(RESEARCH ARTICLE)

Optimization of solar energy using artificial neural network controller with dc-dc boost, cuk, and single-ended primary inductor converter (SEPIC) converters

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Abstract

The challenge of the greenhouse effect today is to find ways to prevent CO_2 emissions, as this harmful gas causes global negative changes. One eco-friendly energy source is solar power, which uses a solar array system composed of various components. A critical part of this system is the Maximum Power Point Tracker (MPPT), which ensures optimal power generation. The MPPT's signal is sent to an Insulated Gate Bipolar Transistor (IGBT) via a Pulse Width Modulator (PWM), adjusting the system's resistance. Traditional controllers used the Perturbation and Observation (P&O) algorithm, which struggled with rapid environmental changes. The new AI-based Artificial Neural Network (ANN) controller improves efficiency by instantly adapting to changes. This work compares the ANN controller with the use of three data sets of 104, 201, and 1001 with three DC-DC converters: Boost, Cuk, and Single-Ended Primary Inductor Converter (SEPIC) converters.

1. Introduction

The greenhouse effect is a pressing issue today because traditional energy generation methods release harmful gases into the atmosphere, contributing to global climate change. To address this, it's crucial to find solutions that eliminate CO2 emissions. Solar energy offers a clean, environmentally friendly alternative. Harnessing solar power involves using a solar array system with various components working together. The main challenge is that the solar system's resistance differs from the connected load's resistance. Directly connecting the solar system to a load result in minimal energy generation, so a DC-DC converter is needed to match the solar system's resistance with the load's resistance, ensuring maximum efficiency [1, 2].

A key component of this system is the Maximum Power Point Tracker (MPPT), which uses mathematical calculations and rules to adjust to changes in temperature and irradiance. When properly tuned, the MPPT guarantees optimal power generation. The MPPT's signal is sent to an Insulated Gate Bipolar Transistor (IGBT) via a Pulse Width Modulator (PWM), which adjusts the duty cycle to match the solar system's resistance to the load's resistance. This setup maximizes energy generation [3, 4].

The MPPT requires a controller to adjust its output. Traditional controllers used the Perturbation and Observation (P&O) algorithm, which struggled with rapid environmental changes, such as passing clouds or sudden temperature shifts. The new Artificial Intelligence (AI)-based controller, specifically an Artificial Neural Network (ANN), improves efficiency by instantly predicting and adapting to these changes [5]. The ANN controller can accurately predict the value to be sent to the MPPT, closely matching the solar array's generated values. ANN controllers need training with data

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samples, and in this study, samples of 104, 201, and 1001 will be used [6]. The AI ANN controller utilizes inputs G and T, yielding outputs V and P. Using these outputs, specifically predicted and computed V and P values, we derive three additional parameters: R, I, and work (w).

R represents the resistance, calculated as the ratio of the voltage (V) to the current (I) (R = V/I). This parameter is crucial for understanding how the electrical load affects the solar array's performance, enabling more precise adjustments to optimize energy extraction under varying conditions.

I stands for the current, a direct measure of the electrical flow generated by the solar array. Monitoring the current is essential for ensuring that the system operates within safe and efficient parameters, preventing potential overloading and ensuring optimal energy capture.

w signifies the work done by the system, typically measured in joules or watt-hours. It provides a quantifiable measure of the energy transferred by the solar array over time. By analyzing the work done, we can assess the overall efficiency and effectiveness of the solar array, offering insights into its performance over different periods and conditions.

These parameters—R, I, and work (w)—provide a comprehensive understanding of the solar array's performance and efficiency, allowing for real-time optimization and improved energy management. Our AI ANN controller design operates independently without requiring supplementary PI or PID controllers. Positioned upstream of the MPPT Block, the AI ANN design ensures the signal fed into the MPPT is precise, negating the necessity for control units within the MPPT Block itself, which is exclusively configured with a P&O algorithm [7, 8].

This paper compares the ANN controller with three different DC-DC controllers: Boost, Cuk, and Single-Ended Primary Inductance Converter (SEPIC) converters to determine which provides the highest efficiency [9].

In our proposed solar system, a DC-DC converter is essential for ensuring maximum efficiency by matching the system's resistance with the load. Due to the nonlinear changes in temperature and irradiance, a predictive method like an Artificial Neural Network (ANN) controller, which handles nonlinearity in its calculations, is required.

This paper is sectioned as:

Section 2: Material and methods

PV System Description and Modeling

- Comprehensive overview of the 213.15-Watt photovoltaic array design.
- Breakdown of the fundamental block model for PV arrays.
- Examination of the solar cell structure and functionality, focusing on p-n semiconductor junctions.
- Description of the model's inputs (irradiance and temperature) and outputs (voltage and power).
- Techniques employed to simulate and analyze the PV system's performance under various scenarios.
- DC – DC Boost Converter Design and Model.
- DC – DC Cuk Converter Design and Model.
- DC – DC Single-Ended Primary Inductance Converter (SEPIC) Design and Model.

Methodology of ANN Controller with DC-DC converters

- Overview of AI-based control systems.
- Detailed discussion of the Artificial Neural Network (ANN) model applied.
- Insight into the application of the AI ANN controller for enhancing the performance of photovoltaic systems, with an emphasis on its capability to manage non-linear and dynamic inputs such as irradiance (G) and temperature (T).

Section 3: Results and Discussion

- Display of the outcomes achieved using the ANN controller.
- Evaluation of the ANN's performance in enhancing photovoltaic systems.
- Examination of the advantages and limitations of the ANN controller approach.
- Analysis of the findings concerning the optimization efficiency and effectiveness of PV systems.
- ANN Controller with a DC – DC Boost Converter Design and Model.

- ANN Controller with a DC – DC Cuk Converter Design and Model.
- ANN Controller with a DC – DC Single-Ended Primary Inductance Converter (SEPIC) Design and Model.
- Comparison of All Used ANN Controllers with DC-DC Boost, Cuk, and SEPIC Converters

Section 4: Conclusion

- Recap of the main discoveries from the research.
- Highlights of the advancements made in renewable energy and photovoltaic system optimization.
- Suggestions for areas of investigation in future studies.
- Final thoughts on the potential benefits of employing AI controllers to improve PV system efficiency.

2. Material and methods

2.1. PV System Model

The proposed model includes a solar array system with a Photovoltaic (PV) array that functions as a two-input, two-output element. The two inputs, temperature (T) and irradiance (G), are sent to the PV array to generate outputs of voltage (V) and current (I). Simultaneously, T and G are also fed into an ANN controller, which is trained using three data sets of 104, 201, and 1001 samples [10]. The PV array generates voltage based on T and G values, while the ANN controller predicts a corresponding voltage and power signals from these inputs, sending the voltage signal to the Maximum Power Point Tracker (MPPT) [11]. The MPPT calculates an unmodulated duty signal, which is then modulated by a Pulse Width Modulator (PWM) before being sent to the gate of an Insulated Gate Bipolar Transistor (IGBT) within a DC-DC converter subsystem. This process produces the output voltage (V_{out}), predicted and generated by the ANN algorithm [12].

2.2. DC-DC Converter Model

The block diagrams for the proposed solar system, including the DC-DC subsystem and load with the ANN model, is shown in Figure 1. Scopes are used to monitor changes in voltages, currents, and power of the PV array and system output at various calculated and predicted values [13].
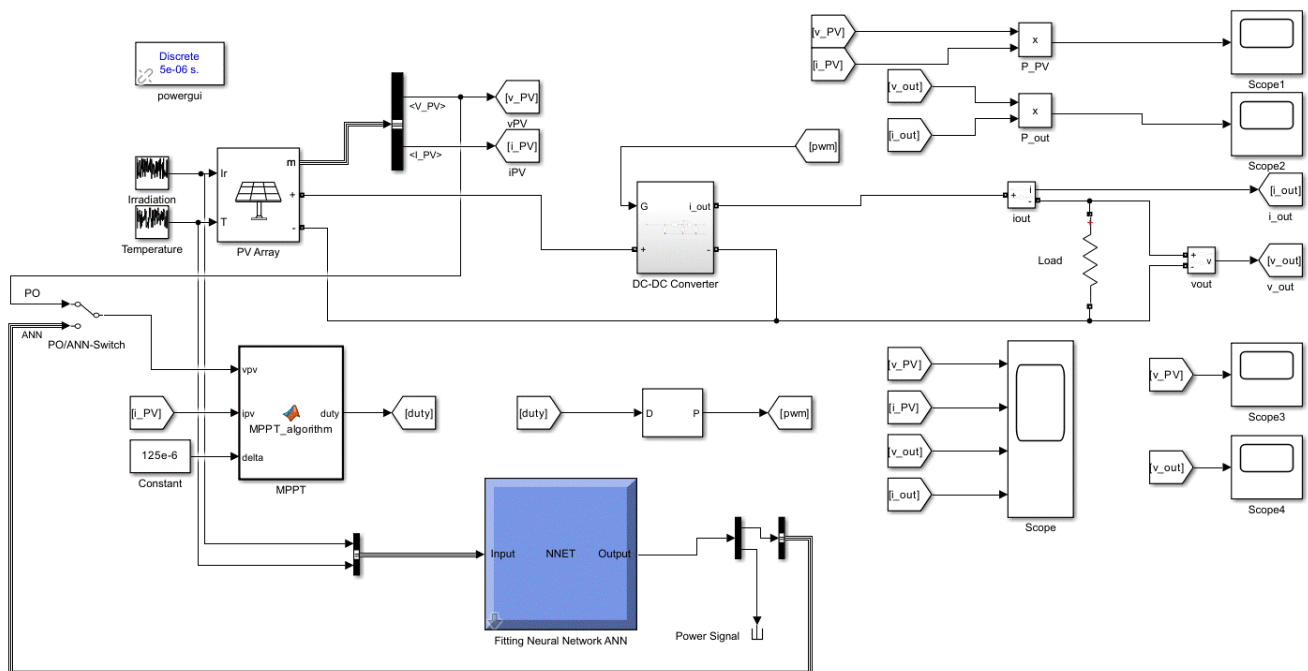

Figure 1 Block Diagram for The Proposed Model

2.2.1. DC-DC Boost Converter Model

The load resistance is not always equal to the resistance of the PV solar system. To align the PV system's resistance with that of the load, a DC-DC converter is necessary [14]. A DC-DC Boost converter model can adjust the system's resistance

by varying its voltage, ensuring maximum efficiency [15]. The output voltage of a DC-DC Boost converter at any duty cycle is higher than its input voltage, while the output current is lower than the input current. The capacitor (C) shown in Figure 2 filters out any ripples, providing a smooth output voltage [16].
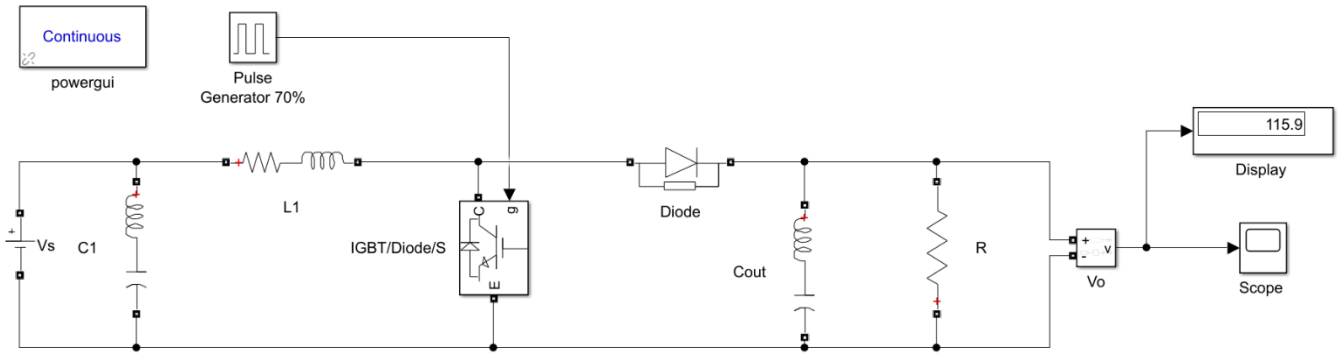
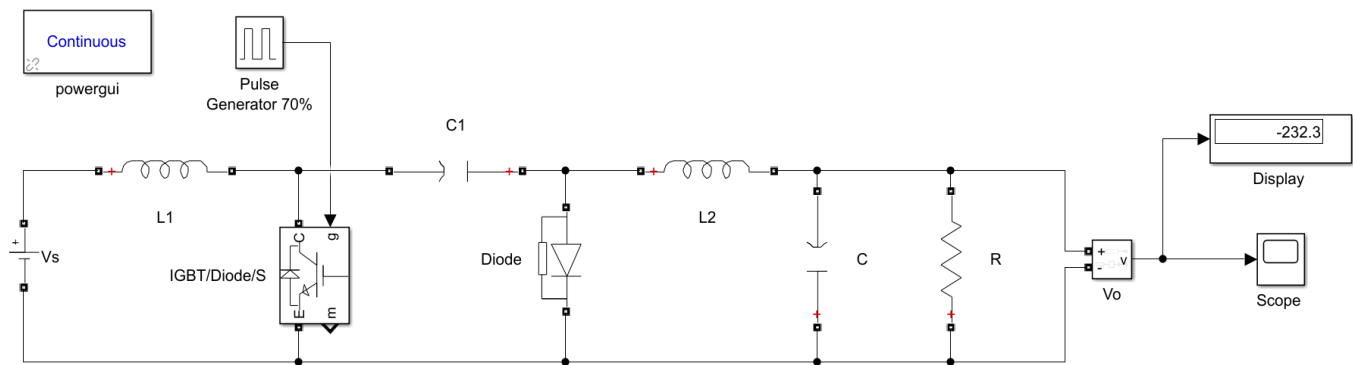**Figure 2** PV Circuit Diagram of a DC-DC Boost Converter Using an IGBT

The observed output voltage is consistently higher than the input voltage, so the conversion ratio of a DC-DC Boost converter is given by:

$$\frac{V_O}{V_S} = \frac{1}{1-D} \quad \ldots\ldots\ldots\ldots(1)$$

The duty cycle impacts the output voltage as described in equation number seven. One of the primary challenges in a DC-DC Boost converter is managing the inductor. The inductance is inversely proportional to the current ripple at the converter's output [17]. To reduce this ripple, a larger inductor is required, ensuring a smoother output voltage before it is connected to any load [18, 19].

2.2.2. DC-DC Cuk Converter Model

A DC-DC Cuk converter can be powered by various DC sources, such as small to medium generators with DC output, lithium batteries, and PV solar panels. This converter changes DC voltage from one level to another, a concept known as DC-DC conversion. The Cuk converter can either increase or decrease the input voltage depending on its duty cycle, making it a step-up step-down converter. Utilizing an Insulated Gate Bipolar Transistor (IGBT), the DC-DC Cuk converter is suitable for low to medium current conduction and control [20]. IGBTs can handle high voltage and power, making them ideal for this application. A DC-DC Cuk converter using an IGBT is designed in MATLAB/Simulink, as illustrated in Figure 3 [21, 22].

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

We can find the DC voltage transfer function of a DC-DC Cuk converter by the following equation:

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

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

A SEPIC converter can be powered by various DC sources, including DC generators, batteries, solar panels, and rectifiers. The process of converting one DC voltage to another is known as DC-DC conversion [23]. A SEPIC converter can adjust the output voltage to be either lower or higher than the input voltage, earning it the name "step-up step-down converter" since it can both increase and decrease the source voltage. In SEPIC converters, the output voltage varies without polarity reversal [24]. A DC-DC SEPIC converter utilizing a power MOSFET is suitable for low to medium current conduction and control. Given its ability to handle high voltage and power, an IGBT is often used. A DC-DC SEPIC converter with an IGBT has been designed in MATLAB/Simulink, with the circuit diagram shown in Figure 4 [25].
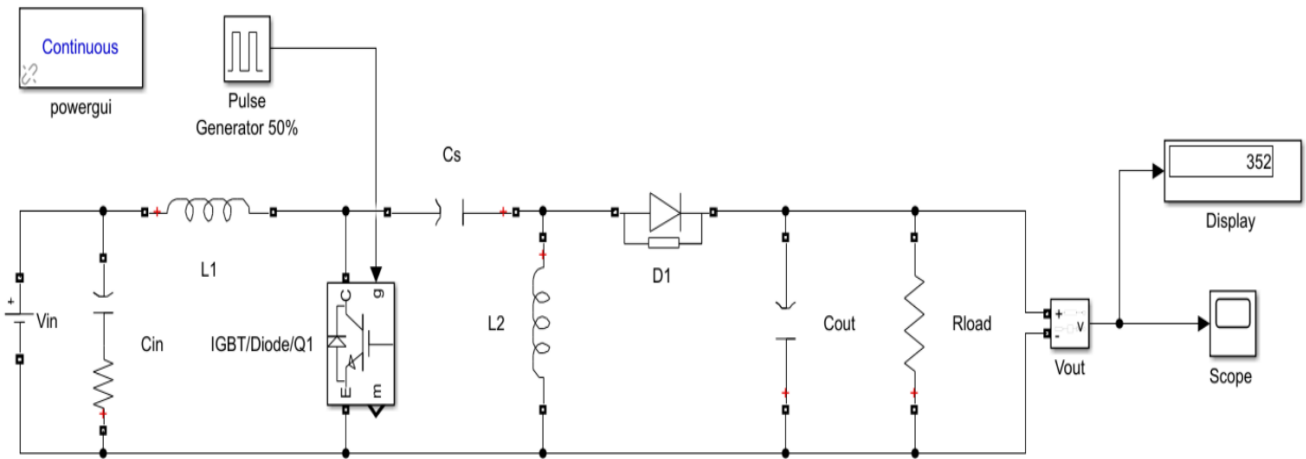

Figure 4 PV Circuit Diagram of a DC-DC SEPIC Converter Using an IGBT

The DC voltage transfer function or duty cycle of a DC-DC SEPIC converter can be determined using the following equation:

$$D = \frac{V_{out}}{V_{out} + V_{in}} \quad \text{.....................} (3)$$

2.3. Artificial Neural Network (ANN)

Artificial Intelligence (AI) controllers, particularly Neural Networks (NN), are utilized to enhance the Maximum Power Point (MPP) tracking of our PV array [26, 27]. Using the Levenberg-Marquardt algorithm in MATLAB, we train ten neural networks integrated within the controller, known for its efficiency in solving complex nonlinear least-squares problems. With the fluctuating irradiance and temperature, power generation and voltage outputs from the PV array exhibit nonlinear behavior [28].

The irradiance (G) and temperature (T) inputs are connected via weighted pathways to hidden layers within the neural network (NN), which then calculates and predicts two outputs: voltage (V) and power (P) [29, 30]. Achieving optimal performance relies on configuring the NN with the right number of hidden layers and neurons in each layer [31, 32]. The NN is trained using a trial-and-error method, featuring two neurons in the input layer (for G and T), two neurons in the output layer (for V and P), and a single hidden layer. The AI ANN controller was designed to sample at rates of 10.4, 20.1, and 100.1 samples per second, resulting in more intelligent predictions and accurate outputs, comparable to the PV array output. In contrast, others have designed AI ANN controllers using only 1 sample per second for training [33].

The MPPT requires a controller to adjust its output. Traditional controllers used the Perturbation and Observation (P&O) algorithm, which struggled with rapid environmental changes, such as passing clouds or sudden temperature shifts. The new Artificial Intelligence (AI)-based controller, specifically an Artificial Neural Network (ANN), improves efficiency by instantly predicting and adapting to these changes. The ANN controller can accurately predict the value to be sent to the MPPT, closely matching the solar array's generated values. ANN controllers need training with data samples, and in this study, samples of 104, 201, and 1001 will be used.

The AI ANN controller utilizes inputs G and T, yielding two predicted outputs: V, and P, with three derived outputs R, I, and work (w). These additional outputs—R, I, and w—offer significant advantages over traditional methods, providing a more comprehensive analysis of the solar array's performance and offering cost-saving benefits.

- **R (Resistance):** Resistance (R) is derived from the relationship R = V/I, where V is the voltage, and I is the current. Deriving resistance allows the ANN controller to offer insights into the array's internal characteristics and how external factors such as temperature and irradiance affect its performance. By accurately predicting R, the system can optimize the load to ensure maximum power extraction and efficient energy utilization under varying environmental conditions. This eliminates the need for external resistance measurement tools, reducing hardware costs.
- **I (Current):** Current (I) is a direct measure of the rate of flow of electric charge generated by the solar array. Deriving the current is crucial for real-time monitoring of the system's output. Accurate current prediction allows the ANN controller to ensure safe operation within the system's limits, preventing potential issues like overloading or underperformance. Traditionally, measuring current requires current transformers (CTs), which add to the overall system cost. By predicting I, the ANN controller reduces the reliance on these additional measurement tools, resulting in cost savings.
- **w (Work):** Work (w) represents the total energy output of the system over a given period, typically measured in joules or watt-hours. Deriving work provides a quantifiable measure of the energy transferred, helping to assess the system's efficiency and productivity over time. This parameter is essential for evaluating the overall performance of the solar array. By accurately predicting w, the ANN controller eliminates the need for external energy meters, further reducing hardware costs and simplifying system design.

These additional derived parameters—R, I, and work (w)—provide a more detailed and nuanced understanding of the solar array's performance. Unlike traditional controllers that might focus solely on voltage prediction, the inclusion of these extra outputs by the ANN controller allows for a holistic approach to energy management and optimization. This multi-faceted analysis ensures that the solar array operates at peak efficiency, maximizing energy extraction and providing reliable performance even under fluctuating environmental conditions.

Moreover, by deriving R, I, and w, the ANN controller significantly reduces the need for external measurement tools, such as current transformers (CTs) and energy meters, leading to substantial cost savings. This advantage not only lowers the initial setup costs but also reduces maintenance expenses and potential points of failure, enhancing the overall reliability and economic feasibility of the solar PV system.

Our AI ANN controller design operates independently without requiring supplementary PI or PID controllers. Positioned upstream of the MPPT Block, the AI ANN design ensures the signal fed into the MPPT is precise, negating the necessity for control units within the MPPT Block itself, which is exclusively configured with a P&O algorithm. By leveraging the advanced predictive capabilities of the ANN controller, this approach provides a robust and adaptive solution to solar energy management, setting a new standard for MPPT systems.
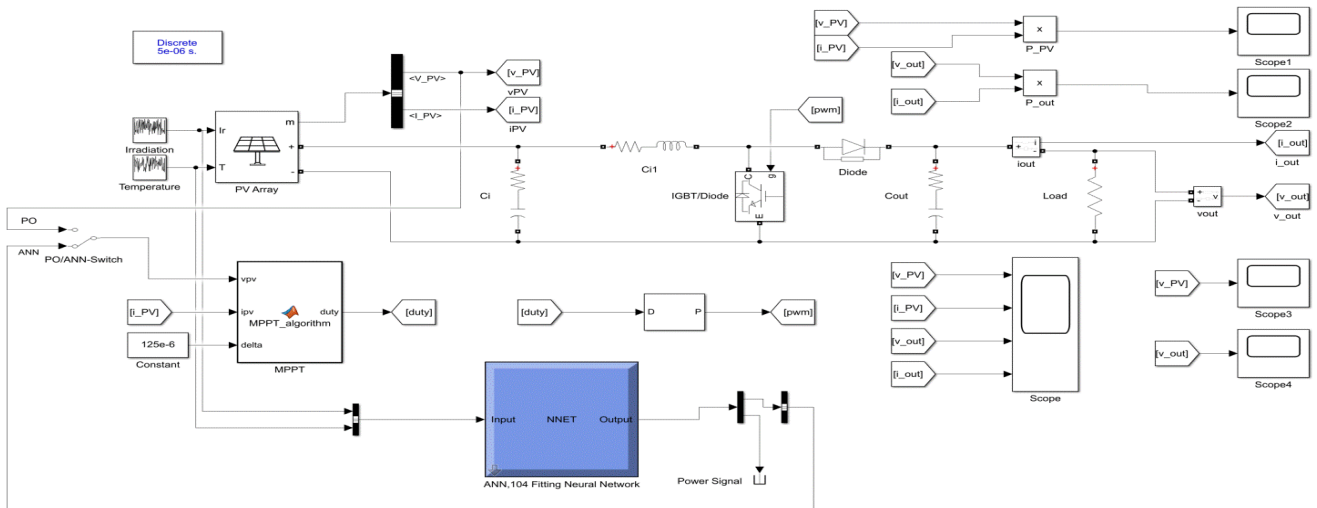
2.4. DC-DC Converters with ANN controller

The suggested DC-DC converter incorporates an Artificial Neural Network (ANN) controller model with a photovoltaic (PV) array, taking irradiance (G) and temperature (T) as inputs and generating voltage (V) and current (I) as outputs [34]. Both G and T are supplied to the PV array and the ANN controller. The PV array generates a corresponding voltage, while the ANN 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 ANN algorithm, powers a connected load [35].

2.4.1. DC-DC Boost Converter with ANN Controller

Boost converter with ANN is best suited for systems where the PV panel voltage is consistently lower than the required load voltage. It offers high efficiency and fast response but is limited to step-up applications [36].

The proposed Boost converter integrates an ANN controller model with a PV array featuring inputs for irradiance (G) and temperature (T), producing outputs V and I. G and T values are fed into both the PV array and ANN controller inputs [37]. The PV array generates a corresponding voltage, while the ANN controller computes a voltage signal for MPPT. MPPT then produces a Duty signal sent to a PWM for IGBT control in a DC-DC Boost converter, regulating output voltage (V_o). This V_o, predicted by the ANN algorithm, powers a connected load. Figure 5 illustrates the block diagram of this proposed model [38].
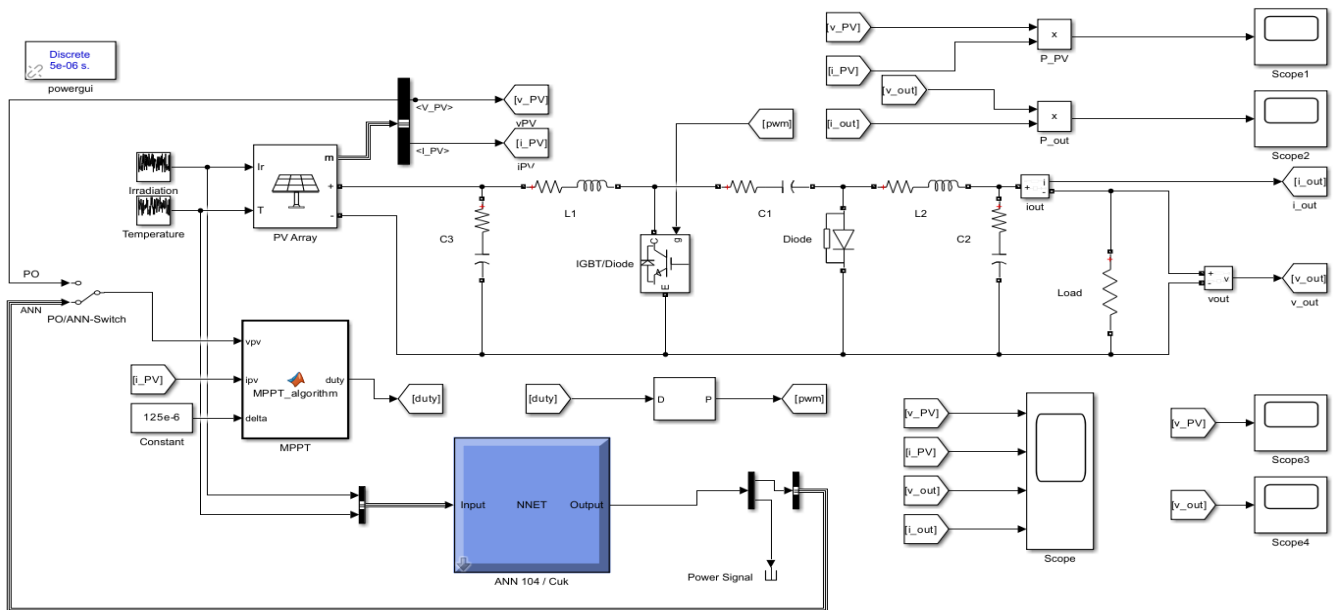
Figure 5 Proposed PV system with a DC-DC Boost converter with an ANN controller

2.4.2. DC-DC Cuk Converter with an ANN Controller

Cuk Converter with ANN is ideal for applications requiring both step-up and step-down voltage conversion with smooth current profiles. It offers versatile voltage conversion and low ripple, making it suitable for systems with variable input voltages [39].

The Cuk converter proposal combines an ANN model with a PV array utilizing inputs G (irradiance) and T (temperature) to generate outputs V (voltage) and I (current). G and T inputs are fed to both the PV array and the ANN controller [40]. The PV array produces a voltage output corresponding to these inputs, while the ANN controller calculates a voltage signal crucial for MPPT operation. MPPT generates a Duty signal directed to a PWM, which controls an IGBT in a DC-DC Cuk converter, ensuring the desired output voltage (V_o). This V_o, predicted by the ANN algorithm, supplies power to a connected load. Figure 6 depicts the block diagram illustrating this integrated model [41, 42].

Figure 6 Proposed PV System with a DC-DC Cuk Converter with an ANN Controller

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

SEPIC Converter with ANN is excellent for PV systems with wide input voltage variations, providing stable and efficient voltage conversion without inverting the polarity. It is highly versatile and effective in tracking the maximum power point under varying solar conditions.

The proposed SEPIC converter integrates an ANN model with a PV array using inputs G (irradiance) and T (temperature) to produce outputs V (voltage) and I (current). Both G and T inputs are applied to the PV array and the ANN controller simultaneously [43]. The PV array generates a corresponding voltage output based on these inputs, while the ANN controller computes a voltage signal crucial for achieving MPPT. MPPT then generates a Duty signal sent to a Pulse Width Modulator (PWM), which controls the IGBT in a DC-DC SEPIC converter to achieve the desired output voltage (V_o) [44]. This output voltage, predicted by the ANN algorithm, is then connected to a load. Figure 7 illustrates the block diagram of this proposed model [45, 46].
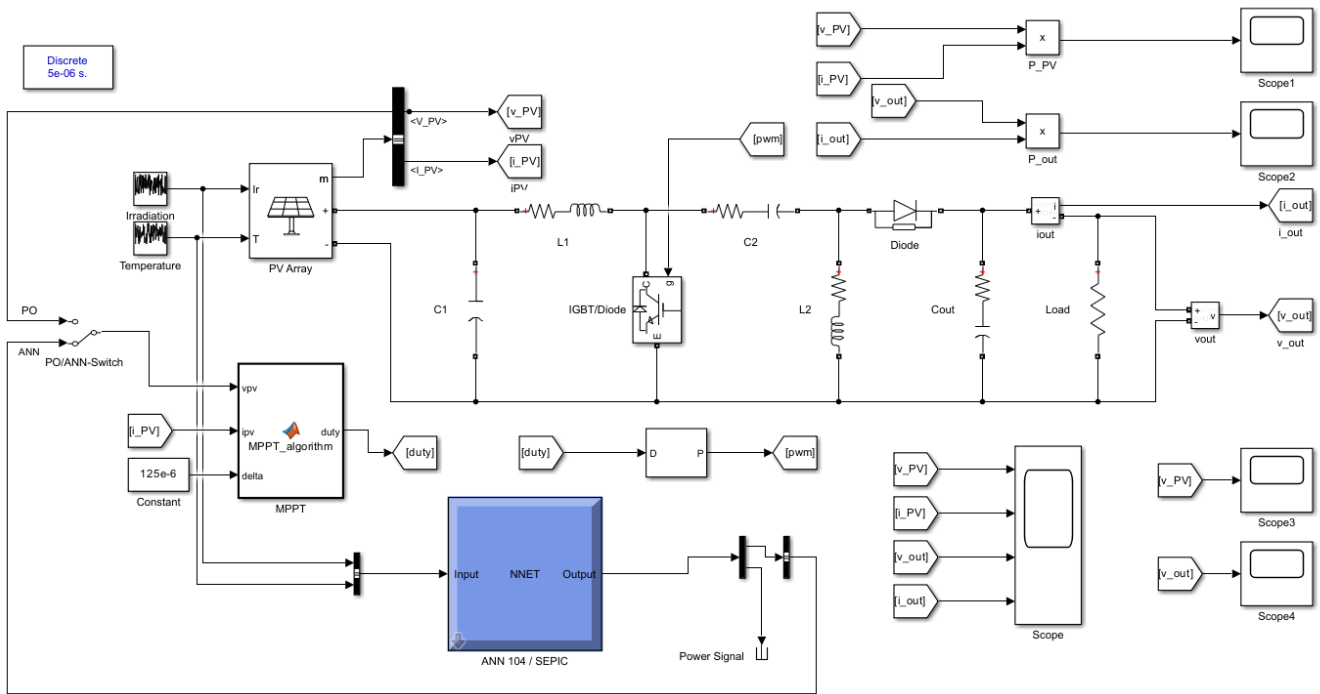
Figure 7 Proposed PV System with a DC-DC SEPIC Converter with an ANN Controller

After training the ANN 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 [47]. Consequently, two alternative datasets were selected: 102 samples and 1001 samples, in addition to the existing 104 samples. Using these datasets, the ANN controller was comprehensively trained, and its performance was evaluated against PV efficiency [48]. The ANN controller with the lowest error output was chosen for further testing. The performance metrics of Boost, Cuk, and SEPIC converters in PV systems are presented in Table 1.

Table 1 Performance Metric of Boost, Cuk, and SEPIC converters in PV Systems

Metric	Boost Converter with ANN	Cuk Converter with ANN	SEPIC Converter with ANN
Efficiency	High in step-up mode	High in both modes	High in both modes
Response Time	Fast due to ANN's adaptive nature	Quick adaptation to varying conditions	Rapid adjustment to input fluctuations
Stability	Improved under dynamic conditions	Better handling of complex topology	Enhanced stability over wide input range
MPP Tracking	Effective tracking, especially in lower voltage scenarios	Efficient tracking in both high and low voltage conditions	Excellent tracking across a wide input voltage range
Ripple	Moderate ripple in output voltage	Low ripple due to dual-inductor design	Low ripple in both input and output currents
Versatility	Limited to step-up applications	Versatile for both step-up and step-down	Highly versatile for varying input voltages

3. Results and Discussion

3.1. ANN Controller with a DC-DC Boost Converter

We evaluated PV panels with a P&O controller, followed by integrating an ANN controller using 104 samples, then increasing to 201 samples, and finally to 1001 samples [49, 50]. Our research assessed the capability of these controllers to enhance energy production and maximize overall system performance across varying environmental scenarios.

Using a P&O controller resulted in an efficiency improvement, reaching 94.7507%. Implementing an ANN controller with 104 samples further boosted efficiency to 95.0846%, surpassing the gains from the P&O controller [51]. Notably, using 201 samples produced even better results, achieving an efficiency of 95.9235%. Finally, increasing the sample size to 1001 led to an efficiency of 96.2275% [52].

Implementing this approach in a real PV plant is feasible with just 1001 samples to achieve peak power efficiency. Instantaneous G and T data from the PV will be input to the controller for prediction and PWM adjustments [53]. As Table 2 illustrates, comparing an ANN controller using 201 samples to one using 104 samples shows that the efficiency of the former exceeds that of the latter [54, 55].

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

No.	Controller Type	Efficiency
1	P&O	94.7507%
2	ANN using 104 Random samples	95.0846%
3	ANN using 201 Random samples	95.9235%
4	ANN using 1001 Random samples	96.2275%

3.2. ANN Controller with a DC-DC Cuk Converter

We assessed PV panels under several conditions: with a P&O controller, with an ANN controller using 104 samples, then with 201 samples, and finally with 1001 samples [56]. Our investigation delved into the potential of these controllers to significantly boost energy production and refine system efficiency across diverse environmental conditions. By examining their performance under varying irradiance and temperature scenarios, we aimed to identify the optimal configuration for maximum power output and system stability. This comprehensive assessment provided insights into the adaptability and robustness of the controllers, highlighting their capacity to enhance the overall efficacy of PV systems.

Using a P&O controller resulted in a notable efficiency improvement, elevating the efficiency to 93.3229%. However, the introduction of an ANN controller with 104 samples brought about a more substantial increase in efficiency, reaching 93.4004%, which is significantly higher than the improvement achieved with the P&O controller [59]. When the sample size was increased to 201 samples, the results were even more impressive, with the efficiency climbing to 93.7181%. This trend continued with the largest sample size tested; using 1001 samples, the efficiency peaked at 93.8493%, demonstrating the benefit of using more data points in the ANN controller [60, 61].

The feasibility of implementing this method in a real PV plant is promising, as achieving optimal power efficiency is possible with just 1001 samples. This involves feeding instantaneous G and T data from the PV array into the controller, which then uses this data to make predictions and adjust the PWM accordingly to optimize performance. Table 3 highlights this efficiency improvement, showing that an ANN controller using 201 samples performs better than one using only 104 samples. This increase in sample size enhances the controller's ability to accurately predict and adjust, thus maximizing the system's efficiency [62, 63].

The implementation of ANN controllers in PV systems significantly enhances efficiency compared to traditional P&O controllers [64, 65]. The study's findings indicate that even with a relatively small increase in sample size, the ANN controller's performance improves markedly [66]. This improvement is crucial for real-world applications, where maximizing efficiency directly impacts the overall energy yield of the PV plant [67]. Therefore, adopting ANN controllers with adequate sample sizes, such as 1001 samples, can lead to substantial gains in efficiency, making it a viable and beneficial approach for optimizing PV system performance [68, 69].

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

No.	Controller Type	Efficiency
1	P&O	93.3229%
2	ANN using 104 Random samples	93.4004%
3	ANN using 201 Random samples	93.7181%
4	ANN using 1001 Random samples	93.8493%

3.3. ANN Controller with a DC-DC SEPIC Converter

We evaluated the performance of PV panels under various conditions: with a P&O controller, and with an ANN controller using 104, 201, and 1001 samples [70, 71]. Our study also examined the effectiveness of these controllers in optimizing energy output and improving overall system efficiency under different environmental conditions.

Introducing a P&O controller improved efficiency to 94.6034%. However, implementing an ANN controller with 104 samples resulted in a slightly lower efficiency of 93.1865% [72]. When the sample size was increased to 201, efficiency climbed to 94.8474%. The highest efficiency was observed with 1001 samples, peaking at 95.5062%, demonstrating the benefits of using more data points in the ANN controller [73, 74].

The feasibility of applying this method in a real PV plant is promising, as optimal power efficiency can be achieved with just 1001 samples [75, 76]. This involves feeding instantaneous G and T data from the PV array into the controller, which then uses this data to make predictions and adjust the PWM accordingly to optimize performance. Table 4 highlights the efficiency improvement, showing that an ANN controller with 201 samples outperforms one with only 104 samples [77]. Increasing the sample size enhances the controller's ability to predict and adjust accurately, maximizing system efficiency.

Implementing ANN controllers in PV systems significantly enhances efficiency compared to traditional P&O controllers. The study indicates that even a small increase in sample size markedly improves the ANN controller's performance [78]. This improvement is crucial for real-world applications, where maximizing efficiency directly impacts the overall energy yield of the PV plant [79]. Therefore, adopting ANN controllers with adequate sample sizes, such as 1001 samples, can lead to substantial efficiency gains, making it a viable and beneficial approach for optimizing PV system performance [80].

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

No.	Controller Type	Efficiency
1	P&O	94.6034%
2	ANN using 104 Random samples	93.1865%
3	ANN using 201 Random samples	94.8474%
4	ANN using 1001 Random samples	95.5062%

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

Figure 8 shows a comparison of all used ANN controllers with DC-DC Boost, Cuk, and SEPIC converters efficiency, The bars represent the efficiency of each converter with different controllers, allowing for an easy visual comparison of their performance.
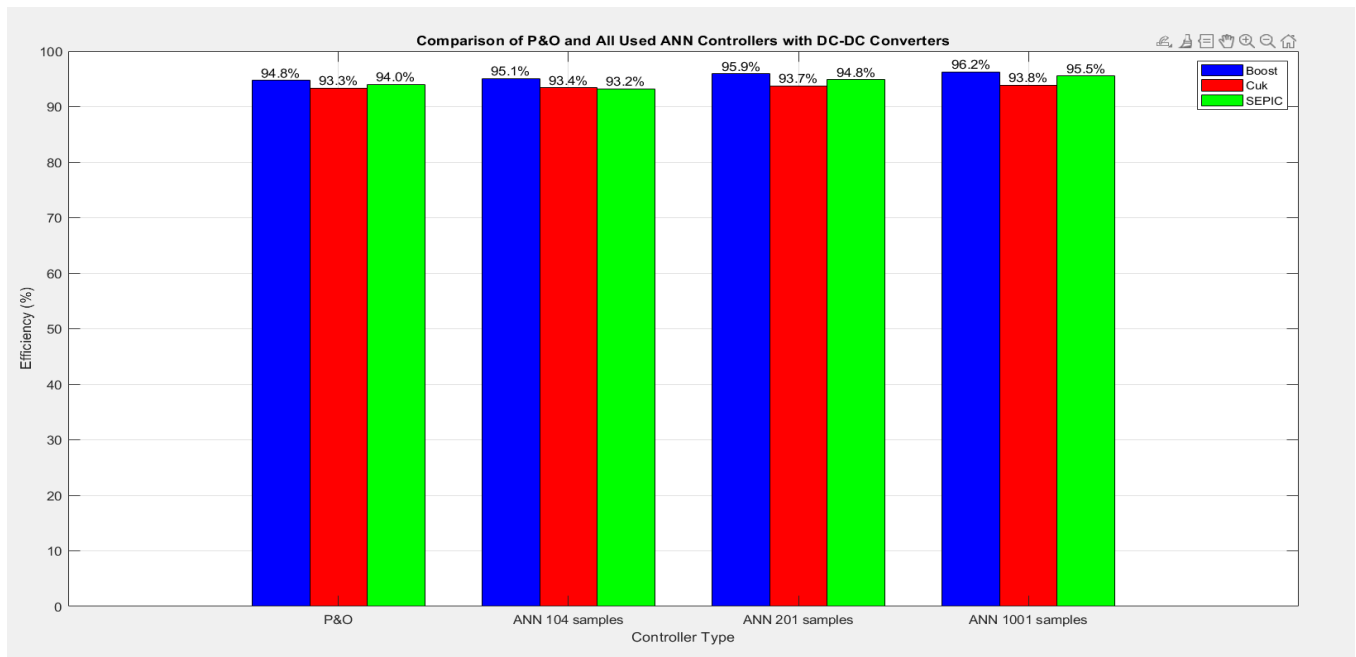
Figure 8 Comparison of P&O and All Used ANN Controllers with DC-DC Converters

- The **Boost Converter** generally shows the highest efficiency when using ANN controllers.
- The **Cuk Converter** has slightly lower efficiency compared to the Boost Converter but still benefits from ANN controllers.
- The **SEPIC Converter** shows varying efficiency, with ANN controllers improving performance significantly compared to no controller and P&O.

4. Conclusion

The ANN control method outperforms the perturb and observe (P&O) algorithm by accurately forecasting output power and voltage in PV arrays, thereby improving the efficiency of solar PV systems. Using ANN controllers for MPPT optimizes power extraction, achieving a peak efficiency of 96.2275% with a DC-DC Boost converter that employs an ANN controller designed with 1001 samples. Although increasing the sample size beyond 1001 might appear advantageous, our research indicates it can decrease the performance of the ANN controller. Therefore, utilizing 1001 samples with a DC-DC Boost Converter ensures optimal ANN controller performance, emphasizing its effectiveness in maximizing solar PV system efficiency.

Compliance with ethical standards

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Disclosure of conflict of interest

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

References

[1] K. A. Mohammad and S. M. Musa, Optimization of Solar Energy Using Artificial Neural Network Controller, *2022 14th International Conference on Computational Intelligence and Communication Networks (CICN)*, Al-Khobar, Saudi Arabia, 2022, pp. 681-685, doi: 10.1109/CICN56167.2022.10008271.

[2] K. A. Mohammad and S. M. Musa, Optimization of Solar Energy Using Recurrent Neural Network Controller, *2022 14th International Conference on Computational Intelligence and Communication Networks (CICN)*, Al-Khobar, Saudi Arabia, 2022, pp. 1-6, doi: 10.1109/CICN56167.2022.10041248.

[3]   H. Ibrahim, and N. Anani, Variations of PV module parameters with irradiance and temperature, Energy Procedia, 2017.

[4]   K. Razieh, and M. Hamiruce, Comparison of ANN and P&O MPPT methods for PV applications under changing solar irradiation, IEEE, 2013.

[5]   A. Mellit, S. Kalogirou, Artificial Intelligence techniques of sizing photovoltic systems, Renewable Sustainable Energy, 2019.

[6]   M. Patil and A. Deshpande, Design and simulation of perturb and observe Maximum Power Point Tracking in MATLAB and Simulink, ICSTM, 2015.

[7]   K. Jobeda, F. Simon, Modeling of photovoltaic array in MATLAB Simulink and maximum power point tracking using neural network, Electrical & Electronic Technology Open Access Journal, 2018.

[8]   K. Ishaque and Z. Salam, A review of Mazimum Power Point Tracking techniques of PV system for uniform insolation and partial shading condition, Renewable Sustainable Energy Rev, 2013.

[9]   A. Nasrudin, P. Rahim, Photovoltaic module modeling using Simulink/Matlab, International Conference on Sustainable Future for Human Security, 2012.

[10]   M. Samiul, and M. Kamrul, Design and simulation of maximum poer point traching of photovoltaic system using ANN, ICEEICT, 2016.

[11]   P. Sahu, and S. Nema, Physical design and modelling of boost converter for maximum power point traching in solar PV systems, ICEPES, 2016.

[12]   N. Patcharaprakiti, S. Premrudeepchacharn, Maximum Power Point Tracking Using Adaptive Fuzzy Logic Control for Grid-Connected Photovoltaic System, IEEE, 2002.

[13]   S. Azadeh, M. Saad, Simulation and Hardware Implementation of Incremental Conductance MPPT With Direct Control Method Using Cuk Converter, IEEE, 2011.

[14]   B. Mark, Neural Network Toolbox for Use with MATLAB, Book, 2004.

[15]   G. Kevin, An introduction to neural networks, Book, 1997.

[16]   F. Kulsoom, A. Mohammad, Optimization of Solar Energy Using ANN Techniques, International Conference on Power Energy, 2019.

[17]   R. Hegazy, A new MATLAB/Simulink model of triple-junction solar cell and MPPT based on artificial neural networks for photovoltaic energy systems, Ain Shams Engineering Journal, 2015.

[18]   G. Yu, J Choi, and G. Kim, A novel two mode MPPT control algorithm based on comparivive study of existing algorithms, Solar Energy, 2004.

[19]   M. Malik, R Kamara, A Novel PV based ANN Optimization Converter for off grids Locomotives, ICTAI, 2021.

[20]   H. Madvar, M Dehghani, and R. Memarzadeh, Derivation of Optimized Equations for Estimation on Dispersion Coefficirnt in Natural Stream Using Hybridized ANN With PSO and CSO Algorithms, IEEE, 2020.

[21]   M. Manimegalai, K. Sebasthiarani, Efficient Routing in Smart Grid Communication by Secured ABC – ANN Algorithm, IEEE, 2022.

[22]   H. Elaissaoui, Z. Zerouali, MPPT Algorithm Based on Fuzzy Logic and Artificial Neural Network (ANN) for a Hybrid Solar/Wide Power Generation System, IEEE, 2020.

[23]   T. Nguyen, M. Pham, and T. Duong, A Recent Invasion Wave of Deep Learning in Solar Power Forecasting Techniques Using ANN, IEEE, 2021.

[24]   O. Savchenko, O. Miroshnyk, Improving the Efficiency of Solar Power Plants Based on Forecasting the Intensity of Solar Radiation Using Artificial Neural Networks, IEEE, 2021.

[25]   Y. Kah, S. Charles, Artificial Intelligence Based MPPT Techniques for Solar Power System: A review, IEEE, 2020.

[26]   H. Ibrahim, and N. Anani, Variations of PV module parameters with irradiance and temperature, Energy Procedia, 2017.

[27]   K. Razieh, and M. Hamiruce, Comparison of ANN and P&O MPPT methods for PV applications under changing solar irradiation, IEEE, 2013.

[28] A. . Mellit, S. Kalogirou, Artificial Intelligence techniques of sizing photovoltic systems, Renewable Sustainable Energy, 2019.

[29] M. Patil and A. Deshpande, Design and simulation of perturb and observe Maximum Power Point Tracking in MATLAB and Simulink, ICSTM, 2015.

[30] K. Jobeda, F. Simon, Modeling of photovoltaic array in MATLAB Simulink and maximum power point tracking using neural network, Electrical & Electronic Technology Open Access Journal, 2018.

[31] K. Ishaque and Z. Salam, A review of Mazimum Power Point Tracking techniques of PV system for uniform insolation and partial shading condition, Renewable Sustainable Energy Rev, 2013.

[32] A. Nasrudin, P. Rahim, Photovoltaic module modeling using Simulink/Matlab, International Conference on Sustainable Future for Human Security, 2012.

[33] M. Samiul, and M. Kamrul, Design and simulation of maximum poer point traching of photovoltaic system using ANN, ICEEICT, 2016.

[34] P. Sahu, and S. Nema, Physical design and modelling of boost converter for maximum power point traching in solar PV systems, ICEPES, 2016.

[35] N. Patcharaprakiti, S. Premrudeepchacharn, Maximum Power Point Tracking Using Adaptive Fuzzy Logic Control for Grid-Connected Photovoltaic System, IEEE, 2002.

[36] S. Azadeh, M. Saad, Simulation and Hardware Implementation of Incremental Conductance MPPT With Direct Control Method Using Cuk Converter, IEEE, 2011.

[37] F. Kulsoom, A. Mohammad, Optimization of Solar Energy Using ANN Techniques, International Conference on Power Energy, 2019.

[38] G. Yu, J Choi, and G. Kim, A novel two-mode MPPT control algorithm based on comparative study of existing algorithms, Solar Energy, 2004.

[39] M. Malik, R Kamara, A Novel PV based ANN Optimization Converter for off grids Locomotives, ICTAI, 2021.

[40] H. Madvar, M Dehghani, and R. Memarzadeh, Derivation of Optimized Equations for Estimation on Dispersion Coefficient in Natural Stream Using Hybridized ANN With PSO and CSO Algorithms, IEEE, 2020.

[41] M. Manimegalai, K. Sebasthiarani, Efficient Routing in Smart Grid Communication by Secured ABC – ANN Algorithm, IEEE, 2022.

[42] H. Elaissaoui, Z. Zerouali, MPPT Algorithm Based on Fuzzy Logic and Artificial Neural Network (ANN) for a Hybrid Solar/Wide Power Generation System, IEEE, 2020.

[43] O. Savchenko, O. Miroshnyk, Improving the Efficiency of Solar Power Plants Based on Forecasting the Intensity of Solar Radiation Using Artificial Neural Networks, IEEE, 2021.

[44] N. . Shyni, M. Linda, An efficient maximum power point tracking in hybrid solar and wind energy system: A combined AMD-RNN technique, Journal of Intelligent & Fuzzy Systems, 2019.

[45] N. Mpho, H. Ali, Comprehensive Evaluation of Machine Learning MPPT Algorithms, Jornal of Electrical Engineering & Technology, 2020.

[46] F. Hassan, E. Ali, Dynamic global power extraction from partially shaded photovoltaic using deep recurrent neural network and improved PSO techniques, WILEY, 2018.

[47] S. Padmanaban, O. Mohammad, LSTM Recurrent Neural Network Classifier for High Impedance Fault Detection in Solar PV Integrated Power System, IEEE Access, 2021.

[48] N. Mpho, H. Ali, Commensurate Evaluation of Suppoer Vector Machine and Recurrent Neural Network MPPT Algorithm for a PV system under different weather conditions, IEEE, 2020.

[49] MPPT PSO - Search - MATLAB & Simulink (mathworks.com)

[50] K. Sudarsan, G. Sreenivasan, Power Quality Enhancement in Grid Connected Hybrid PV/WT System using Tree Seed Algorithm with RNN, Helix, 2020.

[51] V. Kumar, M. Patoway, Solar Plant Integration to Utility Grid with Improved Power Quality by using RNN-Hebbian-LMS Current Controller, IEEE, 2018.

[52] R. Pascanu, T. Mikolov, On the difficulty of training recurrent neural networks, International Conference on Machine Learning, 2013.

[53] L. Sindhura, K. Chaudhary Artificial Neural Network Implementation for Maximum Power Point Traching of Optimized Solar Power Panel, 2020.

[54] R. Das, Application of Recurrent Neural Network using MATLAB SIMULINK in Medicine, Italian Journal of Pure and Applied Mathematics, 2018.

[55] Y. Zhang, G. Xiaojiao MATLAB Simulink Modeling and Simulation of Zhang Neural Network for Online Time-Varying Matrix Inversion, IEEE, 2008.

[56] G. Tina, C. Ventura A State-of-Art-Review on Machine-Learning Based Methods for PV, Applied Science, 2021.

[57] A. Toure, D. Tchoffa Modeling and Control Maximum Power Point Traching of an Autonomous Photovoltaic System Using Atrificial Intelligence, Energy and Power Engineering, 2021.

[58] https://www.mathworks.com/search.html?c%5B%5D=entire_site&q=MPPT%20PSO&page=1

[59] M. Mohamed, C. Ines A Novel Approach Based Deep RNN Using Hybrid NARX-LSTM Model For Solar Power Forecasting, Aexiv, 2019.

[60] M. Nkambule, A. Hasan, A, Ali Comprehensive Evaluation of Machine Learning MPPT Algorithms for PV Systems Under Different Weather Conditions, JEET 2020.

[61] N. Mohan, Department of Electrical and Computer Engineering – University of Minnesota, First Course on Power Electronics and Drives, 2003.

[62] M. Patil, Modelling and simulation of dc drive using PI and PID controller, International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, vol. 2, pp. 1-15, 2014.

[63] N. Ismail, K. Zakaria, N. Nazar, and M. Syaripuddin, DC motor speed control using a fuzzy logic controller, In AIP Conference Proceedings, vol. 1930, pp. 020026, 2018.

[64] M. Ahmad, R. Pankaj, M. Anito, and M. Megha, Speed Control of a D Motor Using Fuzzy Logic Application, International Journal of Research in Engineering, Technology and Science, vol. 7, pp. 3011, 2018.

[65] A. Ahmed, A. Kabir, and M. Shahjahan, IEEE. Speed control of DC motor with FZ-D controller, 3rd International Conference on Electrical Information and Communication Technology (EICT), pp. 1-6, 2017.

[66] K. Passino, S. Yurkovich, and M. Reinfrank, Fuzzy control, Menlo Park, CA: Addison-Wesley, vol. 42, pp. 15-22, 1998.

[67] S. Nasar, Electric Machines and Transformers, New York: Macmillan, pp.16-18, 1984.

[68] H. Beom and H. Cho, A Sensor-based Obstacle Avoidance Controller for a Mobile Robot Using Fuzzy Logic and Neural Networks, in IEEE International Conference on Intelligent Robots and Systems, pp. 1470-1475, 1992.

[69] R. Zulfatman and M. Rahmat, Application of Self-Tuning Fuzzy PID Controller on Industrial Hydraulic Actuator Using System Identification Approach, Malaysia, pp. 120-132, 2009.

[70] R. Arulmozhiyal, and R. Kandiban, Design of fuzzy PID controller for Brushless DC motor, International Conference on Computer Communication and Informatics, pp. 212-230, 2012.

[71] H. Baogang, G. Mann and R. Gosine, New methodology for analytical and optimal design of fuzzy PID controllers, IEEE Transactions on Fuzzy Systems, vol. 7, pp. 521-539, 1999.

[72] H. Li, L. Zhang, K. Cai, and G. Chen, An improved robust fuzzy-PID controller with optimal fuzzy reasoning, IEEE Transactions on Systems, Man and Cybernetics, vol. 35, pp. 1283-1294, 2005.

[73] H. Guoshing, and L. Shuocheng, PC-based PID speed control in DC motor, International Conference on Audio, Language and Image Processing, pp. 13-22, 2008.

[74] A. Hazzabl, M. Zerbo, I. Bousserhanel, and P. Sicard, Real Time Implementation of Adaptive P1 Controller by Fuzzy Inference for Induction Motor Speed Control, IEEE, pp. 9-12, 2006.

[75] https://www.mathworks.com/matlabcentral/fileexchange/73580-pv-system-with-optimization algorithms?s_tid=srchtitle_site_search_3_MPPT+NN.

[76]   M. Latip, M. Udin, M. Othman, I. Yassin, and Z. Rizman, Optimal Capacitor Sizing and Placement Based On Real Time Analysis Using PSO For Energy Efficiency Improvement, International Journal of Advanced and Applied Sciences, pp. 1-7, 2017.

[77]   J. Silva, and H. Huy, A Fuzzy Controller with a Fuzzy Adaptive mechanism for the speed control of a PMSM, IEEE Conference on Industrial Electronics, pp.2-4, 1997.

[78]   https://www.youtube.com/watch?v=WgZgjSkv69Y.

[79]   R. Rajib, and M. Mahmuda, A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System, IEEE Access, pp.102137-102152, Volume 9, 2021.

[80]   B. Rajdeep, D. Anindita, and A. Nabanita, A comparative performance analysis of P&O and ANN algorithm based MPPT Energy Harvesting in PV systems, IEEE (CSITSS), 2023.