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Enhancement of solar energy utilization through an artificial neural network controller featuring a dynamic learning rate and a positive output super lift luo converter

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Abstract

With the increasing demand for sustainable energy solutions, enhancing the efficiency of photovoltaic (PV) systems is critical. PV systems, although effective, often face efficiency variations due to changes in irradiance and temperature. This study aims to address these challenges by integrating a Positive Output Super Lift Luo (P/O SLL) converter with an Artificial Neural Network (ANN) controller utilizing a dynamic learning rate. Known for its high voltage conversion gain, the P/O SLL converter is ideal for various load requirements in PV systems. The ANN controller with a dynamic learning rate adapts to real-time environmental changes, outperforming static learning rate methods. This approach allows the ANN to manage non-linear and variable inputs from PV cells more efficiently, optimizing the Maximum Power Point Tracking (MPPT) process. The research involved simulating a PV system model using MATLAB/Simulink, integrating the P/O SLL converter and ANN controller. The study compared the performance of the ANN controller with a dynamic learning rate against a static learning rate, using 201 data samples for training. The results showed improvements in energy conversion efficiency, with the dynamic learning rate providing more stable voltage and power outputs under varying conditions, demonstrating its potential in enhancing PV system performance.

Keywords: Artificial neural network; DC-DC positive output souper lift luo converter; Dynamic learning rate; Maximum power point tracking; Photovoltaic system; Static learning rate

1. Introduction

Transitioning to renewable energy sources is essential to reduce the environmental impact of fossil fuel consumption. Fossil fuels, while historically vital for industrial development, significantly contribute to pollution and global warming. As environmental awareness grows, there is a strong emphasis on adopting sustainable energy solutions. Renewable energy sources, such as solar power, offer a cleaner alternative to fossil fuels, helping to meet global energy demands sustainably [1].

Among renewable technologies, photovoltaic (PV) systems are notable for converting sunlight directly into electricity. PV systems harness solar energy, one of the most abundant and renewable resources. This technology reduces reliance on fossil fuels and lowers greenhouse gas emissions, playing a crucial role in combating climate change. However, PV system efficiency is affected by environmental factors like irradiance and temperature, which can vary throughout the day and across seasons. These fluctuations pose significant challenges in maintaining optimal performance, often leading to suboptimal energy conversion [2].

To overcome these challenges, advanced power electronic devices, such as DC-DC converters, are utilized. The Positive Output Super Lift Luo (P/O SLL) converter is particularly effective in boosting and regulating voltage levels to meet

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varying load demands efficiently. The P/O SLL converter is renowned for its high voltage conversion gain and its ability to handle a wide range of input conditions, making it ideal for PV systems. By managing power output efficiently, P/O SLL converters enhance the overall efficiency of PV systems [3].

The effectiveness of the P/O SLL converter largely depends on the control strategy employed. Traditional controllers, like Proportional-Integral-Derivative (PID) controllers, often struggle with the dynamic and non-linear nature of PV inputs. These controllers can be slow to respond to rapid environmental changes, resulting in suboptimal performance. Therefore, more advanced control techniques are needed to provide better adaptability and efficiency [4].

This study introduces an Artificial Neural Network (ANN) controller with a dynamic learning rate to address these limitations. The ANN controller continuously adjusts the learning rate in real-time, enhancing the system's ability to adapt to changing conditions. Unlike static learning rate methods, the dynamic learning rate allows the ANN to respond more effectively to the non-linear and variable nature of PV inputs, ensuring optimal performance and higher efficiency even under fluctuating environmental conditions.

Our research investigates the integration of the ANN controller with a P/O SLL converter in a simulated PV system model using MATLAB/Simulink. The study compares the performance of the ANN controller with a dynamic learning rate against traditional static learning rate methods. The findings indicate significant improvements in energy conversion efficiency, with the dynamic learning rate achieving better adaptability and stability under varying irradiance and temperature conditions. These results highlight the importance of advanced control strategies in enhancing renewable energy technologies and optimizing PV system efficiency [5].

The potential of dynamic learning rates in optimizing PV system performance underscores their significance for the future of renewable energy. As the demand for sustainable energy solutions grows, integrating advanced control techniques like the ANN with dynamic learning rates will be crucial in maximizing PV system efficiency and reliability. This study contributes to the growing body of research focused on improving renewable energy technologies, demonstrating that innovative approaches can lead to significant advancements in performance and sustainability.

This paper is sectioned as:

Section 2: Material and methods

PV System Description and Modeling

- Comprehensive outline of the 213.15-Watt photovoltaic (PV) array model.
- Overview of the fundamental block diagram of PV arrays.
- Analysis of the design and functionality of solar cells utilizing p-n semiconductor junctions.
- Examination of the inputs (irradiance and temperature) and the outputs (voltage and power) of the PV array model.
- Techniques employed for simulating and assessing the PV system under various conditions.
- DC – DC Positive Output Super Lift Luo Converter Design and Model.

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 proficiency in managing non-linear and variable inputs, specifically irradiance (G) and temperature (T).

Section 3: Results and Discussion

- • Evaluation of ANN 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 4: Conclusion

- Summary of the key findings from the study.
- Contributions to the field of renewable energy and PV system optimization.
- Recommendations for future research directions.

- Closing remarks on the potential impact of using AI controllers in enhancing PV system performance.

2. PV System Model

This section presents a comprehensive overview of the PV system model, detailing its components and the integration of the ANN controller. The PV array model accepts Solar Irradiance (G) and Temperature (T) as inputs and produces Voltage and Power outputs for the ANN controller. The system utilizes a DC-DC Positive Output Super Lift Luo (P/O SLL) Converter, which is crucial in adjusting the operating point to maximize power output as seen in Figure 1. The reference voltage (V_{pv}) is dynamically generated based on predictions from the ANN algorithm, which employs a dynamic learning rate. This dynamic learning rate enables the ANN controller to adapt in real-time to varying environmental conditions, ensuring optimal performance and efficient real-time optimization of the PV system [6].

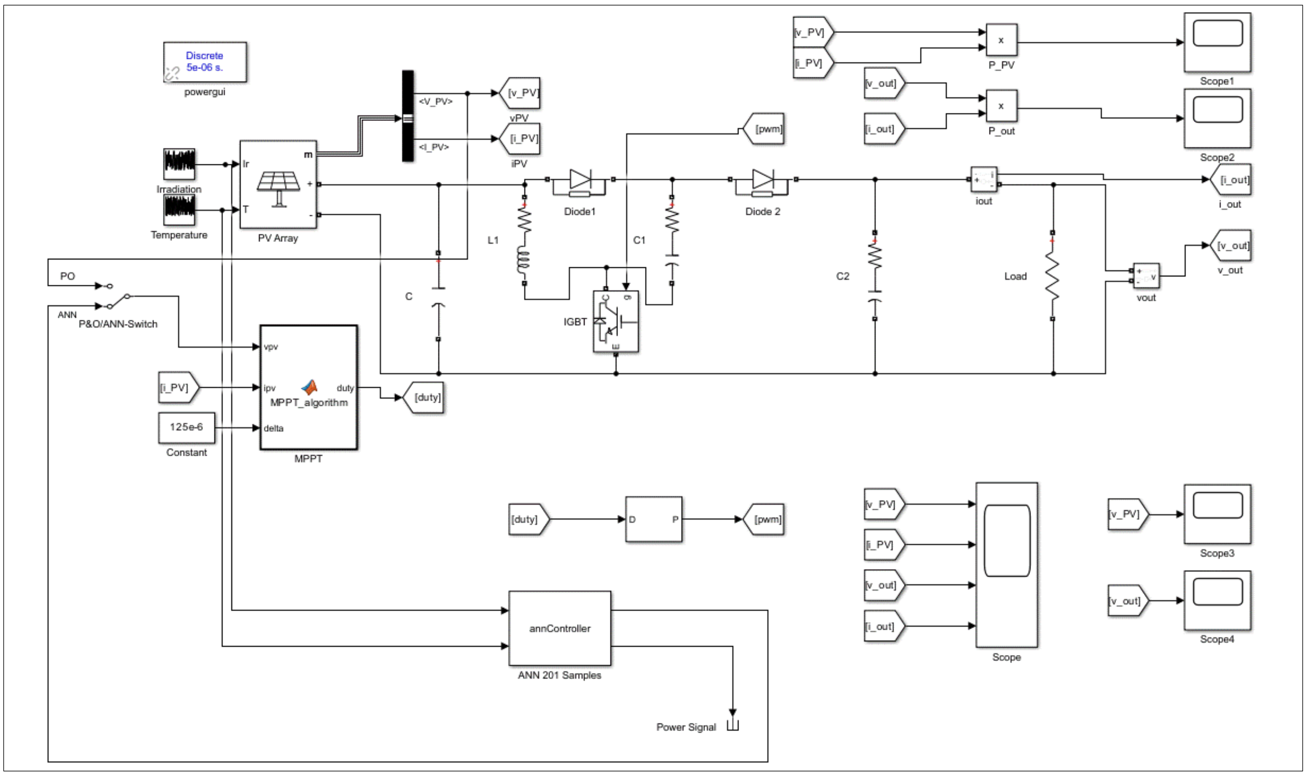

Figure 1 MATLAB/Simulink diagram for The Proposed PV system

2.1. Mathematical Solar Array Modeling

Mathematical modeling of solar arrays is vital for comprehending and forecasting the performance of photovoltaic (PV) systems under different environmental conditions. The main goal of this modeling is to accurately depict the electrical properties of the solar array, which generally consists of numerous solar cells connected in series and/or parallel configurations. The core equation that governs the output current (I) of a solar cell is derived from the Shockley diode equation, modified to incorporate the effects of solar irradiance and temperature. This equation accounts for the photo-generated current (I_{ph}), the diode saturation current (I_D), the series resistance (R_s), the shunt resistance (R_{sh}), and the current through the shunt resistance (I_{sh}), among other parameters. As illustrated in Figure 2, the resulting I-V characteristic curve at a specified irradiances offers a detailed representation of the cell's performance, which is essential for optimizing the operation of the entire PV system [7].

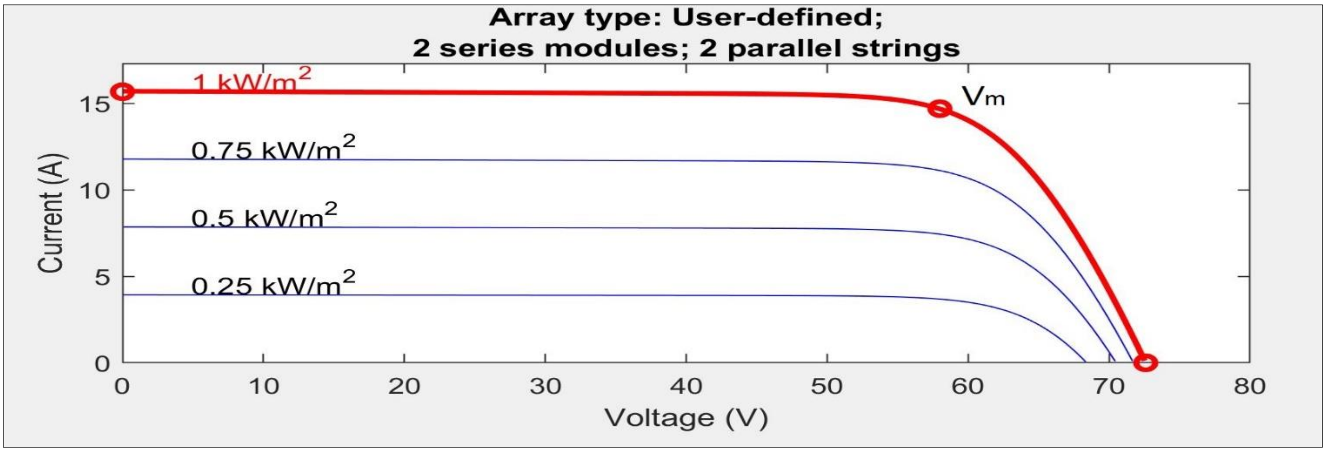

Figure 2 V-I characteristics curves of the PV array at a specified irradiance

$$I = I_{ph} - I_D - I_{sh} \quad \ldots\ldots (1)$$

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.

This investigation highlights the intricate modeling of a 213.15-Watt photovoltaic (PV) array, focusing on its construction utilizing p-n semiconductor junctions and its sensitivity to fluctuating solar irradiance and temperature. Key metrics such as voltage and power outputs are essential for evaluating the PV array's efficiency, which is crucial for its integration into renewable energy systems. Accurate modeling supports AI-based predictions and performance enhancements of the PV array under diverse environmental conditions.

2.2. Modeling and Simulation of 213.15W PV array

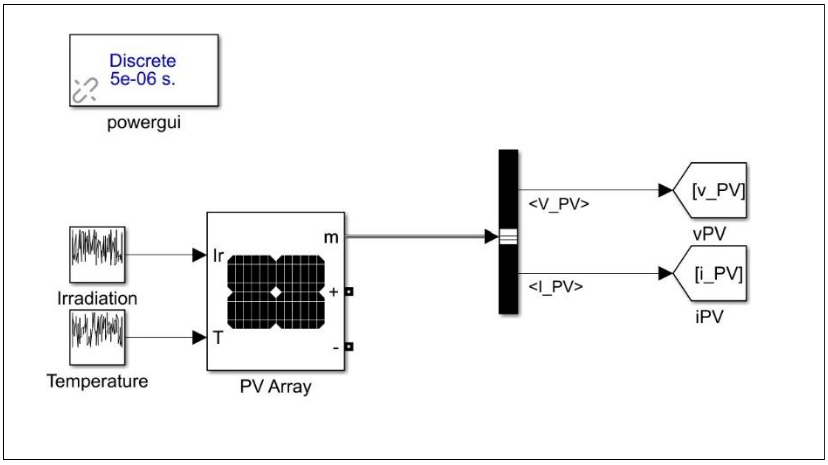

Figure 3 MATLAB/Simulink for the proposed designed PV array model

The study utilized a 213.15-Watt photovoltaic (PV) array, carefully selected from the MATLAB/Simulink toolbox for simulation. This choice provided access to detailed information on the array's electrical properties and included visual aids to demonstrate its performance under varying temperature and irradiance conditions. Figure 3 illustrates the selected PV array model from MATLAB/Simulink, highlighting its response to different environmental factors. Furthermore, Table 1 outlines the array's electrical parameters, offering a comprehensive understanding of its capabilities and performance metrics across various operational scenarios. These parameters are essential for predicting the array's behavior and optimizing its integration into renewable energy systems. Utilizing

MATLAB/Simulink's advanced simulation tools enabled precise modeling and analysis, supporting the development of efficient and resilient PV systems [8].

Table 1 Electrical Characteristics of The PV Module

Description	User-defined
Maximum power	312.15 W
Voltage at Pmax (V_{max})	29.00 V
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 the relationship between the voltage and current output of the PV array under specific conditions, as shown in Figure 4. This curve is essential for analyzing the PV array's performance at different temperatures, particularly at 25 °C and 45 °C. The graph shows that the current output remains relatively stable as voltage increases until it approaches a critical point near the open-circuit voltage, after which the current output decreases sharply. Understanding this behavior is crucial for optimizing the PV array's performance and ensuring efficient operation under diverse environmental conditions.

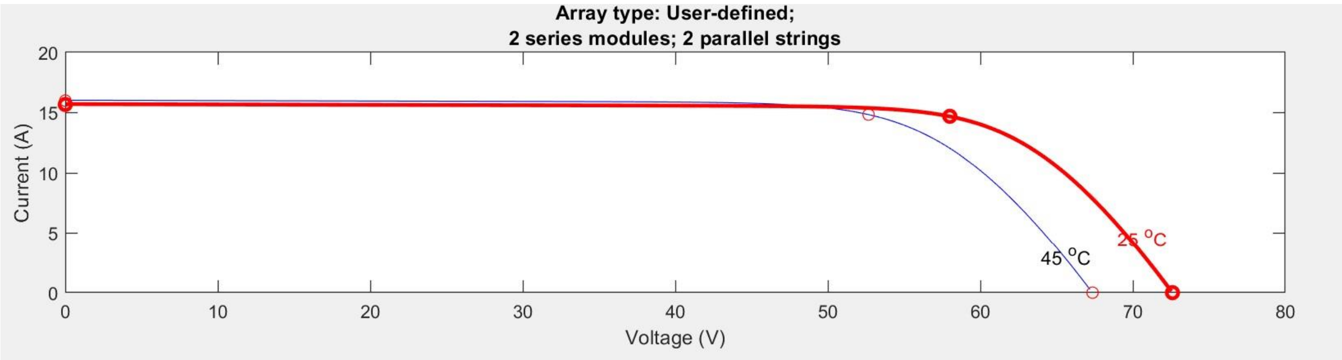

Figure 4 Voltage-current (V-I) characteristics curve at a temperature of 25 °C and 45 °C

2.3. Advanced Positive Output Super Lift Luo Converter Model

2.3.1. Overview of the Positive Output Super Lift Luo Converter

The DC-DC Positive Output Super Lift Luo (P/O SLL) converter is an advanced component engineered to efficiently convert and regulate voltage levels within photovoltaic (PV) systems. It is specifically designed to elevate the typically low and fluctuating output voltage from PV arrays to a more stable and usable level, making it ideal for practical applications [9].

- **Increased Power Density:** The P/O SLL converter's advanced design allows for higher power density compared to conventional converters like Boost, Cuk, and SEPIC. By utilizing smaller and more efficient components, the converter can deliver higher power output in a more compact form factor, making it ideal for space-constrained applications.
- **Reduced Electromagnetic Interference (EMI):** Traditional converters often generate significant electromagnetic interference, which can affect nearby electronic devices and degrade overall system performance. The P/O SLL converter employs advanced filtering techniques and optimized switching sequences to minimize EMI. This results in a cleaner power output and ensures compatibility with sensitive electronic equipment.
- **Improved Thermal Management:** Efficient thermal management is crucial for maintaining converter performance and longevity. The P/O SLL converter features enhanced thermal dissipation mechanisms, such as

integrated heat sinks and optimized airflow designs. These improvements help maintain lower operating temperatures, reducing thermal stress on components and extending the converter's operational life.

- **Dynamic Load Handling:** The P/O SLL converter excels in handling dynamic load conditions, where the power demand varies rapidly. Its advanced control algorithms and high-frequency operation allow for quick adaptation to changing loads, ensuring consistent voltage output and stable performance.
- **Wider Input Voltage Range:** The converter's ability to operate effectively over a broader range of input voltages makes it highly versatile. This flexibility is particularly beneficial in renewable energy applications, where input power sources can vary widely. The P/O SLL converter can accommodate these variations without compromising efficiency or performance, making it an excellent choice for integrating photovoltaic systems with external loads.

2.3.2. Application in Photovoltaic Systems

- **Managing Unregulated PV Output**: Photovoltaic (PV) systems generally produce an unregulated output voltage that fluctuates with changes in solar irradiance and temperature. This unregulated output is often insufficient for directly powering loads or integrating with the electrical grid. The Positive Output Super Lift Luo (P/O SLL) converter plays a crucial role in addressing this issue by converting and stabilizing the fluctuating voltage output of PV systems.
- **Voltage Stabilization**: The P/O SLL converter is vital for boosting and stabilizing the voltage output from PV arrays. By providing controlled voltage enhancement, it ensures consistent and reliable power output, making it suitable for various electronic devices and systems. Maintaining a steady output allows for the efficient utilization of solar-generated electricity, thereby improving the overall performance and reliability of the PV system.

2.3.3. Integration with External Loads

- **Optimizing Power Delivery**: The P/O SLL converter enhances the PV system's ability to deliver stable and reliable power to external loads. It ensures that the voltage output meets the required standards, thereby enhancing the dependability and operational effectiveness of the entire PV system.

Key Components of the P/O SLL Converter

- **Switch:** The Insulated Gate Bipolar Transistor (IGBT) functions as a critical semiconductor switch, regulating the converter's duty cycle and operational efficiency.
- **Diodes:** Standard diodes (D_1, and D_2) are essential for directing current flow in one direction while blocking reverse current, ensuring proper operation and preventing undesirable electrical feedback.
- **Energy Storage Components:** Inductors (L_1) store energy in the form of a magnetic field, promoting consistent current flow and enhancing system stability. Capacitors (C_1 and C_2) smooth out voltage fluctuations, ensuring a stable power supply. Both capacitors are designed with identical values, contributing equally to the circuit's stability and efficiency.
- **Voltage Elevation Technique:** The P/O SLL converter employs an advanced voltage elevation technique to consistently raise the output voltage above the input voltage from the PV array. This method incrementally increases the voltage using a geometric progression, ensuring the output remains positively offset from the input. This design guarantees efficient power transformation, maximizing the converter's performance across various applications. It ensures reliable operation by maintaining a stable output voltage, optimizing the overall efficiency and functionality of the system.
- **Operational Principles and Dynamic Response:** The functional principles and dynamic response of the P/O SLL converter are defined by specific equations that elucidate its operational mechanisms and interactions with varying input parameters. These equations provide a clear understanding of how the converter effectively manages voltage transformation, ensuring optimal performance and efficiency.

The connection between the input voltage (V_{in}), output voltage (V_O), and transfer gain for the Ultra Lift Luo converter is governed by a specific mathematical equation. This equation illustrates how variations in V_{in} influence V_o, scaled by the factor K. It is essential for understanding how the converter amplifies the input voltage to produce the desired output voltage, which is crucial for determining its operational characteristics and efficiency in various applications [10]:

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

This formula provides a quantitative understanding of the voltage amplification process. It illustrates how the input voltage (V_{in}) is converted into the output voltage (V_O) by the P/O SLL converter.

This equation is essential for predicting the behavior of the converter under different operating conditions. By applying this formula, engineers can accurately determine the output voltage for a given input voltage and duty cycle, which is crucial for designing and optimizing the performance of PV systems integrated with P/O SLL converters. This ensures that the converter operates efficiently and delivers the desired voltage levels required for various applications.

The DC-DC Positive Output Super Lift Luo (P/O SLL) converter is a sophisticated and highly efficient device engineered to elevate voltage levels while preserving the same polarity. It employs key components such as Insulated Gate Bipolar Transistors (IGBTs), diodes, inductors, and capacitors to achieve substantial voltage amplification, ensuring stable output with minimal ripples and disturbances. The converter's design principles are encapsulated in its operational equations, which are crucial for engineers to design, optimize, and assess its performance across various applications, particularly in photovoltaic (PV) systems.

These operational equations provide insights into the converter's voltage transformation capabilities, ensuring reliable and efficient power conversion from solar energy sources to meet diverse electrical requirements. The functional dynamics of the P/O SLL converter are further elucidated through its block diagram, depicted in Figure 5, which outlines the core components and the flow of electrical energy within the system. This schematic representation is essential for understanding the converter's architecture and the interactions between its IGBTs, diodes, inductors, and capacitors. Grasping these interactions is key to appreciating how the converter effectively boosts voltage without inversion, making it indispensable for various electronic and energy system applications.

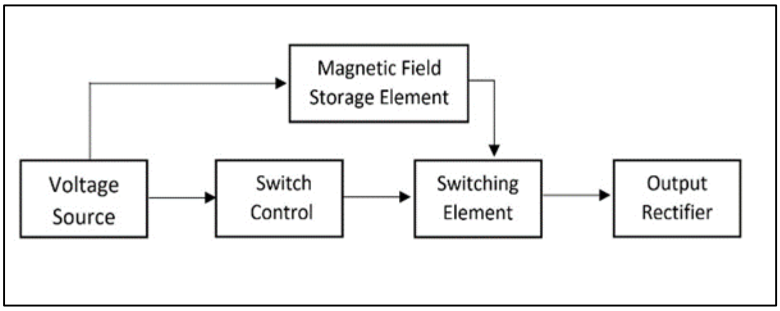

Figure 5 The Designed Block Diagram of a DC-DC Positive Output Super Lift Luo Converter

Using Equation 2, we can calculate the output voltage of the DC-DC Positive Output Super Lift Luo (P/O SLL) converter given an input voltage (V_{pv}) of 12V. This voltage is applied to the input terminals of the converter. For our block diagram test, we will start with a duty cycle (D) of 65.2%. The resulting stepped-up output voltage (V_O) is observed to be 46.48V.

Given the input voltage (V_{pv}=12V) from the DC source and the duty cycle for the P/O SLL converter, we can use the information provided to calculate the expected output voltage (V_O=46.48).

From the equations provided earlier, the transfer gain (K) and the relationship between input and output voltages help us understand the conversion process. Specifically, the relationship can be expressed as:

$$K = (2 - D) / (1 - D)$$

$$K = (2 - 0.652) / (1 - 0.652)$$

$$K = 3.873$$

Now:

$$K = Vo / Vin$$

$$Vo = 3.873 \times 12$$

$$Vo \approx 46.48.$$

This calculation confirms the observed output voltage of ≈ 46.48V for an input of 12V with a 65.2% duty cycle, demonstrating the correctness of the simulation results.

Figure 6 depicts the experimental setup and simulation outcomes using MATLAB/Simulink. Figure 6 also, illustrates the MATLAB/Simulink test setup and simulation results. The simulation confirms that with a 65.2% duty cycle, the input voltage of 12V from the DC source is successfully stepped up to 46.48V at the output of the Positive Output Super Lift Luo converter [11].

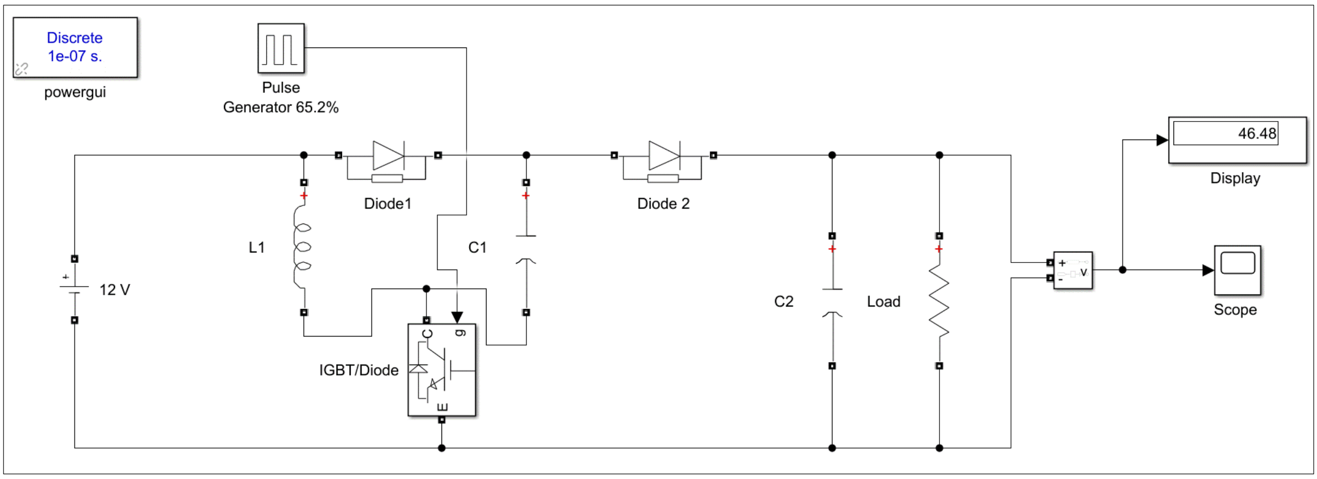

Figure 6 MATLAB/Simulink at 65.2% Duty Pulse Generator

The analysis and evaluation, incorporating both calculations and block diagrams, align seamlessly with the simulation outcomes, affirming the effectiveness of the Positive Output Super Lift Luo (P/O SLL) converter in boosting voltage from a DC source. This converter demonstrates exceptional efficiency in elevating input voltage to a stable and higher output voltage, making it highly suitable for diverse applications.

Figure 7 highlights the converter's capability, showing a rapid and consistent rise in output voltage, which outperforms traditional converters such as Cuk or Boost that often suffer from overshooting and prolonged stabilization periods. Both theoretical calculations and simulations underscore the converter's robustness, making it an ideal choice for integrating photovoltaic systems with external loads requiring stable, regulated higher voltages [12] [13].

The P/O SLL converter ensures a reliable power supply, essential for applications demanding consistent energy delivery without fluctuations. This significantly enhances the reliability and efficiency of renewable energy systems in practical scenarios. The results confirm that the P/O SLL converter is highly effective in converting and stabilizing the voltage output from photovoltaic systems, ensuring optimal performance and efficient energy utilization.

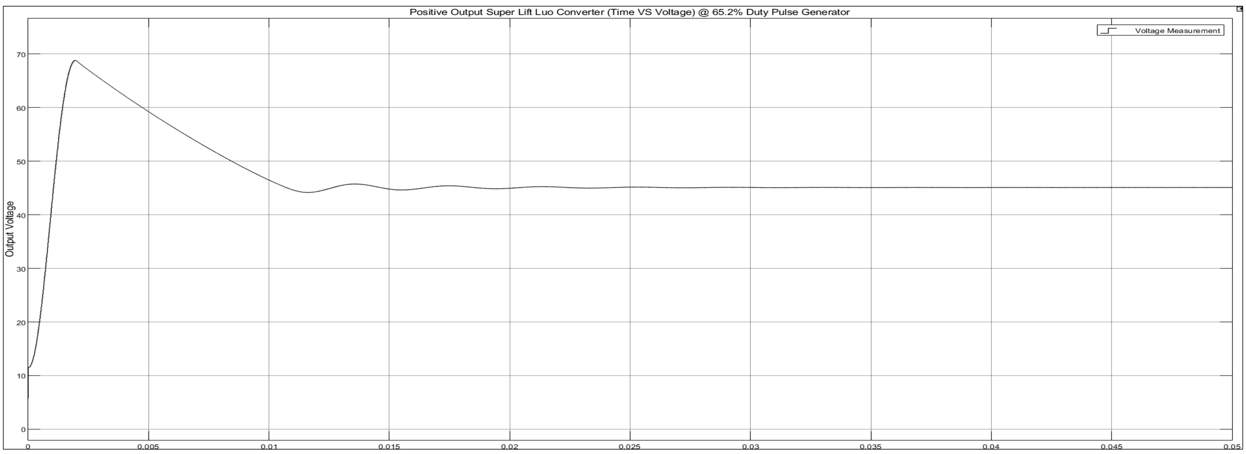

Figure 7 Positive Output Super Lift Luo Converter Time VS Voltage at 65.2% Duty Pulse Generator

2.4. Artificial Neural Network (ANN)

Adopting Artificial Intelligence (AI) controllers has become increasingly prevalent in boosting the performance and efficiency of photovoltaic (PV) systems. Among the various AI methodologies, the use of Artificial Neural Networks

(ANNs) has demonstrated considerable potential in optimizing the Maximum Power Point (MPP) tracking of PV arrays. ANNs enhance system performance by dynamically adapting to fluctuating environmental conditions, thereby maximizing the energy harvested from solar panels [14].

ANNs facilitate real-time adaptability, essential for maintaining high efficiency amid changing weather conditions. These networks are adept at learning and adjusting to the non-linear behaviors of PV systems, enabling precise real-time optimization. By continuously refining the operating parameters based on real-time data, ANNs ensure that the PV system consistently operates at its optimal power point, even with variations in irradiance and temperature.

The development and validation of these AI controllers are greatly supported by advanced simulation tools like MATLAB/Simulink. These platforms provide comprehensive environments for modeling, simulating, and testing the performance of ANN-based controllers under diverse conditions. MATLAB/Simulink allows researchers to construct detailed models of PV systems and ANN controllers, simulate their interaction, and adjust the controllers to achieve optimal performance. This rigorous process ensures that ANN controllers are well-validated and optimized before practical deployment, thus enhancing the overall efficiency and reliability of PV systems in real-world applications.

2.5. Comparative Analysis with Dynamic Learning Rate

In this research, we enhanced the training of the Artificial Neural Network (ANN) controller by utilizing a dataset of 201 random samples. We assessed the efficiency of the ANN with a static learning rate compared to an ANN with a dynamic learning rate. The findings revealed that the ANN with a dynamic learning rate significantly outperformed its static counterpart. The dynamic learning rate enabled the ANN to better adapt to varying environmental conditions, ensuring consistent Maximum Power Point (MPP) tracking, optimized power output, and sustained efficiency. These results were confirmed through MATLAB/Simulink simulations, which demonstrated the improved performance and reliability of the dynamically trained ANN controller. This progress highlights the superior adaptability and efficiency of the dynamic learning rate, positioning it as a crucial improvement for contemporary PV systems aiming for optimal renewable energy generation.

Previous work employed a static learning rate for the ANN controller integrated with the Positive Output Super Lift Luo (P/O SLL) converter in PV systems. While this approach resulted in improvements in voltage regulation and efficiency, it limited the ANN's ability to swiftly adapt to rapid changes in environmental conditions, such as fluctuating solar irradiance and temperature.

In the current study, a dynamic learning rate was introduced for the ANN controller, allowing real-time adjustments based on the operating conditions. This dynamic approach greatly enhances the system's responsiveness to environmental variations, optimizing the MPP tracking process and overall system performance [15].

The dynamically enhanced ANN controller was simulated using MATLAB/Simulink, incorporating the P/O SLL converter. The simulations showed that the dynamic learning rate considerably improved the system's adaptability and efficiency compared to the static learning rate approach. This method not only achieved better voltage regulation but also ensured more stable power outputs, which is essential for dependable energy delivery in practical applications.

The comparative analysis demonstrated that the dynamic learning rate offers a more effective solution for integrating PV systems with external loads, ensuring consistent and efficient energy conversion. This development underscores the importance of adaptive control strategies in boosting the performance and reliability of renewable energy systems, paving the way for more resilient and efficient PV applications.

3. Results and Discussion

3.1. Artificial Neural Network (ANN) Static VS Dynamic Learning Rate

Table 2 presents the efficiency comparison of the ANN controller using 201 samples, evaluated with both static and dynamic learning rates. The ANN controller with a static learning rate achieved an efficiency of 91.8293%. However, when a dynamic learning rate was introduced, the performance improved, demonstrating an efficiency increase to 91.8834%.

These results highlight the crucial role of dynamic learning rates in optimizing the performance of ANN controllers. By allowing the learning rate to adjust in real-time, the ANN can more effectively respond to varying environmental conditions, thereby enhancing the Maximum Power Point (MPP) tracking process. This adaptability results in more efficient power output and overall improved system performance compared to the static learning rate approach.

The improvement in efficiency with the dynamic learning rate underscores its importance in modern PV systems. By providing real-time adjustments, the dynamic learning rate ensures that the ANN controller maintains optimal performance even under fluctuating environmental conditions, leading to more reliable and efficient energy conversion.

Table 2 Comparison of ANN Controllers with Static and Dynamic Learning Rates (201 Samples)

No.	Controller Type	Efficiency
1	ANN with 201 Samples (Static Learning Rate) [16]	91.8293%
2	ANN with 201 Samples (Dynamic Learning Rate)	91.8834%

4. Conclusion

This study demonstrates the significant benefits of integrating an Artificial Neural Network (ANN) controller with a dynamic learning rate into a photovoltaic (PV) system utilizing a Positive Output Super Lift Luo (P/O SLL) converter. The findings reveal that the ANN controller with a dynamic learning rate enhances the Maximum Power Point Tracking (MPPT) process, improving system efficiency to 91.8834%, compared to 91.8293% with a static learning rate. The dynamic learning rate allows the ANN controller to adapt in real-time to varying environmental conditions, such as changes in solar irradiance and temperature, ensuring optimal performance and efficient energy conversion. This adaptability is crucial for maintaining consistent power output and high system reliability, essential for practical renewable energy applications. The research underscores the importance of advanced AI-based control strategies in optimizing PV system performance. By leveraging the dynamic learning rate, the ANN controller effectively manages non-linear and variable inputs from the PV array, ensuring maximum energy yield and enhancing overall system efficiency. The integration of dynamic learning rates in ANN controllers presents a promising approach for advancing renewable energy technologies. This study contributes to the growing body of research focused on enhancing the performance and sustainability of PV systems. Future research should explore further optimization techniques and real-world implementations to continue improving the efficiency and reliability of renewable energy systems. The findings highlight the potential impact of using AI controllers with dynamic learning rates to achieve significant advancements in renewable energy, paving the way for more resilient and efficient PV applications.

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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