliable operation of electrical systems. Overall, these advancements underscore the converter's ability to operate more efficiently while meeting stringent performance standards and enhancing system reliability [32].

Higher Voltage Span

This converter's capability to achieve a broader voltage range makes it well-suited for applications needing significant voltage increases, such as linking photovoltaic systems to external loads.

Practical Application in PV Systems

Unregulated PV Output

PV systems typically produce an unregulated output voltage that can vary with changes in solar irradiance and temperature. This unregulated output is often insufficient for directly powering loads or integrating with the grid.

Voltage Regulation

The Ultra Lift Luo converter plays a vital role in elevating the voltage output of PV systems to a stable, regulated level, making it adaptable for a wide range of applications. This controlled voltage enhancement is essential to ensure the consistency and reliability of power supplied by the PV system, meeting the requirements of different electronic devices and systems. By maintaining a steady output, the converter enables efficient utilization of solar-generated electricity, enhancing overall system performance and reliability [33].

2.3.5. Connection to External Loads

Utilizing the Ultra Lift Luo converter optimizes the PV system's ability to deliver consistent and reliable power to external loads. This converter guarantees that the voltage output meets specified standards, thereby improving the overall dependability and operational effectiveness of the PV system [34].

The Ultra Lift Luo converter is designed with the following key components:

Switch

Insulated Gate Bipolar Transistor (IGBT) functions as a semiconductor switch crucial for regulating the converter's duty cycle and operational efficiency.

Diodes

Standard diodes (D1, D2, and D3) are essential components within the circuit, facilitating current flow in one direction while blocking reverse current to maintain proper operation and prevent undesired electrical feedback.

Energy Storage Components:

Inductors (L1, and L2) are utilized to store energy in the form of a magnetic field, facilitating consistent current flow and enhancing the stability of the electrical system. This ensures reliable operation by minimizing fluctuations and maintaining a steady flow of power through the circuit.

Capacitors (C1, C2) also store energy but primarily smooth out voltage fluctuations, ensuring a consistent power supply. Both capacitors have identical values (C2 = C1), contributing equally to the stability and efficiency of the circuit's operation [35].

The converter employs the ultra-lift technique to consistently elevate the output voltage above the PV array's input voltage. This method incrementally increases the voltage in a geometric progression, ensuring that the output remains positively offset from the input. This design feature guarantees efficient power transformation, essential for maximizing the converter's performance in various applications. It ensures reliable operation by maintaining a stable and suitable output voltage, thereby optimizing the overall efficiency and functionality of the system [36].

The operational dynamics and behavior of the Ultra Lift Luo converter are defined by the set of equations below, which outline its functionality and how it responds to input parameters:

Transfer Gain (K) represents the ratio of the output voltage (V_o) to the input voltage (V_{in}), elucidating how the converter amplifies the voltage from the input to the output:

$$K = \frac{V_o}{V_{in}} \quad \text{.........} \quad (2)$$

The connection between the input voltage (V_{in}), output voltage (V_o), and transfer gain (K) is defined by a mathematical equation that outlines how changes in Vin affect Vo, scaled by the factor K. This equation provides a quantitative understanding of how the converter amplifies the input voltage to produce a desired output voltage, crucial for determining its operational characteristics and efficiency in various applications:

$$K = \frac{V_O}{V_{in}} = \frac{D(2-D)}{(1-D)^2} \quad \text{.........} \quad (3)$$

The output current (I_o) in the circuit can be determined using Ohm's law, which states that the current flowing through a conductor between two points is directly proportional to the voltage across the two points and inversely proportional to the resistance between them:

$$V_O = I_O R \quad \text{.........} \quad (4)$$

The DC-DC Ultra Lift Luo converter is an advanced and efficient device designed to elevate voltages without inverting them. It harnesses components like IGBTs, diodes, inductors, and capacitors to achieve substantial voltage increases while ensuring outputs are free from ripples and disturbances [37]. The operational equations it employs are crucial for engineers to effectively design, optimize, and assess the converter's functionality in diverse applications, especially when paired with PV systems. These equations provide insights into how the converter manages voltage transformation, ensuring reliable and efficient power conversion from photovoltaic sources to meet varying electrical demands [38].

The DC-DC Ultra Lift Luo converter's operational concept is elucidated by its block diagram, illustrating its key components and how electrical energy moves through the system. This schematic in Figure 8 offers a comprehensive view of the converter's architecture, showcasing the interplay among components that include IGBTs, diodes, inductors, and capacitors. Understanding these interactions is essential for grasping how the converter achieves efficient voltage elevation without inversion, which is pivotal for its application in diverse electronic and energy systems [39].

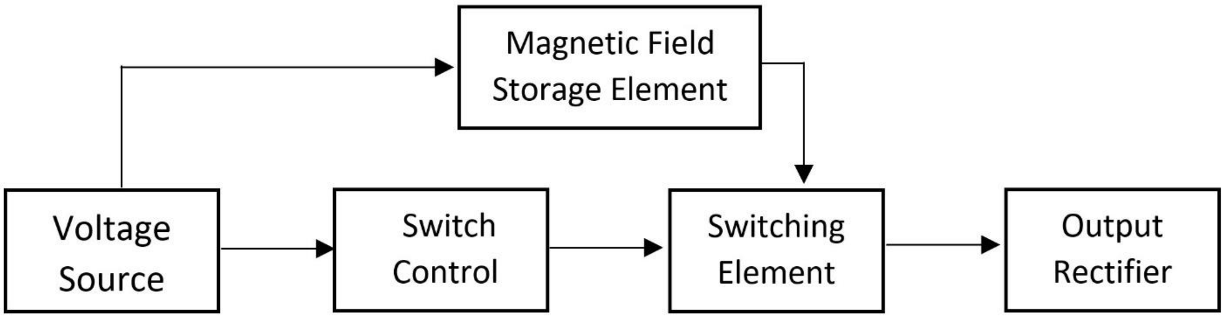

Figure 8 The Designed Block Diagram of a DC-DC Ultra Lift Luo Converter

The block diagram components and descriptions:

PV Array (Input Voltage Source):

The PV array produces a low and unregulated DC voltage as it converts solar energy into electrical power, which serves as the initial DC input voltage for the converter.

Switch Control

The component referred to as the Insulated Gate Bipolar Transistor (IGBT) integrates control circuitry responsible for managing the switching function. Through switch control, it modulates the IGBT's duty cycle, thereby regulating energy transfer and directing the switching element to control the voltage conversion process effectively [40].

The inductors (L1, and L2) play a critical role in the circuit dynamics by harnessing and storing energy within their magnetic field when the switch is turned on. When the switch deactivates, the inductors releases this stored energy, which helps in stabilizing the current flow and enabling efficient voltage amplification. This cycle of energy storage and release ensures smooth operation of the circuit, minimizing fluctuations and optimizing performance. By managing the flow of electrical energy, the inductors contributes significantly to maintaining stability and enhancing the overall efficiency of the circuit, supporting its function in various electronic applications [41].

Capacitors (Energy Storage)

Two capacitors, C1 and C2, of equal value, function to store and filter energy within the circuit. They work together to ensure a steady output voltage, smoothing fluctuations and minimizing ripple effects, thereby contributing to a consistent and stable electrical output [42, 43].

Diodes

Diodes D1, D2, and D3 serve the purpose of facilitating current flow in a single direction while preventing reverse flow, ensuring efficient energy transfer and supporting voltage elevation by maintaining a unidirectional current path [44, 45].

Output Rectifier and Filter

The setup includes capacitors and supplementary diodes designed to guarantee that the output voltage remains stable, devoid of noticeable fluctuations, thereby supplying a consistent high DC voltage to the load [46].

With the DC source providing an input voltage (V_{pv} = 10V) and applying the designated duty cycle D=0.6 to the DC-DC Ultra Lift Luo converter, we utilize this data to compute the anticipated output voltage (V_o = 52V). This calculation hinges on the converter's operational parameters and the relationship between input voltage, duty cycle, and resulting output voltage, as outlined in the converter's specifications and operational principles [47, 48].

The transfer gain (K) and the equations previously outlined offer insights into how the input voltage relates to the output voltage, elucidating the conversion mechanism. By leveraging these equations, one can comprehend the transformation process from the input to the output voltage within the operational framework of the system [49, 50].

$$K = V_o / V_{in} = D(2-D) / (1-D)^2$$

$$K = 0.6(2-0.6) / (1-0.6)^2 = 5.25$$

$$K = 5.25.$$

Now, set up the equation:

$$K = V_o / V_{in}$$

Cross-multiply to solve for V_o:

$$5.25 \times 10 = V_o$$

$$Vo = 52.5V$$

Verify the Gain (K)

Now substitute V_o back into the gain formula to verify:

$$K = 52.5 / 10$$

$$K = 5.25$$

The calculated gain K matches our initial calculation, confirming that K = 5.25.

This computation validates the recorded output voltage of 52.5V when supplied with a 10V input and operated at a 60% duty cycle, affirming the accuracy of the simulation's outcomes [51].

Figure 9 depicts the experimental setup and simulation outcomes using a block diagram. The results confirm that by employing a 60% duty cycle, the converter effectively increases the input voltage of 10V from the DC source to 52.5V as demonstrated in the Ultra Lift Luo converter's output [52, 53].

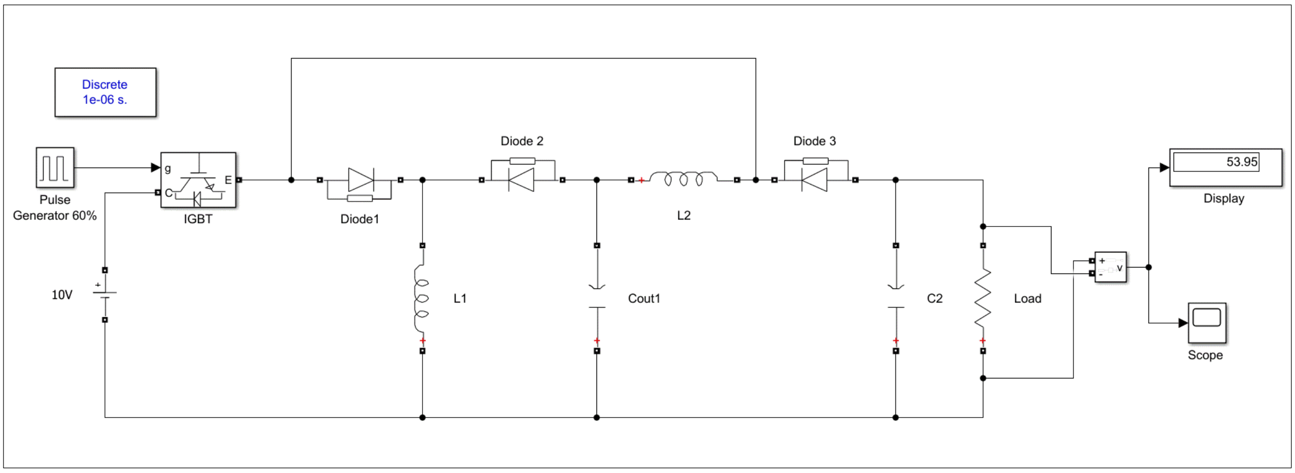

Figure 9 ULL MATLAB/Simulink at 60% Duty Pulse Generator

The analysis and evaluation using calculations and block diagrams are consistent with the simulation outcomes, confirming the efficacy of the Ultra Lift Luo converter in elevating the voltage from a DC source. This converter efficiently enhances the input voltage, delivering a stable and elevated output voltage suitable for a wide range of applications [54, 55].

The Ultra Lift Luo converter stands out for its efficiency in elevating voltage levels. Figure 10 illustrates how its output voltage rises swiftly and consistently, demonstrating superior performance compared to conventional converters like Cuk or Boost, which frequently experience overshooting and extended stabilization phases. Both theoretical calculations and simulations confirm the converter's robustness, highlighting its suitability for integrating photovoltaic systems with external loads that demand stable, regulated higher voltages [56, 57]. This capability ensures reliable power supply adaptation, crucial for applications requiring consistent energy delivery without fluctuations, thus enhancing the overall reliability and efficiency of renewable energy systems in practical use scenarios [58, 59].

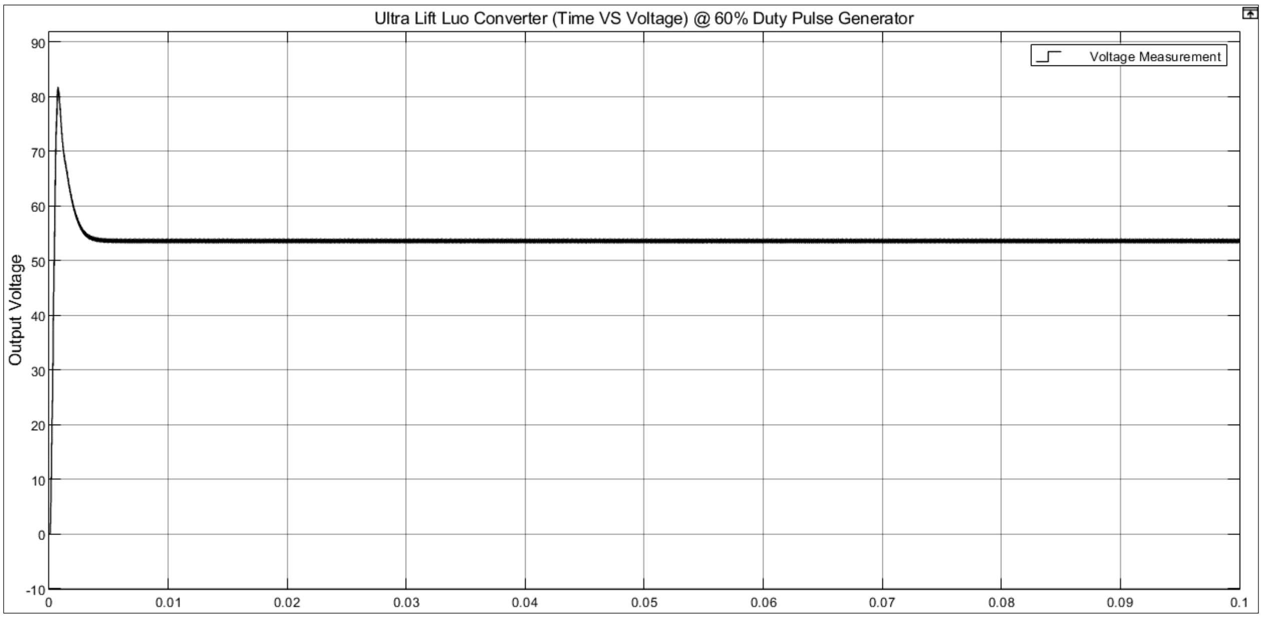

Figure 10 Ultra Lift Luo Converter Time VS Voltage at 60% Duty Pulse Generator

Artificial Intelligence (AI) controllers are becoming more prevalent in enhancing the effectiveness and efficiency of photovoltaic (PV) systems. One effective method involves integrating Artificial Neural Networks (ANNs) to optimize the Maximum Power Point (MPP) tracking of PV arrays. This AI-driven approach helps improve overall system performance by dynamically adjusting to changing environmental conditions and maximizing energy output from solar panels [60, 61].

Training the ANN with a broad and varied dataset markedly improved the PV system's performance. Among the data sets tested, the ANN trained with 1001 samples proved most effective, ensuring robust and dependable operation under diverse conditions and maximizing efficiency in tracking the MPP [62, 63].

Upon analysis, the ANN controller trained with 1001 random data samples was integrated into the PV system to ensure consistent MPP tracking, optimize power output, and maintain efficiency across varying environmental conditions. Utilizing MATLAB/Simulink for simulation and training offered a solid foundation to develop and validate the ANN controller, confirming its efficacy for practical implementation in real-world scenarios [64].

2.4. Artificial Neural Network (ANN)

To improve the performance and efficiency of photovoltaic (PV) systems, the integration of Artificial Intelligence (AI) controllers has become increasingly popular. One effective AI method is using Artificial Neural Networks (ANNs) to track the Maximum Power Point (MPP) of the PV array [65].

To ensure the optimal training and efficiency of the ANN controller for MPP tracking, a thorough comparison was performed using different random data sample sets. The aim was to identify the best random sample data set to achieve the highest efficiency in tracking the MPP. The sample sets used in the comparison included 104, 201, and 1001 random data points.

From the comparison, it was found that the ANN controller trained with 1001 random data samples provided the best results. Implementing this in the PV system ensured reliable MPP tracking, maximizing power output and maintaining efficient operation under varying environmental conditions. MATLAB/Simulink was used for simulation and training, offering a robust framework for developing and testing the ANN controller, and ensuring its effectiveness in real-world applications.

2.5. Recurrent Neural Network (RNN)

To further improve the efficiency of the PV system, a Recurrent Neural Network (RNN) was introduced. The RNN's distinctive architecture, featuring feedback connections within its inner layers, makes it especially suitable for managing time-dependent data and nonlinear input variations. This capability is essential for real-time tracking of the maximum power point (MPP), ensuring the PV array operates at optimal performance [66].

To guarantee the optimal training and performance of the RNN controller for MPP tracking, an extensive comparison was carried out using different random data sample sets. The objective was to identify the most effective sample size for achieving the highest efficiency in MPP tracking. The sample sets used in the comparison consisted of 104, 201, and 1001 random data points.

The results indicated that the RNN controller trained with 1001 random data samples provided the best performance. Implementing this configuration in the PV system ensured reliable MPP tracking, maximized power output, and maintained efficient operation under a variety of environmental conditions. The use of MATLAB/Simulink for simulation and training offered a robust framework for developing and testing the RNN controller, ensuring its effectiveness in practical applications.

3. Results and Discussion

3.1. Artificial Neural Network (ANN)

In Table 2, employing a P&O controller achieved an efficiency of 88.4776%. Introducing an ANN controller with 104 samples increased efficiency to 92.7422%, 92.9241% for 201 samples, and 94.8043% for 1001 samples, surpassing the P&O controller's performance. The significant improvement from 104 to 1001 samples highlights the critical role of a larger and diverse dataset in effectively training the ANN controller. Integrating ANN controllers, particularly with extensive sample sizes, markedly enhances PV system efficiency compared to conventional P&O controllers. These findings underscore the efficacy of AI techniques in maximizing power output and enhancing overall system performance across diverse environmental conditions. Implementing an ANN controller for MPP tracking in PV systems notably improves overall efficiency compared to traditional P&O methods. The benefits of larger training datasets are evident in the ANN's enhanced ability to accurately predict and track MPP under varying environmental conditions, ensuring optimal system operation and energy yield.

Table 2 Comparison of All Used ANN Controllers

No.	Controller Type	Efficiency
1	P&O	88.4776%
2	ANN using 104 Random samples	92.7422%
3	ANN using 201 Random samples	92.9241%
4	ANN using 1001 Random samples	94.8043%

3.2. Recurrent Neural Network (RNN)

Table 3 illustrates that employing a P&O controller yielded an efficiency of 95.4102%. Introducing an RNN controller with 104 data samples resulted in a decrease to 92.5256%, followed by improvements to 95.8761% and 97.7182% with 201 and 1001 samples, respectively, outperforming the P&O controller. This notable enhancement from 104 to 1001 samples underscores the critical role of a larger and more diverse dataset in effectively training the RNN controller. Integrating RNN controllers, particularly with larger sample sizes, significantly boosts PV system efficiency compared to conventional P&O controllers. These findings underscore the efficacy of AI techniques in maximizing power generation and enhancing overall system performance under varying environmental conditions. Implementing an RNN controller for MPP tracking alongside a DC-DC Ultra Lift Luo converter in PV systems substantially improves overall efficiency compared to traditional P&O methods, particularly with expanded training datasets. These outcomes highlight the RNN's superior capability to precisely predict and maintain MPP under diverse environmental conditions, emphasizing the pivotal importance of dataset size in optimizing performance.

Table 3 Comparison of All Used RNN Controllers

No.	Controller Type	Efficiency
1	P&O	95.4102%
2	RNN using 104 Random samples	92.5256%
3	RNN using 201 Random samples	95.8761%
4	RNN using 1001 Random samples	97.7182%

4. Conclusion

In conclusion, our study successfully implemented AI-based ANN and RNN controllers using MATLAB/Simulink to optimize PV system performance. We compared these controllers using varied sample sizes and integrated them with a DC-DC Ultra Lift Luo converter for voltage boosting and impedance matching. Both ANN and RNN controllers predicted maximum output voltage based on nonlinear inputs like irradiance and temperature. The RNN showed superior accuracy and efficiency, especially with a 1001-sample set, highlighting its robust MPP tracking capability. An RNN controller for the DC-DC Ultra Lift Luo converter achieved higher efficiency reaching 97.7182%. Real PV systems, controlled by an RNN controller, will now be efficiently managed with almost 17% increase in efficiency compared to not using a controller at all. Future research should explore larger data sets and diverse AI approaches to further enhance PV system efficiency and reliability in real-world applications, advancing renewable energy technology effectively.

Compliance with ethical standards

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Disclosure of conflict of interest

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

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