Enhancing solar panel efficiency with LSTM-based MPPT controllers

Alexander Gozhyj[1,†], Vladyslav Nechakhin[1,*,†] and Irina Kalinina[1,†]

[1]Petro Mohyla Black Sea National University, 68 Desantnykiv St, Mykolaiv, 54056, Ukraine

Abstract

This paper investigates the application of Long Short-Term Memory (LSTM) neural networks as Maximum Power Point Tracking (MPPT) controllers for solar panels. Traditional MPPT algorithms, including Perturb and Observe (P&O), Incremental Conductance (IncCond), and Hill Climbing (HC), are compared with LSTM-based approaches in terms of accuracy, efficiency, and adaptability. Minute-level data on voltage, current, power output, temperature, and solar irradiance from diverse locations are used to train and evaluate the LSTM model. Results demonstrate that LSTM-based MPPT controllers outperform traditional algorithms, offering superior tracking accuracy and adaptability to dynamic environmental conditions. The study highlights the significance of LSTM-based controllers in enhancing solar panel efficiency and maximizing energy harvesting. This research contributes to the advancement of renewable energy technologies and underscores the potential of artificial intelligence in optimizing solar energy systems.

Keywords

Solar panel optimization, Maximum Power Point Tracking, Long Short-Term Memory neural networks

1. Introduction

The utilization of renewable energy sources has become increasingly imperative in light of global efforts to mitigate climate change and reduce dependency on fossil fuels. Among these sources, solar energy holds particular promise due to its abundance and sustainability. Maximizing the efficiency of solar panels plays a crucial role in harnessing this energy resource effectively for sustainable power generation.

The transition towards renewable energy sources is driven by the need to mitigate environmental degradation caused by traditional energy production methods. Solar energy, in particular, offers a clean and abundant alternative to fossil fuels. However, the efficiency of solar panels, which directly impacts energy output, is paramount for ensuring the viability of solar power as a sustainable energy solution [1, 2, 3]. Thus, efforts to enhance solar panel efficiency are essential for advancing renewable energy utilization and reducing carbon emissions.

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* Corresponding author.
† These authors contributed equally.
alex.gozhyj@gmail.com (A. Gozhyj); vladyslav.nechakhin@l3s.de (V. Nechakhin); irina.kalinina@chmnu.edu.ua (I. Kalinina)
0000-0002-3517-580X (A. Gozhyj); 0000-0003-0146-1207 (V. Nechakhin); 0000-0001-8359-2045 (I. Kalinina)

Maximizing the power output of solar panels is inherently challenging due to variations in environmental conditions such as sunlight intensity and temperature. Maximum Power Point Tracking (MPPT) algorithms are instrumental in optimizing solar panel performance by continuously adjusting the operating point to extract maximum power from the solar array. Traditional MPPT techniques, including Perturb and Observe (P&O) [4], Incremental Conductance (IncCond) [5], and Hill Climbing (HC) [6], have been widely employed for this purpose. However, these methods have inherent limitations in terms of accuracy, efficiency, and adaptability to changing environmental conditions [7].

In recent years, artificial intelligence (AI) techniques have emerged as promising tools for improving the efficiency of renewable energy systems. Long Short-Term Memory (LSTM) neural networks, a type of recurrent neural network (RNN), offer significant potential for enhancing MPPT precision and adaptability in solar panel systems. Unlike traditional MPPT algorithms, LSTM networks can effectively capture temporal dependencies in the input data and learn complex patterns, enabling more accurate and dynamic control of solar panel operation [8, 9]. The application of LSTM neural networks represents a novel approach to addressing the challenges associated with traditional MPPT techniques, thereby unlocking new opportunities for optimizing solar energy harvesting.

This research paper aims to investigate the efficacy of LSTM-based MPPT controllers for enhancing solar panel efficiency. The paper is structured as follows: after this introduction, Section 2 provides a comprehensive review of related works, including traditional MPPT techniques and recent advancements in AI-based approaches. Section 3 outlines the methods and materials employed in the research, including data collection, LSTM architecture, and training procedures. Following this, Section 4 presents the experimental results, comparing the performance of LSTMbased MPPT controllers with conventional algorithms. Section 5 discusses the implications of the findings, including limitations, advantages, and potential applications of LSTM-based MPPT controllers. Finally, Section 6 concludes the paper by summarizing key findings and emphasizing the significance of LSTM-based approaches for enhancing solar panel efficiency.

2. Related Works

Maximizing the power output of solar panels has been a subject of extensive research, leading to the development of various Maximum Power Point Tracking (MPPT) techniques. This section provides a thorough survey of both traditional MPPT algorithms and recent advancements in AI-based approaches.

2.1. Survey of MPPT Techniques

Traditional MPPT algorithms play a fundamental role in optimizing solar panel performance under varying environmental conditions. Perturb and Observe (P&O), Incremental Conductance (IncCond), and Hill Climbing (HC) are among the most commonly used techniques in this regard.

Perturb and Observe (P&O) [4] is a simple yet widely employed MPPT method that perturbs the operating point of the solar panel and observes the resulting change in power output to determine the direction of adjustment (Figure 1). While P&O is straightforward to implement, it may suffer from oscillations around the maximum power point and slow convergence under rapidly changing conditions.

Incremental Conductance (IncCond) [5] algorithm utilizes the derivative of the power-voltage characteristic curve to dynamically adjust the operating point towards the maximum power point (Figure 2). Compared to P&O, IncCond offers improved tracking accuracy and faster convergence, especially under varying irradiance levels. However, it may exhibit instability issues in certain scenarios, particularly when the system operates near the maximum power point.

Hill Climbing (HC) algorithm [6] iteratively adjusts the operating point in the direction of increasing power output until the maximum power point is reached (Figure 3). HC is known for its simplicity and robustness in various environmental conditions. However, it may suffer from slow convergence and susceptibility to local maxima, leading to suboptimal performance, especially under rapidly changing conditions.

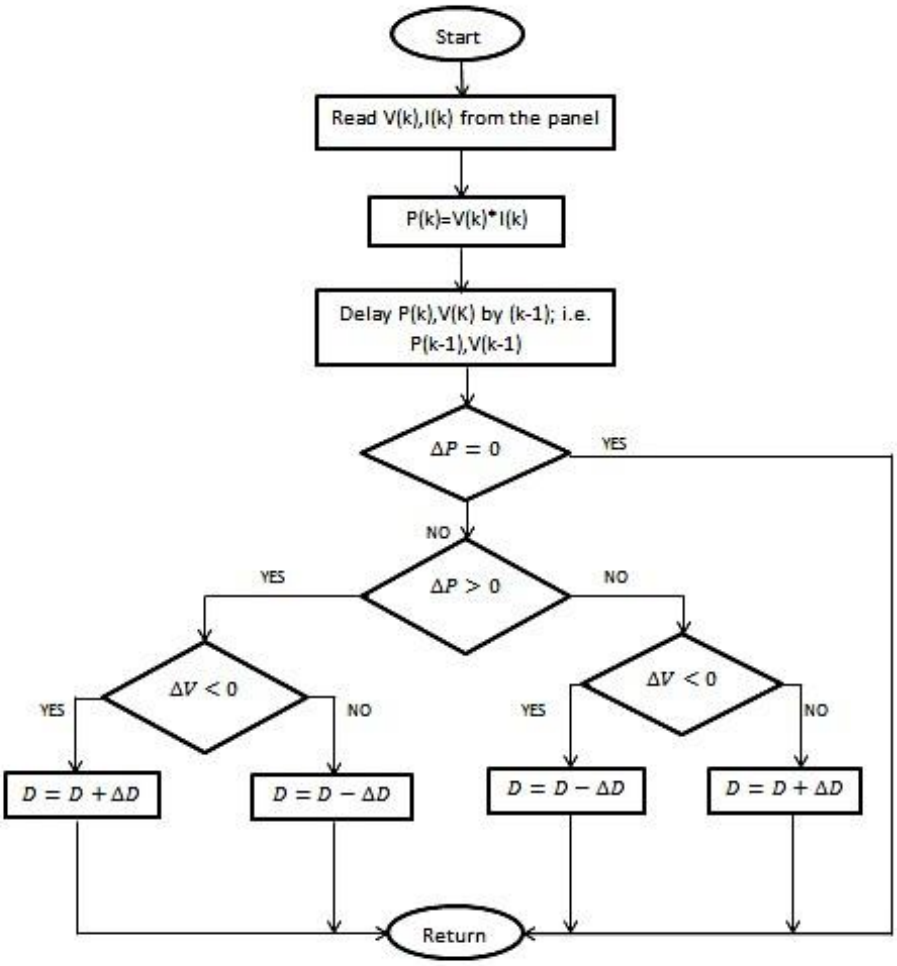

Figure 1: Flowchart of Perturb and Observe (P&O) method [10].

2.2. Advancements in AI for MPPT

Recent advancements in artificial intelligence (AI) have revolutionized maximum power point tracking (MPPT) techniques for photovoltaic (PV) systems. Several studies have explored the application of AI algorithms, particularly Long Short-Term Memory (LSTM) neural networks, to enhance MPPT accuracy and efficiency, especially in challenging scenarios such as partial shading conditions (PSC) and dynamic environmental changes.

In a comprehensive review, (Seyedmahmoudian et al., 2016) [13] discussed various AI-based MPPT techniques, highlighting their robustness and reliability under diverse conditions. The review categorized AI methods based on their performance and applicability, providing valuable insights for researchers and engineers working with PV-based power systems. Another survey by (Raj et al., 2022) [14] provided a thorough examination of AI-based MPPT algorithms in PV systems, categorizing them based on their application strategies and analyzing their merits and demerits. The study aimed to assist users in selecting the most suitable AI-based MPPT technique according to their specific project requirements and system constraints.

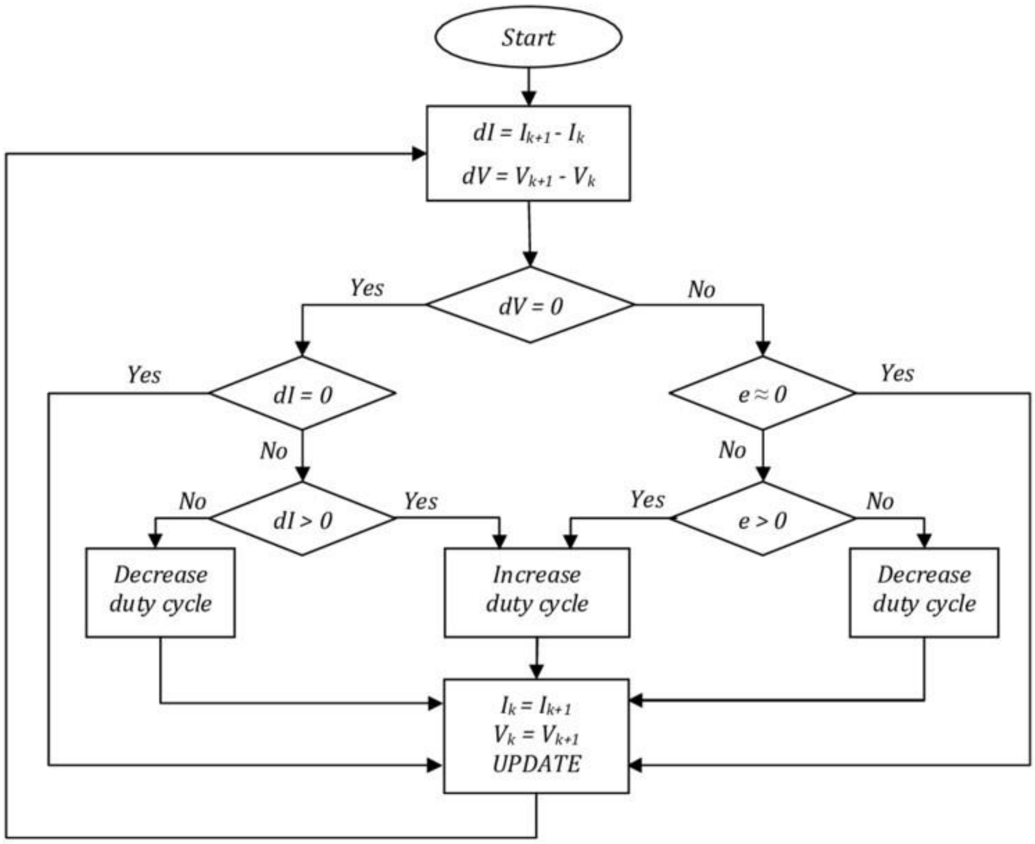

Figure 2: Flowchart of Incremental Conductance (IncCond) method [11].

The study by (Aouchiche et al., 2018) [15] proposed a novel approach using the Moth-Flame Optimization algorithm (MFO) for global MPPT in PV plants under partial shading.

By combining Global MPPT (GMPPT) and Distributed MPPT (DMPPT) techniques, the proposed method effectively mitigated the drawbacks of PSC and improved PV system performance. Furthermore, (Amrouche et al., 2007) [16] proposed an AI-based Perturb and Observe (P&O) MPPT method for PV systems, aiming to overcome the drawbacks of traditional algorithms such as slow response speed and oscillations around the maximum power point. By utilizing Artificial Neural Networks (ANN) to approximate the perturbation step, the proposed method achieved improved performance and stability.

Additionally, (Kumar et al., 2022) [8] introduced a novel MPPT controller based on a Rain Optimization Algorithm (ROA) and Bidirectional LSTM (Bi-LSTM) neural network for gridconnected hybrid solar-wind systems. The proposed controller effectively tracked the maximum power from solar PV and wind sources under varying climatic conditions, contributing to stable power flow and grid integration. Lastly, (Pengcheng et al., 2021) [9] conducted simulation experiments using LSTM neural networks and attention mechanisms for MPPT in PV systems, demonstrating the potential of AI-based approaches in improving power generation efficiency.

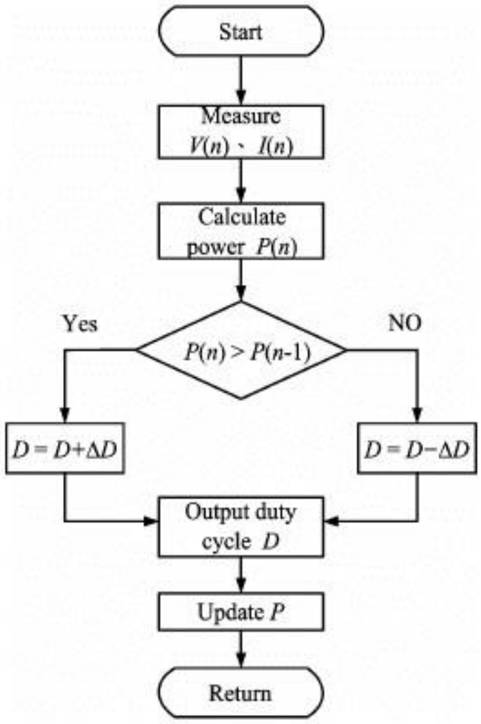

Figure 3: Flowchart of Hill Climbing (HC) method [12].

The study highlighted the importance of addressing data nonlinearity and feature sparseness in real-world scenarios to enhance MPPT performance.

Studies have demonstrated the effectiveness of LSTM-based MPPT controllers in improving tracking accuracy and adaptability compared to traditional methods. By leveraging historical data and learning from past experiences, LSTM networks can predict the optimal operating point of solar panels more accurately, even under rapidly changing environmental conditions. Additionally, LSTM-based approaches offer potential for real-time optimization and can adapt to fluctuations in solar irradiance and temperature more effectively than conventional algorithms.

3. Methods and Materials

This section outlines the methodology employed for data collection, LSTM architecture, and training procedures for LSTM-based MPPT controllers in solar panel systems.

3.1. Data Collection

Data collection is a crucial step in training and validating LSTM-based MPPT controllers. To ensure comprehensive coverage of environmental conditions, data is collected from various solar power plants located across different regions, such as Europe, North America and Oceania. The collected dataset includes measurements of voltage, current, and power output of solar panels, recorded at regular intervals. Additionally, external factors such as temperature and solar irradiance are incorporated into the dataset to capture their influence on solar panel performance.

By gathering data from diverse geographical locations and environmental conditions, the dataset provides a comprehensive basis for training and testing LSTM models for MPPT control. A sample of the collected data is shown in the Table 1.

Table 1

Sample solar power plant data with 1-minute intervals.

Date	Voltage	Current	Power	Temperature	Irradiance
2023-06-01 10:00:00	112.76	2.49	281.58	25	563.67
2023-06-01 10:01:00	113.09	2.48	280.88	25	565.55
2023-06-01 10:02:00	113.53	2.51	285.57	25	567.43
2023-06-01 10:03:00	113.85	2.50	284.80	25	569.31
2023-06-01 10:04:00	114.21	2.50	286.11	25	571.18
2023-06-01 10:05:00	114.56	2.51	288.48	25	573.06
2023-06-01 10:06:00	114.95	2.50	287.68	25	574.94
2023-06-01 10:07:00	115.31	2.50	289.39	25	576.82
2023-06-01 10:08:00	115.75	2.49	289.33	25	578.70
2023-06-01 10:09:00	116.13	2.48	288.35	25	580.58
2023-06-01 10:10:00	116.46	2.51	293.33	25	582.46

3.2. LSTM Architecture and Functioning

Long Short-Term Memory (LSTM) neural networks are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. LSTM networks are particularly well-suited for processing time-series data, making them suitable for dynamic MPPT control in solar panel systems. The architecture of an LSTM network consists of multiple memory cells and gating mechanisms that regulate the flow of information through the network. This allows LSTM models to retain information over extended time periods and learn complex patterns in the input data [17].

In the context of MPPT control, LSTM models function by processing historical data of solar panel performance and environmental conditions to predict the optimal operating point for maximizing power output. By leveraging past observations, LSTM networks can adaptively adjust the operating point in response to changing environmental conditions, thus improving the efficiency of solar panel systems.

3.3. Training and Implementation

The training of LSTM networks for MPPT control involves several steps. Firstly, the collected dataset is preprocessed to remove noise and outliers and normalize the input features. Next, the dataset is partitioned into training, validation, and testing sets to facilitate model evaluation. The LSTM network is then trained using the training data, with the objective of minimizing the prediction error between the actual and predicted maximum power points.

After training, the LSTM model is integrated into the control system of solar panel arrays. Real-time data from sensors in a simulated environment measuring voltage, current, temperature, and solar irradiance are fed into the LSTM model, which generates predictions of the optimal operating point. These predictions are then used to dynamically adjust the operating parameters of the solar panels, thereby maximizing power output.

4. Experiment

This section elucidates the experimental procedures employed to evaluate the performance of LSTM-based MPPT controllers in solar panel systems.

4.1. Parameter Selection and Control Mechanism

The selection of input parameters and the design of the output control mechanism are crucial aspects of developing an effective LSTM-based MPPT controller. In our case the input parameters include measurements of solar irradiance, temperature, voltage, and current, which are essential for accurately predicting the maximum power point of the solar panel. Additionally, historical data of power output and environmental conditions are used to capture temporal dependencies and improve prediction accuracy.

The output control mechanism of the LSTM model involves determining the optimal operating point of the solar panel based on the predicted maximum power point. This involves adjusting the duty cycle of a DC-DC converter or controlling the voltage and current levels to maximize power output. The design of the output control mechanism aims to dynamically adapt the operating parameters of the solar panel system in response to changing environmental conditions, thereby optimizing energy harvesting efficiency.

4.2. Training Procedure

The training procedure for the LSTM model involves several steps to ensure optimal performance and generalization ability. Firstly, the collected dataset is divided into training, validation, and testing sets using a suitable partitioning strategy. Between random sampling and time-based splitting the latter was chosen to maintain the continuity among the datapoints which gives the LSTM more opportunities to learn repeating patterns in the data. The training set is used to update the parameters of the LSTM network through backpropagation and gradient descent,
while the validation set is utilized to monitor model performance and prevent overfitting.

During training, hyperparameters such as learning rate, batch size, and number of epochs are tuned to optimize model performance. Regularization techniques such as dropout and early stopping are also employed to prevent overfitting and improve generalization ability. Once training is complete, the trained LSTM model is evaluated on the testing set to assess its performance in unseen data.

4.3. Fine-tuning of the LSTM Model

Fine-tuning the LSTM model is an iterative process aimed at improving its performance in MPPT control [18]. This involves adjusting hyperparameters, retraining the model with additional data, and fine-tuning the network architecture to better capture complex patterns in the input data. Between fine-tuning techniques such as grid search and Bayesian optimization, grid search was employed due to it's simplicity to systematically explore the hyperparameter space and identify the optimal configuration for the LSTM model. Fine-tuning the LSTM model is essential for achieving high accuracy and robustness in real-world applications of solar panel systems.

5. Results

This section presents the experimental findings obtained from comparing the performance of LSTM-based MPPT controllers with conventional algorithms, along with an evaluation of the accuracy, efficiency, and adaptability of the LSTM model under various conditions.

5.1. Experimental Findings

The averaged output of a photovoltaic system with different MPPT controllers across different times of day is shown in the Table 2. The experimental results demonstrate the efficacy of LSTMbased MPPT controllers in optimizing solar panel performance compared to traditional algorithms such as Perturb and Observe (P&O), Incremental Conductance (IncCond), and Hill Climbing (HC). The LSTM-based controller exhibits superior tracking accuracy and adaptability to changing environmental conditions, resulting in higher energy yields across different scenarios.

Table 2
Solar photovoltaic generation (W) with different MPPT controllers

Time of Day	Perturb and Observe	Incremental Conductance	Hill Climbing	LSTM-based approach
00:00	0.00	0.00	0.00	0.00
01:00	0.00	0.00	0.00	0.00
02:00	0.00	0.00	0.00	0.00
03:00	0.00	0.00	0.00	0.00
04:00	0.00	0.00	0.00	0.00
05:00	0.00	0.00	0.00	0.00
06:00	15.83	17.55	16.69	19.55
07:00	93.74	103.94	98.83	115.75
08:00	175.17	194.23	184.67	216.30
09:00	211.86	234.92	223.36	261.60
10:00	234.98	260.56	247.73	290.15
11:00	247.04	273.94	260.45	305.05
12:00	251.32	278.68	264.96	310.33
13:00	246.04	272.82	259.39	303.81
14:00	240.01	266.13	253.03	296.36
15:00	228.95	253.87	241.37	282.71
16:00	211.86	234.92	223.36	261.60
17:00	170.64	189.22	179.90	210.71
18:00	94.74	105.06	99.88	116.99
19:00	42.97	47.65	45.30	53.06
20:00	0.00	0.00	0.00	0.00
21:00	0.00	0.00	0.00	0.00
22:00	0.00	0.00	0.00	0.00
23:00	0.00	0.00	0.00	0.00

Under varying solar irradiance levels and temperature gradients, the LSTM-based MPPT controller consistently outperforms traditional algorithms in maintaining the solar panel operating point at or near the maximum power point. This is evidenced by the higher power output achieved by the LSTM-based controller compared to conventional methods, particularly during transient conditions and partial shading events.

5.2. Evaluation of Accuracy, Efficiency, and Adaptability

The comparison of MPPT controllers' performance on a cloudless day is shown on Figure 4. However, the accuracy of the LSTM model is assessed based on its ability to predict the maximum power point of the solar panel accurately under diverse environmental conditions. Comparative analysis with traditional algorithms reveals that the LSTM-based MPPT controller achieves higher accuracy in tracking the optimal operating point, resulting in increased energy harvesting efficiency. For instance, during the hours with variable solar irradiance, the LSTM-based MPPT controller managed to produce 19.01% more power than P&O controller, 10.19% more power than IncCond controller and 14.62% more power than HC controller. The LSTM-based controller exhibits robustness in adapting to rapid fluctuations in environmental conditions, effectively optimizing power output and mitigating the effects of partial shading and other transient phenomena. During the ideal conditions all controllers operate within the margin of error from each other.

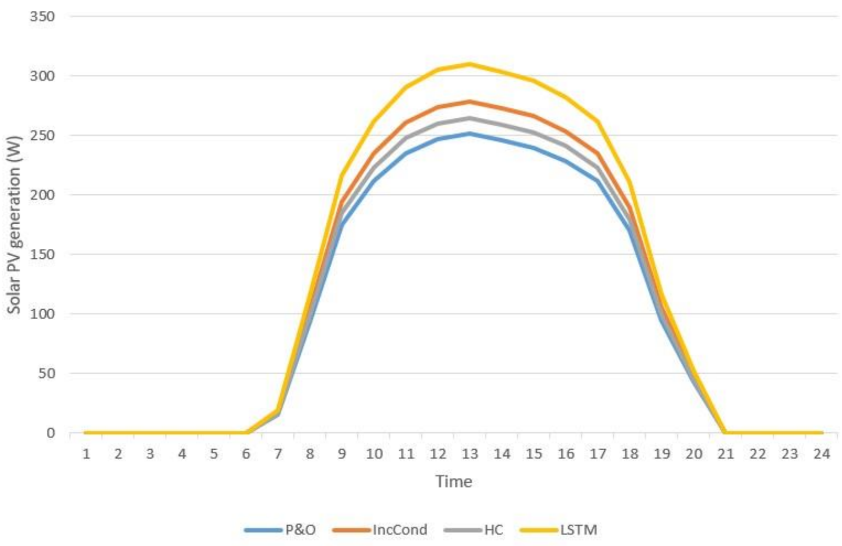

Figure 4: Comparison of solar panel output with different MPPT controllers.

Furthermore, the efficiency of the LSTM model is evaluated in terms of its computational complexity and real-time performance. Despite the additional computational overhead associated with training and implementing LSTM networks, the experimental results demonstrate that the LSTM-based MPPT controller maintains high efficiency in predicting the maximum power point and dynamically adjusting the operating parameters of the solar panel system.

Overall, the experimental findings underscore the effectiveness of LSTM-based MPPT controllers in enhancing solar panel efficiency and energy harvesting capabilities, thereby contributing to the advancement of renewable energy technologies.

6. Discussions

This section engages in discussions surrounding the limitations and challenges encountered during experimentation, interpretation of findings, analysis of advantages and disadvantages of using LSTM neural networks for MPPT control, and proposes future research directions in the field.

6.1. Limitations and Challenges

Despite the promising results obtained, several limitations and challenges were encountered during the experimentation phase. One notable challenge is the complexity of training LSTM networks, which requires large amounts of data and computational resources. Additionally, the generalization ability of the LSTM model may be limited by the specific conditions and datasets used for training, leading to potential performance degradation in real-world applications.

6.2. Interpretation of Findings

The experimental findings underscore the potential of LSTM-based MPPT controllers in significantly improving solar panel efficiency and energy harvesting capabilities. By leveraging the temporal dependencies in input data, LSTM networks demonstrate superior accuracy and adaptability compared to traditional MPPT algorithms. The interpretation of findings suggests that LSTM-based approaches hold promise for enhancing the performance of solar panel systems under diverse environmental conditions, contributing to the advancement of renewable energy technologies and sustainability efforts.

6.3. Advantages and Disadvantages

The analysis of advantages of using LSTM neural networks for MPPT control highlights their ability to capture long-term dependencies and complex patterns in time-series data, enabling more accurate and dynamic control of solar panel systems. Additionally, LSTM-based approaches offer potential for real-time optimization and adaptability to changing environmental conditions. However, disadvantages such as computational complexity, requirement for extensive training data, and potential overfitting remain challenges to be addressed.

6.4. Future Research Directions

Future research in the field of LSTM-based MPPT controllers may explore potential applications, scalability, and hybrid approaches to further enhance performance and applicability. One direction is the investigation of hybrid models that combine traditional MPPT algorithms with LSTM-based approaches to leverage the strengths of both methods. Additionally, research on optimizing the computational efficiency of LSTM networks and improving generalization ability in realworld scenarios is warranted. Furthermore, scalability and deployment of LSTM-based MPPT controllers in large-scale solar panel systems merit exploration to facilitate widespread adoption and maximize energy harvesting efficiency.

7. Conclusions

This section provides a summary of the key findings and contributions of the study, emphasizing the significance of LSTM-based MPPT controllers in enhancing solar panel efficiency and contributing to sustainable energy production.

7.1. Key Findings and Contributions

In summary, the study investigated the efficacy of LSTM-based MPPT controllers for optimizing solar panel performance. Experimental results demonstrated that LSTM-based controllers outperform traditional MPPT algorithms in terms of accuracy, efficiency, and adaptability. By leveraging the temporal dependencies in input data, LSTM networks accurately predict the maximum power point of solar panels under diverse environmental conditions, thereby maximizing energy harvesting efficiency. The study contributes to advancing the field of renewable energy technologies by showcasing the potential of AI-based approaches in enhancing solar panel efficiency.

7.2. Significance of LSTM-based MPPT Controllers

The significance of LSTM-based MPPT controllers lies in their ability to address the inherent challenges of traditional algorithms and improve the efficiency of solar panel systems. By leveraging the capabilities of LSTM neural networks, these controllers offer enhanced accuracy and adaptability, enabling more effective utilization of solar energy resources. LSTM-based MPPT controllers play a crucial role in advancing sustainable energy production by maximizing the power output of solar panels and reducing dependency on fossil fuels. As such, they represent a promising avenue for realizing the transition towards a more sustainable and environmentally friendly energy future.

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