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Flocking-Inspired Solar Tracking System with Adaptive Performance in Varied Environmental Conditions

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Abstract: Traditional solar trackers are designed to follow the sun's exact position, assuming that perfect sun alignment always results in optimal energy generation. However, despite perfect alignment, external factors such as shading, dust, and wind can reduce power output in real-world conditions. To address these challenges, our novel system draws inspiration from the flocking behavior of birds, where individual entities adjust their behavior based on their energy output and the energy outputs of neighboring panels. The system uses Particle Swarm Optimization (PSO) to mimic this behavior, dynamically adjusting the solar tracker's position to respond to varying environmental conditions. One key innovation is introducing a power threshold strategy, set between 1.5 W and 2 W, to avoid continuous tracker movement and conserve energy by minimizing unnecessary adjustments when the power difference is insignificant. The proposed system demonstrated an impressive 8% increase in energy gain and a reduction of up to 11% in energy consumption compared to the traditional continuous tracker. The tracking accuracy improved by 84%, with the mean tracking error reduced in the range of 0.78° to 1.09°. The system also captured 17.4% more solar irradiance, showcasing its superior efficiency. Despite environmental challenges such as dust and shading, the proposed system consistently outperformed the traditional tracker regarding energy savings and overall performance, offering a more resilient and energy-efficient solution for solar energy generation.

Keywords: bird flocking behavior; particle swarm optimization (PSO); power threshold; solar energy; solar trackers

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1. Introduction

Traditional solar tracking systems typically rely on sun sensors or sophisticated sun position algorithms to follow the sun's trajectory throughout the day. Sun sensors detect solar angles, adjusting the tracker's position to ensure optimal exposure to sunlight. This widely adopted approach has been explored in numerous studies, including those by Hoffmann et al. [1], Morón et al. [2], Abouzeid [3], and Skouri et al. [4]. To further enhance tracking accuracy, some researchers have incorporated GPS sensors, as demonstrated by Sidek et al. [5], Verma et al. [6], and Wu et al. [7], which allow for more precise alignment of the tracker with the sun's movement, compensating for slight misalignments and improving overall system performance.

Another alternative method involves using webcams as sensor components to detect solar intensity, as demonstrated by Arturo and Alejandro [8]. Rather than relying on physical sensors, some systems employ sun position algorithms to calculate the optimal position of the tracker. These algorithms use geographic coordinates, time, and date to compute the sun's elevation and azimuth angles, enabling the system to adjust the tracker's position without the need for direct sensors. This approach was investigated by researchers such as Seme and Stumberger [9], Ghabusnejad et al. [10], and Pirayawaraporn et al. [11], who highlighted the potential for reducing hardware requirements while maintaining tracking accuracy.

Irradiance sensors have further improved tracking accuracy, as demonstrated in the studies by Abdollahpour et al. [12] and Canada-Bago et al. [13]. In addition to irradiance sensors, other optimization techniques were explored by researchers such as Sidek et al. [14], Nazir et al. [15], Tirmikci and Yavuz [16], and Loon and Daud [17], highlighting various approaches to fine-tuning tracking systems for enhanced performance. More recently, Fathabadi has focused on integrating Maximum Power Point Tracking (MPPT) systems for energy optimization [18,19], providing significant advancements in system efficiency. Additionally, Carballo has combined deep learning techniques with cost-effective hardware to improve tracking precision and overall efficiency [20], offering a promising direction for future solar tracking innovations.

Despite their sun-tracking effectiveness, traditional solar tracking systems encounter several challenges that compromise their overall efficiency and reliability. A significant issue is their high energy consumption. Solar trackers using sun sensors or GPS require continuous power to operate and adjust to changing conditions throughout the day [21,22]. This constant energy demand can diminish the system's overall efficiency, as the power consumed for tracking may offset the energy generated by the panels, particularly in systems that require frequent recalibration or adjustments [23,24].

Moreover, these systems are vulnerable to environmental factors such as shading, dust, and cloud cover, which can impair the accuracy of sun sensors or cause misalignment of the trackers, leading to reduced energy output. While sun position algorithms offer theoretical calculations for the sun's position, they fail to account for real-world uncertainties, such as shifting environmental conditions [25,26]. If initial positioning is even slightly incorrect or the tracking intervals were not set optimally, it can result in significant tracking errors and low accuracy. These inherent limitations in accuracy, combined with higher energy consumption and increased maintenance requirements, undermine these systems' long-term performance and reliability [27,28].

This study aims to overcome these limitations by presenting an innovative solar tracking system inspired by the collective dynamics of bird flocking behavior. In nature, birds adjust their position based on the relative movements of nearby birds to optimize energy use while maintaining cohesion [29,30]. Similarly, the proposed solar tracking system uses local power sensors (current and voltage sensors) on each panel to monitor energy output and make adaptive adjustments based on the relative energy outputs of neighboring panels rather than relying on sun position calculations or specific sun sensors.

The system employs a Particle Swarm Optimization (PSO) algorithm. This computational method simulates the collective behavior of swarms to solve optimization problems, which allows each panel to iteratively refine its position, balancing individual energy maximization with the best-known positions of its neighbors. The PSO algorithm proves especially effective in accounting for dynamic environmental factors, such as shading, obstacles, dust, or clouds, that can impact the optimal positioning of the panels [31–34]. This method enhances PV systems by improving efficiency, reducing consumption, and increasing adaptability. It may enable PV systems to respond more effectively to dynamic conditions such as shading, dust, and cloud cover, aiming to achieve optimal performance. Minimizing unnecessary movements is anticipated to lower maintenance costs and contribute to extending the lifespan of solar trackers.

Key contributions of this work include (1) the novel application of a bio-inspired solar tracking system modeled after reference to the natural behavior of birds called bird flocking behavior, (2) the use of decentralized decision-making to enhance scalability and robustness, (3) the development of a dynamic, sensor-based adjustment strategy that achieves high tracking accuracy, and (4) experimental validation demonstrating less energy consumption compared to traditional trackers. These innovations establish a new paradigm in solar tracking technology tailored to improve energy generation efficiency and sustainability across diverse photovoltaic applications.

This paper is organized as follows:

Section 1 introduces the context and challenges of traditional solar tracking systems, highlighting their limitations in efficiency and adaptability to dynamic environmental conditions. It also presents the motivation behind the innovative flocking-inspired approach.

Section 2 describes the proposed strategy, detailing the integration of the Particle Swarm Optimization (PSO) algorithm and the innovative flocking-inspired approach for solar tracking. It also presents the experimental setup and evaluation metrics used to assess the system's performance under various conditions.

Section 3 discusses the results, including tracking accuracy, energy efficiency, and adaptability to environmental factors such as shading and dust. We also compare the proposed system with traditional solar trackers and explore its potential applications and implications for the future of renewable energy technologies.

Finally, Section 4 concludes the study, summarizing the key findings and suggesting directions for future research.

2. Methods and Materials

2.1. Proposed Strategy

This research presents an innovative solar tracking system inspired by the collective movement dynamics of flocking birds (see Figure 1). Unlike conventional trackers that aim to align precisely with the sun, our system prioritizes maximum power production by adapting to real-world environmental conditions.

Conventional solar trackers are designed to follow the sun's exact position, assuming that direct solar alignment always results in optimal energy generation. However, this is not always true in real environments. External factors such as shading from surrounding objects, dust accumulation, wind direction, and overheating due to continuous sun exposure can reduce power output despite perfect sun alignment. In many cases, the best position for energy generation is not the one facing the sun directly.

Our system mimics flocking behavior by using decentralized decision-making, where panels behave like birds in a flock. Instead of following a fixed trajectory, panels continuously adjust their position based on the energy output of its neighbors. Just as birds in a flock respond to the movement of those around them to find an optimal flight path, our panels adjust collectively to maintain the highest possible group energy yield.

This is achieved through a Particle Swarm Optimization (PSO) algorithm, which enables panels to communicate and reposition themselves only when a new position offers significant energy improvement. This prevents unnecessary movement, reduces energy consumption, and ensures that the system adapts dynamically to real-world disturbances.

Instead of simply tracking the sun, our system tracks the most productive energy position, considering real environmental challenges. Combining swarm intelligence with an adaptive movement strategy offers a more resilient and efficient alternative to traditional continuous solar tracking methods.

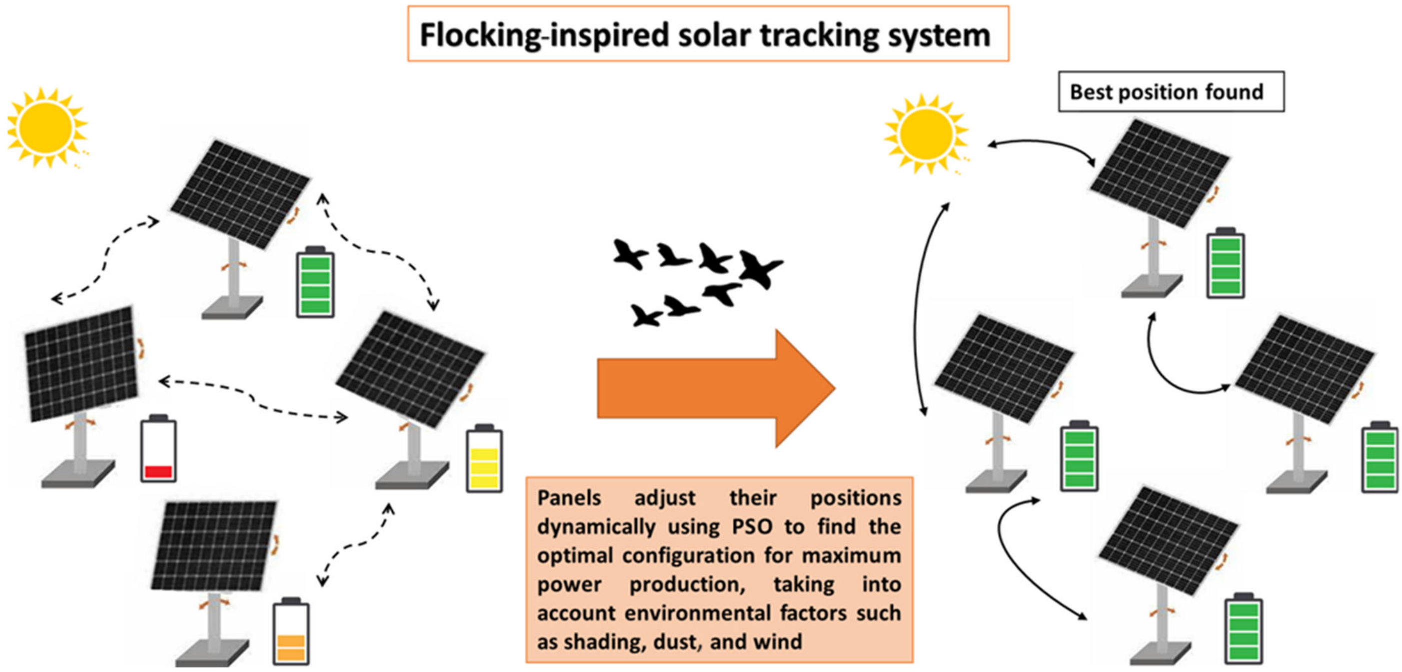


Figure 1. Proposed flocking-inspired solar tracking system.

2.2. Particle Swarm Optimization (PSO)

This work relies on Particle Swarm Optimization (PSO) because traditional tracking methods cannot adapt to real-time environmental changes. This algorithm is particularly useful when factors other than sun position, such as shade, obstacles, dust, or clouds, affect the optimal orientation of the solar panels [25,26]. PSO is a computational algorithm inspired by the social behavior of birds flocking and fish schooling. Introduced by Kennedy and Eberhart in 1995, PSO simulates the movement of individuals within a population to explore and exploit a search space, converging toward optimal solutions through iterative adjustments of their positions and velocities. Each particle represents a potential solution, and through collaboration and information sharing, the swarm collectively navigates the problem space to find the best possible outcome [34].

PSO has been effectively applied in solar energy systems to optimize Maximum Power Point Tracking (MPPT) algorithms. MPPT is crucial for photovoltaic (PV) systems to operate efficiently by continuously adjusting the operating point to the maximum power point. Traditional MPPT methods, such as Perturb and Observe (P&O), often face challenges under rapidly changing environmental conditions, leading to slower convergence and reduced efficiency [35,36]. A study by Regaya et al. (2024) introduced a modified multiswarm PSO algorithm with an adaptive factor selection strategy, demonstrating enhanced tracking accuracy and robustness under partial shading conditions [37]. Additionally, Lin and Liao (2024) proposed an adaptive PSO-based dynamic MPPT algorithm that effectively addresses rapid irradiance changes, improving convergence speed and stability [38].

PSO addresses these challenges by dynamically adjusting the search parameters, enabling faster convergence to the maximum power point and improved energy capture. PSO-based control systems for MPPT in a real-time PV system significantly reduced settling time and energy losses compared to traditional P&O algorithms [39,40]. For instance, a study published in *Scientific Reports* (2024) conducted a comparative analysis of conventional and digital MPPT techniques, highlighting the superior performance of PSO-based methods in maximizing solar power generation [41]. Furthermore, Ahessab et al. (2024) developed an enhanced MPPT controller using a modified PSO algorithm combined with an artificial neural network, achieving improved performance in partially shaded PV systems [42].

Beyond MPPT, PSO has also been applied to designing and implementing solar tracking systems. Solar trackers adjust the orientation of PV panels to follow the sun's path, thereby enhancing energy absorption. By employing PSO, these systems can optimize the tracking parameters, accounting for factors such as shading, temperature variations, and mechanical constraints [43,44]. Boubii et al. (2023) proposed an integrated control and optimization approach for grid-connected PV systems, utilizing model-predictive control and PSO to enhance system performance [45]. Additionally, a study by Regaya et al. (2024) introduced a modified multiswarm PSO algorithm with an adaptive factor selection strategy, demonstrating improved tracking accuracy and robustness in partially shaded conditions [37].

The adaptability and efficiency of PSO make it a valuable tool in the renewable energy sector, particularly for optimizing solar energy systems. Its ability to handle complex, nonlinear optimization problems and adapt to dynamic environmental conditions positions PSO as a promising approach for enhancing the performance and reliability of solar energy technologies [46,47]. For example, the study of Sarang et al. conducted a comparative analysis of conventional and digital MPPT techniques, highlighting the superior performance of PSO-based methods in maximizing solar power generation [41]. Furthermore, Boubii et al. proposed an integrated control and optimization approach for grid-connected PV systems, utilizing model-predictive control and PSO to enhance system performance [45]. In addition, Lin and Liao proposed an adaptive PSO-based dynamic MPPT algorithm that effectively addresses rapid irradiance changes, improving convergence speed and stability [38]. Similarly, Ahessab et al. developed an enhanced MPPT controller using a modified PSO algorithm combined with an artificial neural network, achieving improved performance in partially shaded PV systems [42].

Previous research has used Particle Swarm Optimization (PSO) primarily in solar tracking systems to optimize photovoltaic panel alignment with the sun, aiming to maximize solar irradiance and energy production. These systems adjust tracker positions based on the sun's angle to capture the most solar energy. In contrast, our approach introduces a novel application of PSO by incorporating a wider range of real-time environmental factors, such as shading, dust accumulation, wind, and temperature variations, which can significantly impact panel performance. Our flocking-inspired system allows panels to adjust based on local conditions and neighboring panels, aiming to optimize overall energy production. PSO is essential for navigating the complex, dynamic environment and adjusting panel positions accordingly, as traditional methods cannot effectively handle such diverse and changing conditions. Therefore, PSO is critical for ensuring optimal performance in our system.

2.3. The Workflow of the System

The workflow of the system follows several key steps (see Figure 2):

1. Random Initial Positioning: The system begins by assigning random initial positions to the solar panels. These random positions simulate the natural variability in the environment, where each panel has an initial guess of its optimal position. This randomness mirrors the behavior of birds in a flock, where they start without knowing the best direction but move toward it by interacting with their neighbors.
2. Energy Output Calculation: Each solar panel has sensors that measure its energy output (voltage, current, or power). The energy output is a proxy for how "good"

the current position is relative to the sun. This measurement reflects the panel's effectiveness in capturing sunlight in its current orientation.

3. Fitness Function Evaluation: Each solar panel's performance is evaluated using a fitness function designed to quantify the quality of the panel's position. The fitness function typically takes the following into account:
   - Energy output of the panel: Higher energy output indicates a better position.
   - Relative energy output compared to neighboring panels: The panel compares its energy output with its neighbors to evaluate if it is in an optimal position within the group.

   The fitness function is formulated as follows:

$$f = E - \alpha \times \Delta\mathrm{P} \tag{1}$$

   where f represents the fitness value of a solar panel's position, E is the panel's energy output, α is a weighting factor that adjusts the influence of neighboring panels' positions, and ΔP is the deviation from the optimal position of neighboring panels. This fitness function is used to evaluate the current state of each particle (solar panel) in the swarm.

4. Velocity and Position Update (PSO Mechanics): PSO works by adjusting each particle's (panel's) position and velocity based on its own best-known position (personal best, pbest) and the best-known position in the entire swarm (global best, gbest).
   - Personal best (pbest): Each panel remembers its best position based on its highest energy output.
   - Global best (gbest): The panel performing the best in terms of energy output in the entire system is considered the global best.

   The velocity update formula for each panel is given by [34] the following:

$$V_i^{(t+1)} = w.V_i^{(t)} + c_1.r_1.\left(P_{best\,i} - X_i^{(t)}\right) + c_2.r_2.\left(P_{best\,neighbor_i} - X_i^{(t)}\right) \tag{2}$$

   where $V_i^{(t)}$ is the velocity of panel "i" at iteration "t", $P_{best\,i}$ is the personal best position of panel "i", $P_{best\,neighbor_i}$ is the best position among the neighboring panels of panel "i", c_1 and c_2 are cognitive and social coefficients, and r_1 and r_2 are random numbers between 0 and 1.

   The position update formula is [34] as follows:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \tag{3}$$

   This formula updates the panel's position based on its velocity.

5. Convergence to Optimal Solution: As the PSO algorithm iterates, the panels gradually converge to positions where the collective energy output is maximized. The swarm of panels adapts based on the changing energy output of each panel, ensuring that they follow a path toward optimal alignment with the sun, even if shading or environmental factors cause deviations in individual panel performance.
6. Threshold for Energy Consumption: To prevent excessive energy consumption, a threshold is set where panels only move if the change in energy output is significant. Suppose the improvement in energy output is below a predefined threshold. In that case, the panels do not move, reducing unnecessary adjustments and ensuring that the system does not waste energy by continuously seeking a better position when it is already close to optimal.

7. Re-evaluation of Positions: Each iteration of the PSO algorithm recalculates the energy output and evaluates the fitness function for each panel. As the panels adjust their positions, the PSO process repeats, continually refining the positions based on the panels' own best-known locations and the overall best position in the system.
8. Final Adaptation: After several iterations, the system converges to an optimal set of panel positions that maximize the energy capture based on the dynamic environmental conditions. The panels work collaboratively, adjusting to changing factors like shading, clouds, or nearby obstacles.

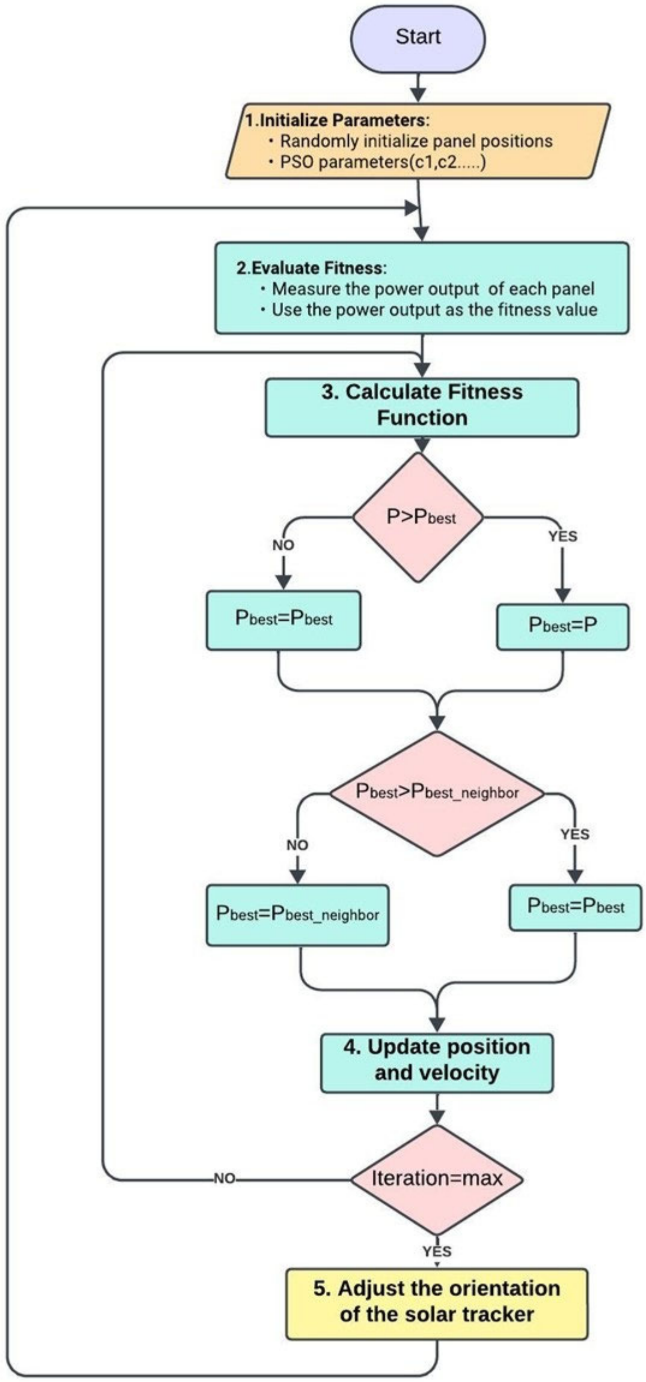
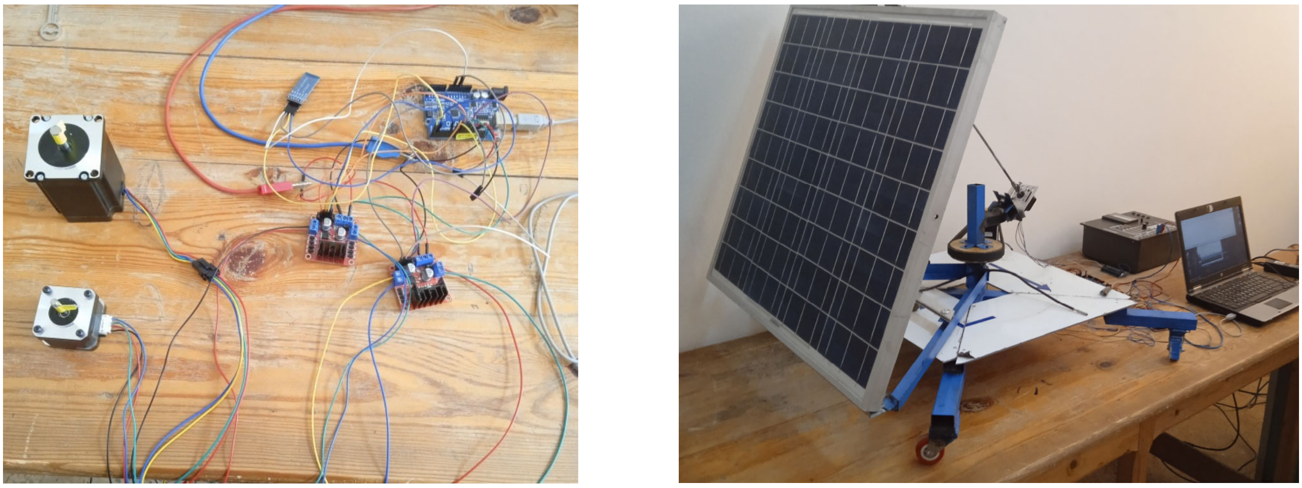


Figure 2. Proposed tracking system flow chart.

2.4. Experimental Setup and Simulation Methodology

The proposed flocking-inspired solar tracking system was tested and compared to a traditional continuous tracking system, which was implemented as shown in Figure 3. The prototype was designed to benchmark our system and evaluate its performance under different power thresholds. To assess its effectiveness, we tested the same prototype under three environmental conditions: dust accumulation, shading, and wind exposure.



(**a**) (**b**)

Figure 3. The designed solar tracker: (**a**) control unit, (**b**) prototype.

2.4.1. Implementation Details

The control unit, depicted in Figure 3a, is powered by an Arduino Uno. Mechanical operations are powered by two stepper motors, a NEMA 17 for elevation rotation and a NEMA 23 for azimuth rotation, both driven by L298N motor drivers. Communication between trackers is facilitated through an H05 Bluetooth module. The prototype consists of an elevation driver using a linear screw mechanism for tilt and stow positioning and an azimuth driver employing a V-belt pulley system for both azimuth and wind attack angles, as shown in Figure 3b. Table 1 provides the detailed specifications of the components used in the implemented system, which were also used in the simulation.

The specifications of each component used in this study are summarized in Table 1 below.

Table 1. The specifications of the components used in the proposed solar tracking system (Hardware components were supplied by the university's laboratory (L2GEGI Laboratory at Ibn Khaldoun University of Tiaret, Tiaret, Algeria) which are usually sourced from AliExpress).

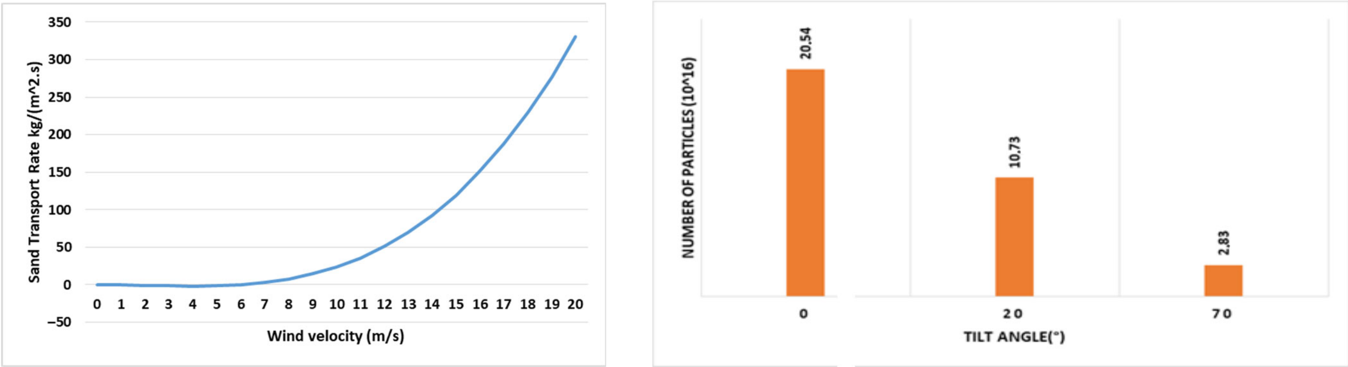
Category	Item	Specifications
Control Unit	Arduino UNO	Microcontroller: ATmega328PDigital I/O
		Pins: 14
		Flash Memory: 32 KB
		Communication Interfaces: 1 UART serial communication port
	Bluetooth Module	Model: HC-05 module
		SPP (Serial Port Protocol) module
	L298N Motor Drivers	Maximum Motor Voltage: 46 V
		Maximum Continuous Current: 2 A
		Motor Control Type: The dual H-bridge driver

Table 1. *Cont.*

Category	Item	Specifications
Azimuth Rotation System	V-Belt	2 cm wide belt
	Wooden Pulley	the drive pulley 4 cm diameter the driven pulley 12 cm diameter
	NEMA 23 Stepper	Model: 1m-57HS76-3004
		Step Angle: 1.8°
		Holding Torque: 4 Ncm
		Current Rating: 1.68 A
Elevation Rotation System	Lead Screw	69 cm screw and a 2 cm nut
	NEMA 17 Stepper	Model: 1m-42HS34-1334AC
		Step Angle: 1.8°
		Holding Torque: 26 Ncm
		Current Rating: 0.4 A
Structural Elements	Base with Four Wheels	/
	Support Structure for Solar Panel	/
	Suntech STP050D-12/MEA Solar Panel	Rated Maximum Power: (Pmax) 50 W
		Output Tolerance: ±5%
		Current at Pmax: (Imp) 2.93 A
		Voltage at Pmax: (Vmp) 17.4 V
		Short-Circuit Current: (Isc) 3.13 A
		Open-Circuit Voltage: (Voc) 21.8 V
		Nominal Operating Cell Temp: (TNOCT) 45 °C + 2 °C
		Weight: 5.3 kg
		Dimension: 665 × 631 × 30
		Maximum System Voltage: 1000 V
		Maximum Series Fuse Rating: 10 A
		Cell Technology: multi-Si
		Application Class A
		AM = 1.5 E = 1000 W/m^2 Tc = 25 °C

2.4.2. Tracker 1—Dust Accumulation

Tracker 1 was used to test the adaptability of the proposed system to dust accumulation. The tracker was tilted at 0°, making it more susceptible to dust particles than the other two trackers, which were tilted at 70° and 20°. The sand transport rate on 6 June 2023, shown in Figure 4a, and the estimated dust accumulation in Figure 4b (based on tilt angles) helped assess how well the system adapted to the dusty environment. Rather than focusing on dust's effect on efficiency, we aimed to demonstrate how the system maintained its performance despite this condition. The methodology for obtaining these estimates is detailed in [48].



(**a**) (**b**)

Figure 4. (**a**) Sand transport rate on 6 June 2023. (**b**) Estimated accumulated dust on surface of solar trackers.

2.4.3. Tracker 2—Shading Effect

This test assessed the system's adaptability to shading conditions. Tracker 2 was placed in front of a 0.3 m high building, while the other two trackers were positioned in unshaded areas. The shadow length throughout the day, shown in Figure 5, was used to evaluate how the tracker responded to periodic shading. More details on the shading setup can be found in [24].

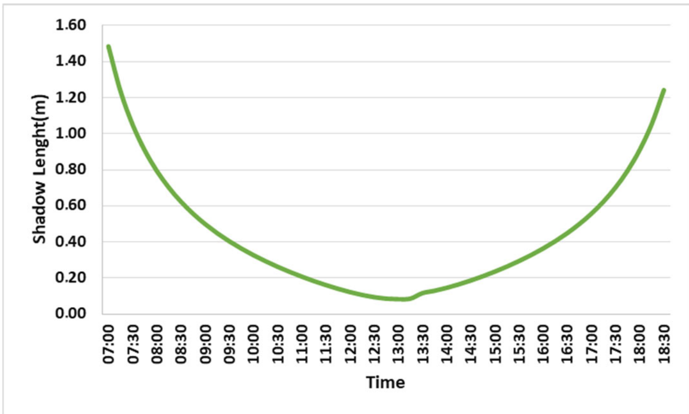
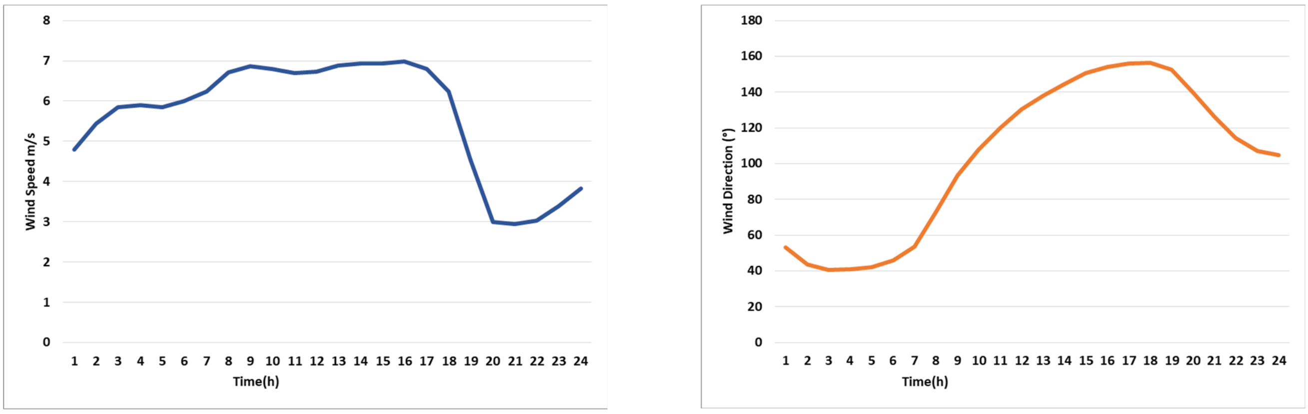


Figure 5. Shadow length of building affecting Tracker 2 on 6 June 2023.

2.4.4. Tracker 3—Wind Influence

Tracker 3 was used to assess the adaptability to wind exposure. To maximize wind exposure, Tracker 3 was tilted at 70° and rotated to 200°, while the other two trackers were positioned at 100° and 0° to minimize their wind exposure. This configuration reflects a wind impact phenomenon discussed in [48–52]. The wind speed and wind direction data for 6 June 2023 are shown in Figure 6a,b. Since the test site is a plateau, the wind behavior at 10 m was used to capture the true impact of wind forces, as the ground-level wind conditions do not fully reflect the forces affecting the tracker. The data were sourced from NASA POWER [53]. The goal here was to demonstrate how the system adapted to wind forces and maintained its performance despite exposure to this environmental factor.



(**a**) (**b**)

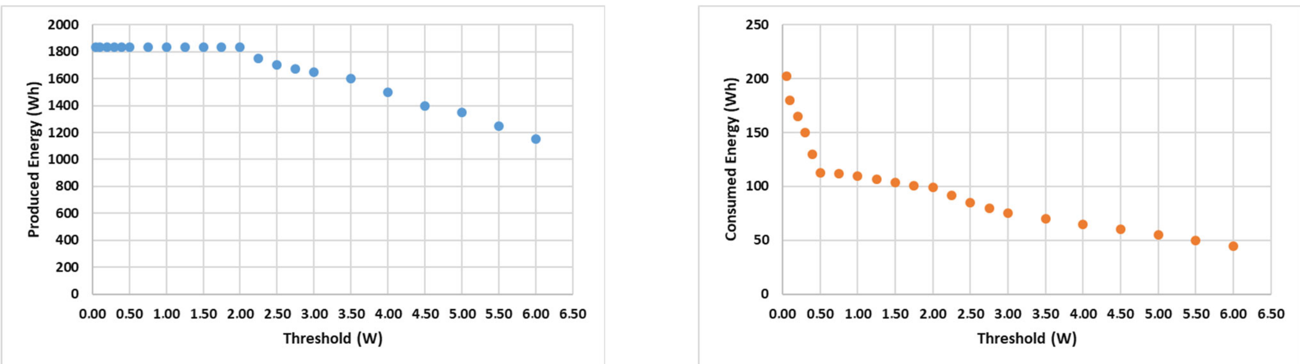
Figure 6. (**a**) Wind speed at 10 m on 6 June 2023. (**b**) Wind direction at 10 m on same day.

2.4.5. Testing and Simulation

The prototype was tested under real conditions on 6 June 2023, at the University of Ibn Khaldoun Tiaret, Algeria, located at latitude 35.3879, longitude 1.32282, with clear weather. In addition to the physical testing, the system was simulated in MATLAB 2019a using real-world characteristics and data from the prototype to further evaluate its performance and adaptability under various environmental conditions. The results of both the real-world and simulated tests are detailed in Section 3.

3. Results and Discussion

This research presents a solar tracking system inspired by flocking behavior, where each solar panel autonomously adjusts its position based on its power output and the alignment of neighboring panels. The system optimizes energy, reliability, and efficiency while accounting for uncertainties and dynamic factors like shading, clouds, and dust. It adjusts panel positions only when the power output difference exceeds a specified threshold, minimizing unnecessary movements and conserving energy. We tested the system's energy generation and consumption with different power thresholds, as shown in Figure 7. Figure 7a demonstrates that when the threshold exceeds 2 watts, the produced energy significantly drops. Figure 7b shows that energy consumption increases when the threshold is below 0.5 watts.



(**a**) (**b**)

Figure 7. Impact of power thresholds on energy output and consumption of proposed system: (**a**) energy production, (**b**) energy consumption.

Based on these observations, we chose to test the system's performance with power thresholds ranging from 0.5 W to 2 W to determine the optimal value illustrated in Figure 8.

The results show that a 0.5 W threshold reduces energy consumption but leads to a lower net energy gain compared to the traditional tracker. A 1.5 W threshold provides a better balance, offering a net energy gain similar to that of the traditional tracker but with lower energy consumption. The 2 W threshold results in the highest net energy gain of 1737 Wh while minimizing energy consumption to 5.4%. Therefore, the 2 W threshold is identified as the optimal choice for maximizing energy efficiency, with thresholds between 1.5 W and 2 W being the most effective.

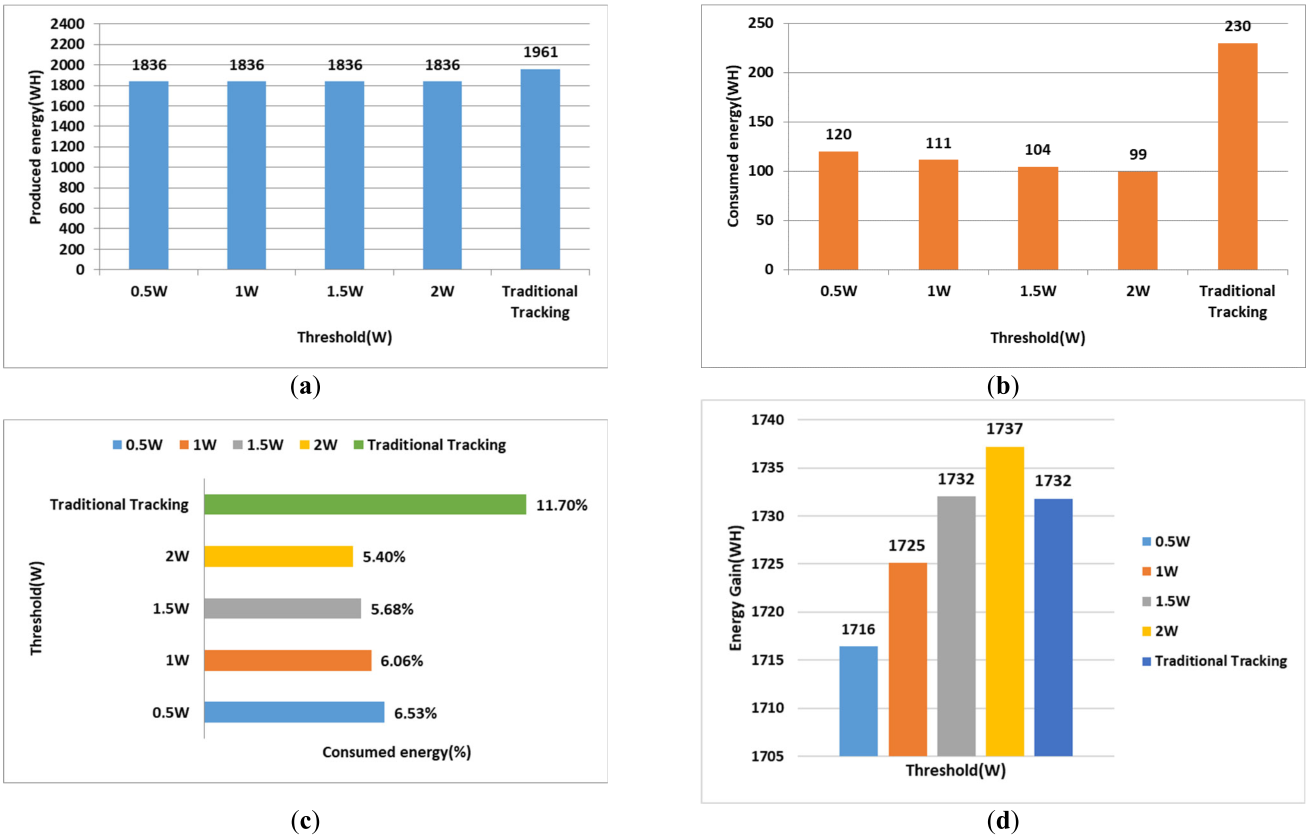
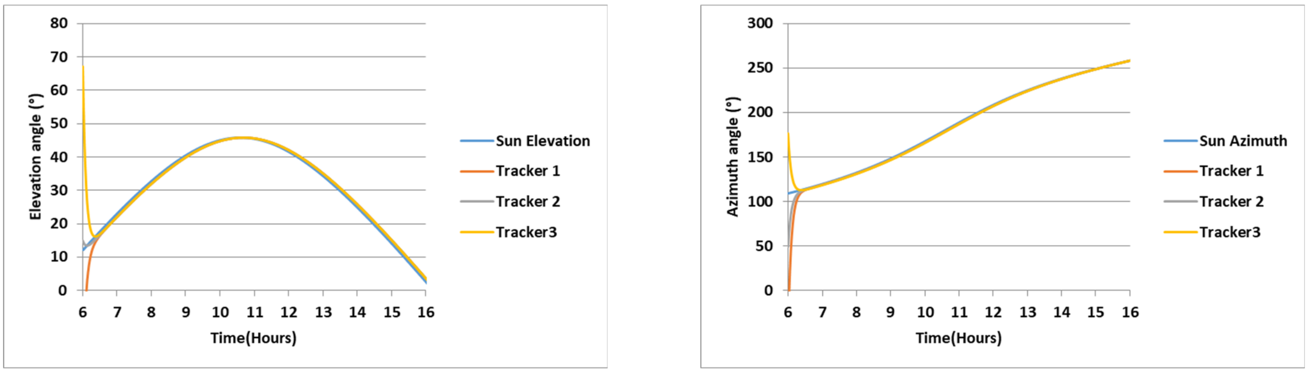


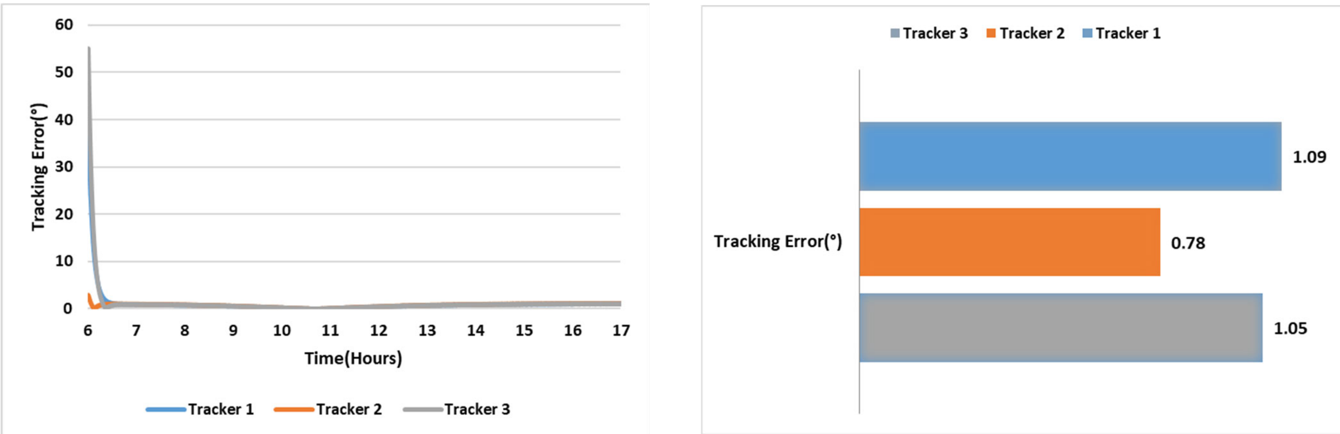
Figure 8. Choosing power threshold: (**a**) produced energy, (**b**) consumed energy, (**c**) energy consumption rate, and (**d**) net energy gain.

The second test assessed the tracking accuracy of the system by comparing the sun's position with the actual position of the solar trackers. Figure 9 represents the comparison between the calculated sun position and the position of the solar tracker throughout the day. The results indicate that the trackers require 15 min to adjust their position before achieving stable alignment, which is considered a rapid convergence in the context of multi-agent coordination. Following this period, they accurately tracked the sun's trajectory. This is reflected in the tracking error analysis shown in Figure 10, where the instantaneous tracking error quickly stabilizes near zero, and the mean tracking error of each tracker remains within 0.78° to 1.09°. With these tracking errors, the solar trackers capture 93% to 96.5% of the available direct solar irradiance, as shown in Figure 11. These results confirm the system's high solar alignment and energy capture accuracy.



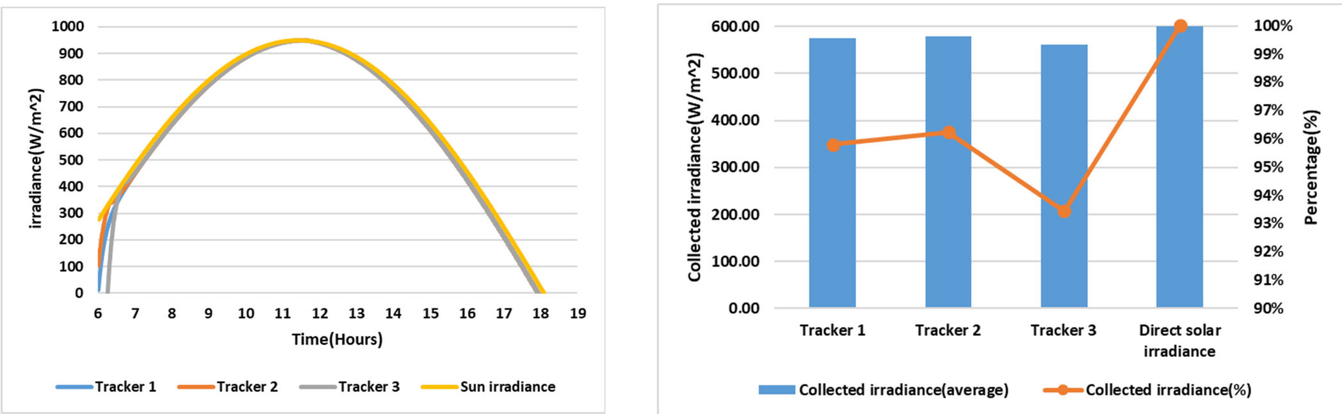
(**a**) (**b**)

Figure 9. Solar trackers' position vs. sun's position: (**a**) elevation angle and (**b**) azimuth angle.



(**a**) (**b**)

Figure 10. Sun tracking error of solar trackers: (**a**) calculated error through day, (**b**) average.



(**a**) (**b**)

Figure 11. The solar irradiance captured by the solar trackers vs. the total available direct solar irradiance: (**a**) instantaneous irradiance and (**b**) daily average irradiance.

Figure 12 compares the performance of the proposed system with the traditional continuous solar tracker. While the traditional tracker produced slightly more power on a clear day, the proposed system was tested under various environmental conditions (dust, shade, and wind). Despite these challenges, the proposed system consumed significantly less energy due to reduced movements, resulting in higher energy gains (see Figure 12d). Trackers 1 and 2, which were subjected to dust and shade, produced the most energy, while

Tracker 3, influenced by wind, performed similarly to the traditional tracker in terms of energy gain. This suggests that the proposed system is better adapted to dust and shade but maintains stability under wind conditions.

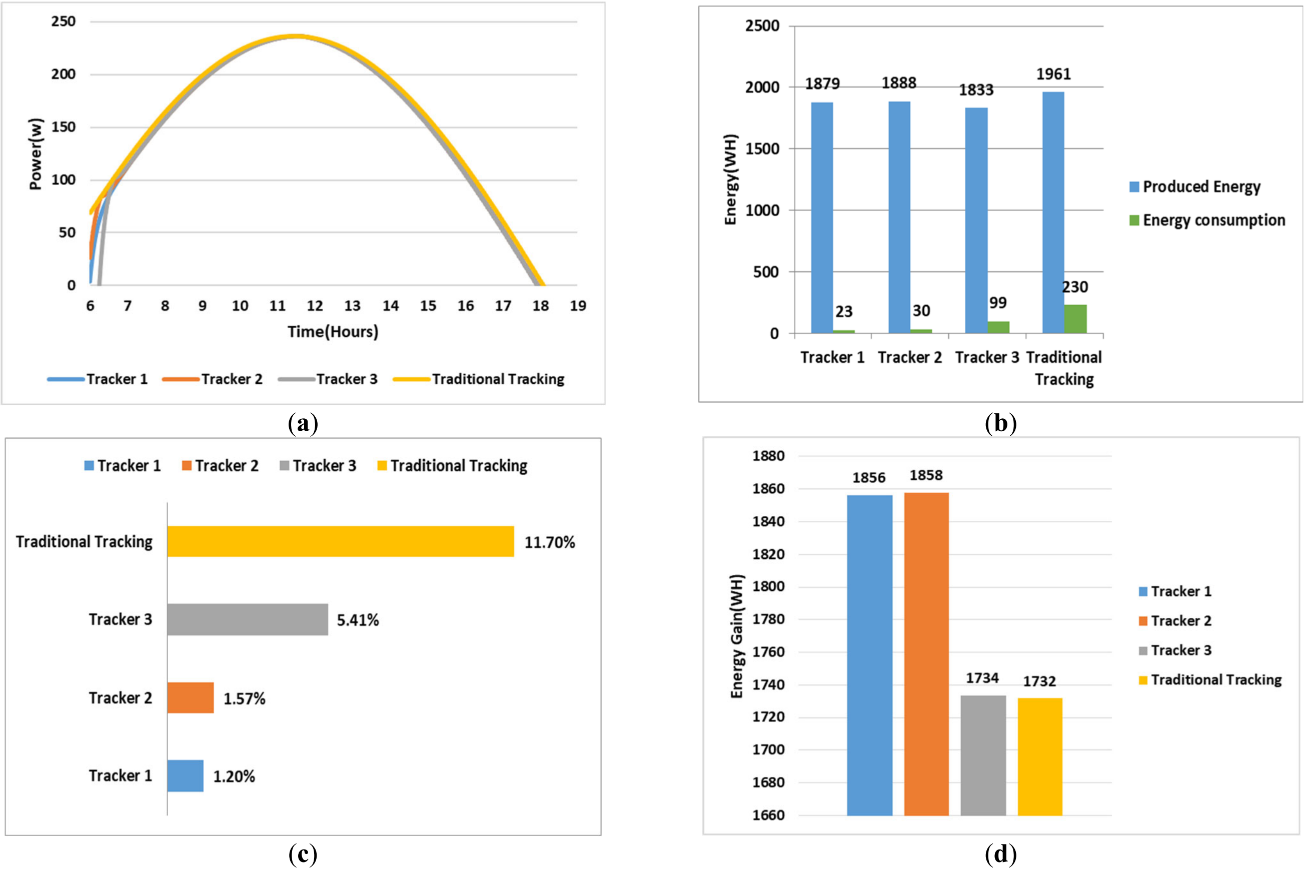


Figure 12. The performance of the proposed system: (**a**) power output, (**b**) produced and consumed energy, (**c**) energy consumption rate, and (**d**) net energy gain throughout the day.

Table 2 summarizes the improvements of the proposed system compared to the traditional tracker. The proposed system achieved 8% higher energy gain while reducing energy consumption by up to 11% compared to the traditional tracker. It also improved tracking accuracy by 84%, ensuring better alignment with the sun. Additionally, the system collected 17.4% more solar irradiance than the traditional tracker. Although energy output was not significantly higher due to testing under real environmental conditions (dust, shade, and wind), the proposed system would perform significantly better in clear and clean conditions.

Table 2. The performance of the proposed system vs. the traditional tracker.

Parameter	Tracker 1	Tracker 2	Tracker 3	Traditional Tracker	Improvement (%)
Energy Gain (Wh)	1856.37	1857.94	1733.51	1731.79	+8%
Energy Consumption (Wh)	22.60	29.56	99.10	229.50	−11%
Tracking Accuracy (°)	1.09°	0.78°	1.05°	5.0°	+84%
Collected Solar Irradiance (W/m^2)	95.80%	96.24%	93.44%	82%	+17.4%
Stability in Wind (m/s)	Stable	Stable	Stable	Unstable	✔

4. Conclusions

This study introduces an innovative solar tracking system inspired by birds' natural flocking behavior, offering a transformative approach to addressing the limitations of traditional solar trackers. By combining local power sensors with a Particle Swarm Optimization (PSO) algorithm, the proposed system dynamically adapts to real-world uncertainties such as shading, cloud cover, and dust. This design eliminates the need for dedicated sun sensors or complex sun position calculations, reducing system complexity and energy consumption.

The main contributions of this research are as follows:

- The system eliminates dedicated solar sensors by using power output adjustments, achieving precise solar alignment with tracking errors of 0.78° to 1.09°.
- The Particle Swarm Optimization (PSO) algorithm identifies the optimal positions for solar panels rather than determining the sun's position. This method considers real-world uncertainties and dynamic factors like shading, cloud cover, and dust accumulation, which static calculations cannot address.
- The threshold-based tracking approach reduces energy consumption to 1.2% and 5.4% of produced energy, unlike traditional systems, which consume 11%.
- The proposed system achieved a 10% increase in net energy production over traditional tracking systems, improving energy efficiency.
- Power thresholds of 1.5 W to 2 W optimize energy efficiency by reducing unnecessary movements in tracking systems.
- The system has a rapid response time, synchronizing solar trackers to achieve optimal power output and align with the sun's position within just 15 min.
- The method is adaptable to different photovoltaic configurations, making it scalable and suitable for both large-scale and small-scale applications.
- This decentralized approach reduces system failure risk by distributing decision-making among multiple panels, enhancing overall robustness and reliability.

This research has the potential to redefine solar tracking technology by enhancing energy efficiency, sustainability, and operational reliability. The system's ability to reduce maintenance needs and improve net energy gains establishes a pathway for more cost-effective and environmentally friendly photovoltaic systems. The combination of adaptive algorithms, minimal energy consumption, and rapid convergence to optimal positions within 15 min positions this approach as a next-generation solution for renewable energy applications.

The proposed flocking-inspired solar tracking system is well suited for both large-scale solar farms and off-grid solar installations. In solar farms, the system's adaptive and decentralized approach optimizes panel positioning under dynamic conditions such as shading, dust, or weather variations, enhancing energy efficiency and sustainability. Low energy consumption and minimal maintenance requirements for off-grid installations make it an ideal solution for remote locations where reliability and efficient energy utilization are critical. This versatility highlights its potential to improve renewable energy generation across diverse applications.

While the proposed flocking-inspired solar tracking system demonstrates significant advantages in energy efficiency, adaptability, and scalability, its performance under extreme climatic conditions, such as heavy snowfall [54], sandstorms [55], or high winds [56], warrants further investigation. Additionally, our system relies on real-time local power measurements, which may be affected by sensor inaccuracies or communication delays. Future work will focus on refining sensor accuracy, optimizing communication strategies, and testing under diverse environmental conditions. These advancements will support the broader adoption of solar energy by addressing key operational challenges, ultimately contributing to global renewable energy goals.

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Nomenclature

α	Weighting factor for neighbor influence
ΔP	Position deviation from neighbors' optimal positions
E	Panel energy output
f	Fitness function value
V_i	Velocity of panel i
X_i	Position of panel i
w	Inertia weight (PSO parameter)
c_1, c_2	Cognitive/social coefficients (PSO)
r_1, r_2	Random numbers $\in [0, 1]$
P_best	Personal best position
G_best	Global best position
PSO	Particle Swarm Optimization
PV	Photovoltaic
MPPT	Maximum Power Point Tracking
GPS	Global Positioning System
NEMA	National Electrical Manufacturers Association (motor standard)
Wh	Watt-hour
CFD	Computational Fluid Dynamics

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