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Leveraging AI for Sustainable Energy Development in Solar Power Plants Operating Under Shading Conditions

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Abstract: In a photovoltaic (PV) system, shading caused by weather and environmental factors can significantly impact electricity production. For over a decade, artificial intelligence (AI) techniques have been applied to enhance energy production efficiency in the solar energy sector. This paper demonstrates how AI-based control systems can improve energy output in a solar power plant under shading conditions. The findings highlight that AI contributes to the sustainable development of the solar power sector. Specifically, maximum power point tracking (MPPT) control systems, utilizing metaheuristic and computer-based algorithms, enable PV arrays to mitigate the impacts of shading effectively. The effect of shading on a PV module is also simulated using MATLAB R2018b. Using actual PV data from a solar power plant, power outputs are compared in two scenarios: (I) PV systems without a control system and (II) PV arrays equipped with MPPT boards. The System Advisor Model (SAM) is employed to calculate the monthly energy output of the case study. The results confirm that PV systems using MPPT technology generate significantly more monthly energy compared to those without MPPTs.

Keywords: solar energy; energy forecasting; PSC; sustainable development; MPPT; SDGs

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1. Introduction

The total world energy consumption is expected to grow by 14% between 2020 and 2030 [1]. By 2035, fossil fuels are predicted to account for approximately 75% of the global energy mix [2]. Economic development and prosperity are heavily dependent on energy resources. However, the use of fossil fuels emits harmful gases into the atmosphere, raising environmental concerns, whereas renewable energy sources provide sustainable alternatives [3]. Consequently, the global adoption of clean energy, including solar power, has been increasing. As a freely available and sustainable energy source, solar power can be harnessed almost anywhere in the world. The share of solar energy has risen significantly, from approximately 180 MW in 2014 to 1418 MW in 2023 [4]. In 2022, solar power generation produced about 4323 gigawatt–hours of electricity—enough to supply power to over 470,000 Canadian residences [5].

Photovoltaic (PV) panels convert solar irradiance into electricity. These affordable and easy-to-install systems offer a promising and sustainable clean energy solution for consumers. PV systems can be deployed in both urban and remote areas, providing consistent electricity generation. However, PV power output depends heavily on the level of irradiance received from the sun. Shading caused by weather or environmental conditions can significantly reduce energy production. While there is no substitute for sunlight, shading due to snowfall is one of the most common challenges faced by PV systems. The depth of accumulated snow determines the severity of shading. This study focuses on scientific methods to mitigate shading effects caused by ambient and weather conditions. However, complete shading—where no irradiance reaches the PV surface due to heavy snow, dust, pollution, or other obstructions—is beyond the scope of this research. In practice, maximum power point tracking (MPPT) methods are employed to optimize power output under partial shading conditions. In a solar power plant, MPPT control systems help PV arrays operate at optimal points by running artificial intelligence (AI)-based algorithms.

In recent years, AI-based approaches have gained prominence in addressing PV shading issues. Although AI lacks a universally agreed-upon definition, in this paper, we refer to AI as the use of advanced, computer-based techniques and algorithms to process complex data.

This work presents a study on the use of AI-based MPPT algorithms for photovoltaic systems. These methods determine the maximum power point for each cycle by examining voltage–current characteristics. They utilize a dynamic adaptive voltage range for optimal performance and incorporate AI-based algorithms. Traditional MPPT algorithms encounter difficulties in accurately tracking maximum power points, leading to diminished efficiency. An efficient and adaptive MPPT system is essential to accommodate fluctuating and unexpected irradiance profiles, along with other environmental factors [1].

Comparative investigations demonstrated that AI-based MPPT surpasses traditional algorithms in tracking precision, response time, and energy output [2]. AI-augmented MPPT systems markedly boost the feasibility of solar energy solutions in areas with inconsistent illumination, facilitating the development of sustainable urban energy infrastructures [2]. Recent artificial intelligence methodologies, including fuzzy logic controllers (FLC), Gauss–Newton optimization, and artificial neural networks (ANN), have enhanced maximum-power point-tracking (MPPT) traditional algorithms and forecasted the optimal charging conditions [3].

The ability of AI methods to handle intricate input–output relationships in a data-driven manner allows for optimal solutions with improved speed and reliability [6]. While a vast body of research has explored the application of AI algorithms in MPPT, their direct impact on power generation in a solar power plant has not yet been fully investigated. In addition, a real-world application of AI with actual PV system data is examined in this paper. This study examines energy output in a case study located in Golden, Colorado. Using the System Advisor Model (SAM), we compare the power generation of a PV system with and without an MPPT hardware device. The results demonstrate that PV arrays equipped with MPPT systems can significantly enhance energy production in a solar power plant.

Section 2 provides an overview of PV electricity generation and the impact of shading on system performance. Section 3 briefly reviews AI-based MPPT techniques and their role in sustainable development. Section 4 presents the monthly power production of the PV system in the case study, comparing two scenarios: with and without MPPT systems. Section 5 interprets the results of electricity generation under both conditions, followed by the conclusion in Section 6.

2. PV Systems and Shading Conditions

2.1. PV Cell Model

A PV is configured in a series-parallel arrangement to attain the specified output power and voltage. Utilizing an appropriate electrical circuit model and accurately identifying its properties are crucial for predicting solar performance and energy yield. Creating a photovoltaic model and its associated electrical circuit facilitates the analysis of variations in the I-V and P-V curves under diverse environmental conditions and climatic factors. A carefully articulated PV model that includes the system's characteristics enables designers to accurately calculate the system's power output.

The most critical component of a PV module is the PV cell [7]. The cell functions as a simple p-n junction diode, consisting of two layers of semiconductor material. The relationship between current I and voltage V in a single-diode Rp model is described by the following equation:

$$I = I_L - I_0[\exp\,(q\,(V + IR_s)/\alpha kT) - 1] - (V + IR_S)/R_{SH}, \quad (1)$$

where I represents the PV current, which is directly affected by the intensity of the sun and temperature fluctuations. The saturation current I_0 is influenced by temperature variations, α denotes the diode's ideality factor, and q ($-1.6021764 \times 10^{-19}$) signifies the charge of one electron. K ($-1.380653 \times 10^{-23}$) denotes Boltzmann's constant, T (K) represents the absolute temperature of the p-n junction, and R_S and R_{SH} signify the series and shunt (parallel) equivalent resistances of the solar panel, respectively [4].

Figure 1 illustrates an analogous circuit of a photovoltaic cell, comprising a current source, a diode, and a configuration of resistors arranged in parallel and in series.

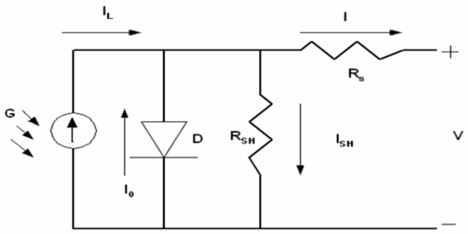

Figure 1. Equivalent circuit of a PV cell.

2.2. The Effect of Partial and Full Shading on Energy Production

Shading an individual cell in a PV module can diminish the power output to nil. A conventional PV system for energy generation comprises a PV array, a DC-AC inverter, and a load. Photovoltaic modules are arranged in various series and parallel configurations to attain the requisite output voltage and current. Each module has bypass diodes that enable current from unshaded areas to circumvent the shaded region, thus confining the shading impact to the specific set of cells safeguarded by the same bypass diode [5,6]. When the bypass diode activates, the module voltage decreases by an amount equivalent to the total voltage of the safeguarded cells plus the forward voltage of the diode. Nevertheless, the current from adjacent unshaded cells persists in circulating around the shaded cluster [5].

A PV module may operate under reduced irradiance due to limited sunlight exposure or adverse weather conditions, such as dust, snow, ice, pollution-related particles, or cloud cover [7]. Unlike partial shading, which affects only some portions of a PV module, full shading occurs when the entire module surface is obstructed. The thickness of the object covering the solar panel—such as accumulated snow—determines the level of irradiance received by the PV module [8].

In this study, the SunPower SPR-E19-310-COM (EnergySage, 3 Center Plaza, Boston, MA, USA) module was selected to design the PV system. Table 1 presents the module's characteristics under standard reference conditions (1000 W/m^2; cell temperature = 25 °C), as provided by the System Advisor Model (SAM) program [9]. Since PV modules generate less electricity when operating under limited irradiance, shading conditions can significantly impact power output.

Table 1. Technical characteristics of the SunPower SPR-E19-310-COM module.

Technical Term	Value
Nominal Efficiency	19.02%
Maximum Power (Pmp)	310.149 (W)dc
Maximum Power Voltage (Vmp)	54.7 (V)dc
Maximum Power Current (Imp)	5.7 (A)dc
Open Circuit Voltage (Voc)	64.4 (V)dc
Short Circuit Current (Isc)	6.0 (A)dc
Length × Width	1.559 × 1.046 (m^2)

The amount of snowfall, typically the prime cause of shading, affects the total irradiance received by a solar panel. Daily energy losses due to snowfall can be estimated as follows [10]:

1. For a module angle of 30°:
   - Snowfall depth greater than 1″ results in a 45% daily energy loss.
   - Snowfall depth less than 1″ results in an 11% daily energy loss.
2. For a module angle of 40°:
   - Snowfall depth greater than 1″ results in a 26% daily energy loss.
   - Snowfall depth less than 1″ results in a 5% daily energy loss.

Alternatively, partial shading conditions (PSCs) occur when only some parts of a PV surface are affected by an obstruction. Depending on the latitude and longitude, weather can be the primary cause of partial shading in a solar power plant. For instance, clouds, snowfall, wind, heavy rain, hail, freezing rain, sandstorms, or a combination of these elements can impact energy production. In addition to climatic factors, the environment and location of a PV site can also contribute to shading due to nearby objects such as buildings, trees, vegetation, pollution, and sand dunes.

When a PV module is partially exposed to sunlight, its I-V and P-V curves exhibit one global maximum and two local maximum points. In a previous study using MATLAB simulations [11], these curves were analyzed for a PV array consisting of four PV modules connected in a parallel-series configuration. Figure 2 illustrates the P-V and I-V characteristics, current (I), and voltage (V) of the circuit under uniform shading conditions (irradiance = 1000 W/m^2; temperature = 25 °C). As shown, with uniform shading, there is only one maximum point in each of the P-V and I-V curves, representing the maximum functional point of the PV system. However, under partial shading conditions, these curves exhibit multiple operational points, with each corresponding to a different module.

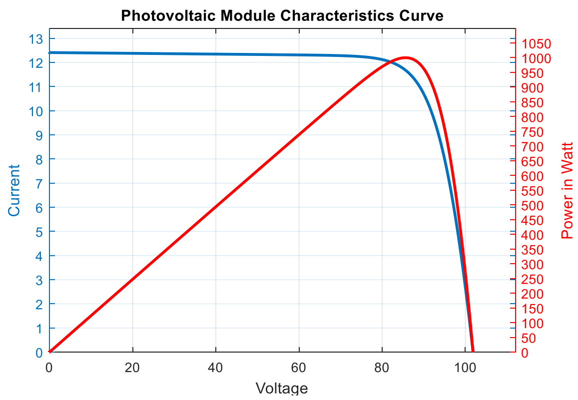

Figure 2. The P-V and I-V characteristics of the uniformly shaded PV arrays.

Figure 3 illustrates the P-V and I-V curves of partially shaded PV modules within the array, with each being affected by different levels of solar radiation: 500 W/m^2, 100 W/m^2, 1000 W/m^2, and 300 W/m^2. The presence of two local maxima and one global maximum demonstrates the P-V and I-V relationships of the PV system. Similarly, the I-V curves exhibit three distinct slopes, corresponding to the points where P-V changes occur.

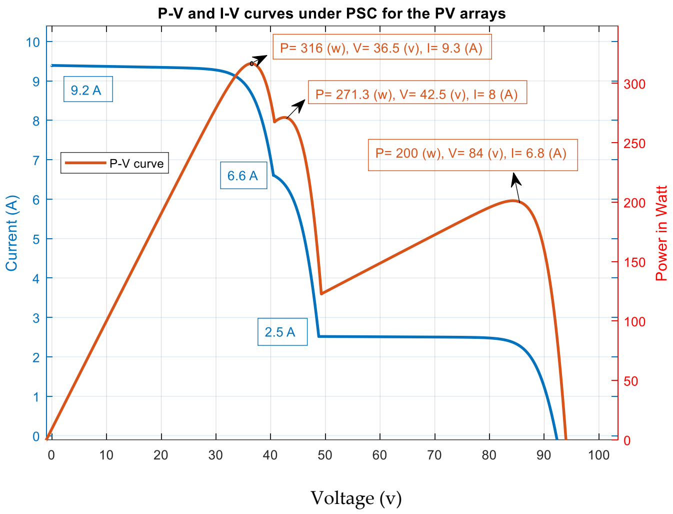

Figure 3. The P-V and I-V characteristics of the partially shaded PV arrays.

As expected under partial shading conditions, the generated power of the circuit results in multiple I-V and P-V curves, with each representing the operational characteristics of the system when different modules experience shading.

2.3. The Application of an MPPT Method

An MPPT system extracts the optimal output energy from a solar panel operating under partial shading conditions (PSCs). The nonlinear characteristics of a PV array under PSCs will result in multi-peak P-V and I-V curves with one global maximum point (GP) and multiple local maximum points [12,13].

MPPT approaches are designed to alleviate the effects of PSCs on PV system performance, assuring optimal operation at the maximum power point (MPP). An MPPT controller utilizing an optimization technique is deployed to do this. In an MPPT-based control system, the control parameters affect the performance of each algorithm, potentially leading to minor discrepancies in compared outcomes [14]. The controller supplies the reference voltages or currents necessary for the photovoltaic module. According to these references, the pulse width modulation (PWM) generator establishes the suitable duty cycle for the converter.

A voltage regulator is an essential element of any MPPT control system, as it monitors the reference value supplied by the operational algorithm [15]. This reference value is identified using a microcontroller (MCU) that is integrated with current and voltage sensors. Microcontroller units (MCUs) are pivotal in solar energy harvesting, facilitating system management and communication technologies that empower designers to manage the output power of photovoltaic (PV) arrays [16].

Microcontroller units (MCUs) can identify power supply conditions (PSCs) and react appropriately due to their dynamic modulation abilities. Moreover, MCU-based photovoltaic systems need fewer components, hence enhancing their reliability and decreasing costs in comparison to traditional or analog technology. Contemporary sophisticated microcontrollers have a range of technical capabilities, including the simultaneous generation of numerous PWM signals. Consequently, the MPPT system can precisely determine the best operating point for the PV system [17].

3. Related Works: The Application of AI in PV Systems

AI-driven technologies have been applied across various research fields in the solar power sector, primarily to handle complex data generated from multiple sources. These applications range from energy forecasting to analyzing data from control and monitoring systems.

For example, in [18], AI methods are effectively utilized in geographic information system (GIS) databases to determine the optimal sites for solar farm installations. Site selection models consider various interrelated and sometimes unrelated factors, including environmental, socio-economic, legal, and political considerations. Similarly, as presented in [19], anomaly detection for PV system maintenance can be performed using deep learning techniques.

One of the major research areas benefiting from AI is solar power production forecasting. In [20], machine learning models are used to predict the energy output of a PV system. Additionally, AI and machine learning techniques contribute to system modeling and energy cost predictions [21]. AI applications have also been explored for cost reduction, climate impact mitigation strategies, and energy efficiency improvements, as outlined in a literature review [22]. However, MPPT methods have gained significant advantages through the integration of AI-powered algorithms [23].

Since this paper focuses on PV shading, we examine the advancements in sustainable electricity production in the context of MPPT systems. Furthermore, we investigate the role of AI in enhancing energy efficiency for PV systems operating under shading conditions. The following subsection provides an overview of AI-based algorithms that improve PV energy generation efficiency and enhance the functionality of MPPT control systems.

3.1. The Role of AI in MPPT Algorithms

Numerous algorithms have been developed by researchers to identify the maximum power point (MPP) at which a PV system can operate efficiently under shading conditions.

The literature reviews categorize these algorithms according to their functionality, and the distinctions among the approaches are considerable. These classifications largely emphasize MPPT applications, optimization approaches, costs, utilized parameters, efficiency, tuning mechanisms, system complexity, and convergence speed [14,24].

The predominant classifications of MPPT approaches are as follows: (1) conventional or classical methods, (2) modern or soft computing methods, (3) hybrid methods, and (4) power electronics (PE)-based methods.

Conventional approaches, although simple to execute, may become ensnared in local maxima, leading to one of the local sites being erroneously designated as the MPP in PV systems functioning under partial shadowing conditions (PSCs) [25]. Moreover, shadowing circumstances can profoundly affect photovoltaic performance.

Soft computing technologies are often classified into AI-based approaches and meta-heuristic optimization strategies [26,27]. Meta-heuristic approaches are categorized into (1) evolutionary algorithms (EA) and (2) population-based or swarm intelligence (SI).

This study categorizes all soft computing MPPT algorithms and prospective hybrid methods as AI techniques, as stated in Section 1. These strategies are proficient in rapidly identifying the MPP and improving PV performance efficiency.

Methods based on power electronics (PE) utilize hardware components and the technical attributes of microcontrollers in MPPT control systems [28]. These technologies, categorized as AI-based approaches, are recognized for their high efficiency and rapid response times, akin to soft computing techniques [29].

3.2. Solar Power Generation and Sustainable Development

The United Nations has defined 17 guiding aims, known as the Sustainable Development Goals (SDGs), which establish a framework for addressing the environmental, political, economic, and human aspects of project developments involving technology [30]. Set to be achieved by 2030, these goals cover various aspects of life and socioeconomic progress, including the alleviation of poverty, good health, equality, economic growth, clean water, and more.

Solar power is considered a key driver of economic development due to its role in electricity generation. The seventh SDG—Affordable and Clean Energy—directly aligns with AI-driven techniques that enhance the efficiency and sustainability of solar power generation. To ensure the sustainable development of electricity generation, the technologies used in solar energy systems should be examined. The role of deep learning and machine learning in fulfilling the SDGs is explored in [31].

Although the benefits of AI technologies have been widely acknowledged in most studies, a few papers also highlight the potential negative impacts of utility-scale solar power plants on SDGs [32]. For instance, one study emphasizes the importance of understanding the local communities in which a power plant is located—in this case, Madagascar. However, the majority of research focuses on the strong relationship between solar power generation and its positive contributions to SDGs.

Given the focus of this article, we examine the seventh SDG, exploring how to advance affordable and clean energy. According to the definition of sustainable development [31], the primary objective is to ensure that future generations can meet their own needs without compromise. Compared to fossil fuels, solar energy offers significant environmental benefits, supporting long-term human development [33].

At the same time, the initial phases of renewable energy projects require careful planning and consideration. AI-based technologies have been integrated into smart grids and renewable energy systems for over two decades [34]. AI has had a significant impact on forecasting, monitoring, controlling, and managing energy production in the solar power sector [35]. As stated in Section 3.1, most advanced computational techniques rely on AI technology to optimize MPPT algorithms.

By enabling the implementation of diverse optimization algorithms and enhancing system flexibility, AI allows for sustainable and efficient improvements in solar power generation. The study in [36] underscores the important role of local communities in the sustainable development of solar power plants. However, our focus remains on technological advancements in AI methods that support sustainability and align with the seventh SDG.

4. Monthly Power Production of the Case Study

Solar energy practitioners and non-technical solar power users employ PV planning tools, online applications, and software products to estimate the energy output generated by a system. In order to submit a reliable PV planning software to report the most accurate electricity output by this paper's case study, we investigated thirty-one commercial and open-source software (the complete list is available in Annex I [37]). We finally selected the System Advisor Model (SAM) to calculate the energy production of our case study. The PV model used in the tool and the validity of the research studies are presented in [38–41]. Provided by the U. S. Department of Energy [9], National Renewable Energy Laboratory (NREL), this model has been widely utilized by researchers and PV practitioners to plan solar energy projects. The output data of more than 10 solar power plants for certain years are publicly available on the website [9]. The hourly power production of the solar power plants is available in [42]. The reported data were measured and collected at the power plants. The recorded output powers are available in Excel files for the entirety of 2012. This paper examines a case study of a photovoltaic system installed at the Research Support Facility 2 (RSF 2) of the National Renewable Energy Laboratory (NREL) in Golden, Colorado, United States. The PV system comprises a 408 kW solar power plant installed on the top of the A-wing addition of the RSF. It is situated at 39.74° N, 105.18° W, with an elevation of 1829 m. The whole technical explanation of the case study is available in [42].

SAM is a free desktop application allowing for renewable energy practitioners to examine the technical, economic, and financial feasibility of renewable energy projects [9]. In addition, it provides various output reports, including daily, monthly, and annual energy production. The model uses the meteorological data available in its weather library. Using SAM simulation (version 2023.12.17), we designed a PV power system, choosing the same inverter and module as the actual project. Two different planning scenarios were applied to design a separate PV system for the case study. Later, the monthly power generation of these solar plants was compared. The new version of the design tool incorporates MPPTs, whereas previous versions of SAM did not account for MPPT design. We employed two different versions of the SAM to simulate the following two scenarios:

1. A system designed without MPPT.
2. A system equipped with MPPT.

SAM provides both monthly and annual energy production summaries, along with the technical characteristics of the designed systems. The brand and type of PV module used in the designs were selected similarly to ensure consistency across both systems. The following section outlines the two scenarios and the designs of the PV systems.

Scenario 1. PV arrays without MPPT

To design a PV system without MPPT, we employed an older version of SAM (version 2014.1.14). Table 2 projects the technical features of the designed system, which generated 408.3 kW power.

Table 2. Technical characteristics of the case study without MPPT.

Technical Term	Value
Nameplate DC	408.3 DC (kW)
Modules—number and type	1323 (SunPower SPR-E19-310-COM)
Strings	162
Modules per string	8
Inverters—number and type	1 (SC2500U)
Number of strings	63

Scenario 2. PV arrays equipped with an MPPT control system.

Using SAM (version 2023.12.17), Table 3 depicts the technical characteristics of the designed PV system equipped with MPPT. Since choosing a one- or three- MPPT systems for the PV system does not affect the estimated output power, we used a single MPPT system to reduce complexity and minimize the additional cost of the final design.

As depicted in Tables 2 and 3, the two different versions of SAM designed two slightly different PV systems, despite the similarity in the input data used for the case study. The fact is that the SAM was improved, along with its libraries, offering more PV types with an upgraded technical performance. Consequently, the same number of modules resulted in noticeable differences in energy production; approximately 0.5% extra (410.33 kW vs. 408.3 kW).

Table 3. Sizing summary of the PV system for NREL's RSF 2 building.

Technical Term	Value
Nameplate DC	410.33 DC (kW)
Modules—number and type	1323 (SunPower SPR-E19-310-COM)
Strings	63
Modules per string	21
Inverters—number and type	1 (SC2500U)
Number of strings	63
MPPT voltage range	800–1500 (V) DC

5. Discussion of Results

Using the SAM, we compared the monthly power outputs of two scenarios to determine which design produces more energy. Figure 4 presents the monthly power generation of the designed systems. It is important to note that the designed systems do not reflect the actual monthly energy generation of RSF2, as the SAM uses default typical-year (TMY) weather files for most long-term analyses. For instance, heavy snowfall results in zero energy output for the power plant on certain days, which is not accounted for in the TMY. However, the simulation reports distinct monthly power production levels. Comparing the two monthly power production results shows that the PV system equipped with MPPTs generates more energy than the system configured without MPPTs.

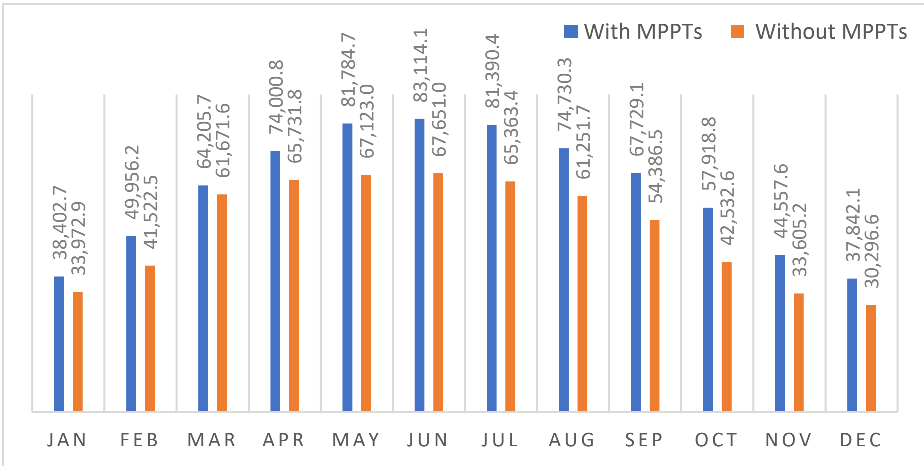

Figure 4. Monthly power production for the case study.

5.1. Hypothesis Testing for Both PV Systems: With and Without MPPTs

As illustrated in Figure 4, there are two sets of data presenting power generation with respect to MPPT for the case study (RSF 2) over 12 months in a typical year. To understand the important role of an MPPT-based control system in increasing energy production, we performed a *t*-test on the results. The one-tail *t*-test formula in Excel was used to calculate the results in the table. Our hypothesis is defined as the PV system equipped with an MPPT control system providing the same power generation as the system without MPPT. The alternative hypothesis is defined as the designed PV system with MPPT providing greater monthly power production. The hypotheses are described as follows:

H_0: *Monthly Power Production (with MPPTs) = Monthly Power Production (without MPPTs).*

H_A: *Monthly Power Production (with MPPTs) > Monthly Power Production (without MPPTs).*

The test has an $\alpha = 0.05$ level of significance, and normal distribution is not assumed since the number of comparable data points is only 12 months. Table 4 presents the results, showing a high correlation in power production for both scenarios of about 97%. As presented, the p-value (about 2.5×10^{-6}) is significantly less than $\alpha = 0.05$, so the null hypothesis is rejected, indicating that the monthly power generation for the designed PV system equipped with MPPT offers greater energy production.

Table 4. *t*-test results for monthly productions: Adding MPPTs to the PV system (RSF 2).

	With MPPTs	Without MPPTs
Mean	62,969.37	52,092.4
Variance	286,554,699.79	214,483,699.21
Pearson correlation	0.9683194	
t stat	8.2306124	
P (T ≤ t) one-tail	2.4902145×10^{-6}	
T critical one-tail	1.7958848	

5.2. Comparison with Other Methods

As noted in Section 3, most previous studies considered AI as a promising means of tracking the maximum power point more efficiently. Metaheuristic algorithms and machine learning techniques are AI-based methods that provide rapid optimization. However, the role of an MPPT control system equipped with microcontrollers implementing AI algorithms has not been investigated in an actual solar power plant. This study highlights the importance of MPPT control systems in solar power generation when ambient conditions cause partial or full shading, which degrades PV power outputs.

5.3. AI-Based Approaches and Sustainable Development

As stated in Section 3, solar power plants play an undeniable role in achieving the seventh goal of the SDGs. The ecological footprint of a solar power plant, compared to other fossil fuel energy resources, is remarkably low. Considering the technological aids offered by AI to the solar energy sector, we argue that AI-driven methods provide greater efficiency when shading conditions play an important role in the site's location. Furthermore, using soft computing techniques and microcontrollers for MPPT purposes addresses the need for sustainable development, as no additional environmental resources are needed to enhance an existing power plant. Therefore, to establish maximum efficiency and improve the technical characteristics of a solar power plant, we must utilize AI in the plant's development. We also argue that using MCU-based systems for MPPT purposes demonstrates the potential hardware applications of AI-based technologies.

6. Conclusions

AI-driven approaches have demonstrated significant potential in advancing sustainable development within the solar power generation sector. This progress aligns with the goal of achieving affordable and clean energy (SDG 7) by 2030. This paper demonstrates that MPPT systems can increase power generation, using a solar power plant as a case study. The PV design system equipped with MPPT offers additional energy production, by approximately 20%, depending on the month of operation. These AI-powered devices not only address shading conditions but also increase the sustainability of developing solar power plants. Project managers, engineers, and policymakers can leverage AI methods to optimize solar power plants by incorporating MPPT-based control systems. The primary challenge lies in the additional costs associated with integrating AI-powered MPPT systems into existing PV plants, which may impact the development of older solar power plants that currently operate without MPPT solutions.

Future research directions can experiment with adapting AI to different environmental conditions, including different latitudes and the effect of various seasons. In addition, the integration of such solar power plants using MPPT control systems should be studied.

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Conflicts of Interest: Author Farhad Khosrojerdi was employed by the company Cando Green Construction Inc. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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