

Autonomous solar tracking with β -optimized particle filter for enhanced performance in dynamic shading environments*

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Abstract

Solar tracking systems are critical for maximizing Photovoltaic (PV) energy output, yet their performance degrades significantly under Partial Shading Conditions (PSCs). Traditional sensor-based methods struggle in shaded environments due to reliance on irradiance data. This paper proposes a novel sensorless solar tracking algorithm, the Beta-Particle Filter (BPF), which integrates a β parameter into the particle filter framework to enhance tracking accuracy and efficiency under PSCs. Simulations and experiments demonstrate that BPF outperforms existing methods, achieving up to 12% higher energy generation compared to fixed panels under shading.

Keywords

Solar tracking, particle filter, partial shading, sensorless control

1. Introduction

Solar energy systems face persistent challenges in maintaining efficiency under dynamic environmental conditions. While solar tracking systems enhance energy yield by aligning PV panels with the sun's trajectory, partial shading caused by obstructions (e.g., buildings, clouds) disrupts irradiance distribution, leading to significant power losses [1]. Traditional sensor-based trackers, which rely on Light-dependent Resistors (LDRs) or cameras, fail under PSCs due to inconsistent irradiance signals [2]. Sensorless methods, such as those based on sun-earth geometry or power sampling, offer alternatives but often suffer from slow convergence and excessive energy consumption during global searches [3].

The Particle Filter (PF) algorithm has emerged as promising a solution for sensorless tracking by iteratively sampling and weighting candidate positions to locate Maximum Power Points (MPPs) [4]. However, under PSCs, particles may converge to low-power regions due to shading effects, degrading performance. Solar tracking under partial shading remains a challenging task due to rapidly varying irradiance and the presence of multiple local maxima in the power curve. This paper addresses these limitations by introducing the BPF algorithm, which incorporates a β parameter to constrain particle sampling intervals and accelerate convergence.

The contributions of this work are:

1. A β parameter derived from PV output characteristics is introduced to quantify irradiance levels and dynamically limit particle sampling regions.

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2. A reserved-discarded strategy is proposed to eliminate low-power particles, reducing unnecessary global searches.
3. The proposed BPF solar tracking method eliminates the need of sensors, and establishes the restricted area in real time during the tracking process, which reduces the search time and increases the power generation.

2. Methodology

The PV panel consists of multiple PV cells that function based on the PV effect. As stated in [5], when illuminated, the I-V characteristics of these cells can be modeled using a Single Diode Model (SDM), as shown in Figure 1.

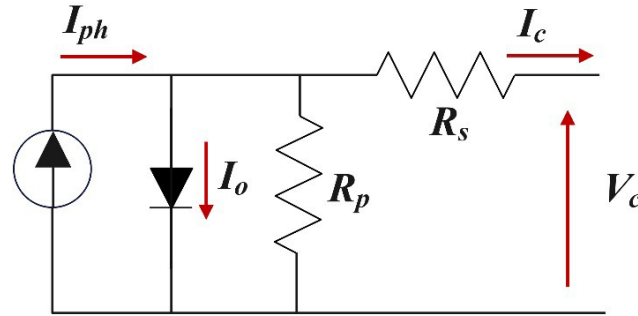


Figure 1: Single diode model.

This model comprises an independent current source, a series resistor R_s , and a shunt resistor R_p . The I-V characteristic is described as:

$$I_c = I_{ph} - I_o \left[\exp\left(\frac{V_c + I_c \cdot R_s}{A \cdot V_t}\right) - 1 \right] - \frac{V_c + I_c \cdot R_s}{R_p}, \quad (1)$$

where I_c denotes the PV cell current, I_{ph} represents the photocurrent, and I_o is the reverse saturation current. V_c corresponds to the terminal voltage, V_t indicates the thermal voltage, and A is the diode ideality factor. The photocurrent I_{ph} , which serves as the source of the PV cell's output current, increases almost linearly with irradiance levels. Thus, the PV output power is directly influenced by irradiance. The objective of the solar tracking system is to determine the optimal position where the PV panel receives the highest irradiance.

This paper presents a sensorless BPF solar tracking method. By integrating the β parameter into the conventional PF framework, the method establishes a well-defined interval for particle positions during tracking. The method has three key components: PF-based tracking, reserved-discarded strategy, and tracking termination.

2.1. Particle Filter

The PF method is a Monte Carlo-based tracking algorithm. It operates by representing the posterior probability density function using a set of weighted sampled particles. In the context of solar tracking, positions with higher power are more likely to correspond to the maximum power point. The standard PF process consists of three main steps: sampling, measurement and weighting, and re-sampling.

The initial sampling phase of the PF establishes the starting states of the particles. In the sensorless solar tracking system, each particle's state is defined by two degrees of freedom: the tilt angle θ_T and the azimuth angle θ_A . These angles are randomly sampled within the designated three-dimensional search space. Once the initial particle states are established, the system measures the power P_k^i at each particle's position. The weight of each particle is then computed using:

$$w_k^i = e^{P_k^i - P_m}, \quad (2)$$

where w_k^i represents the weight of the k_{th} particle in the i_{th} iteration, P_m denotes the maximum output power of the PV panel under Standard Test Conditions (STC). The weights are then normalized as \tilde{w}_k^i , ensuring that the total sum of all normalized weights equals 1.

During the re-sampling process, particle weights are updated to refine the estimation. Particles with higher weights have a greater chance of being chosen, while those with lower weights are more likely to be eliminated. The newly formed particle set consists of duplicated high-weight particles along with a few selected low-weight particles, all assigned equal weights. This updated set then advances to the next iteration of sampling, measurement, and weighting.

2.2. β -Limited Reserved-Discarded Strategy

This paper introduces the β parameter, as defined in [6], it is a negative value that serves as an indicator of both the irradiance level and the operating point of the PV panel. It is expressed by:

$$\beta = \ln\left(\frac{I_p}{V_p}\right) - c \cdot V_p, \quad (3)$$

where I_p and V_p represent the output current and voltage of the PV panel, respectively, while c is the diode constant, typically set to 0.8. When there are power differences between the two samplings, it suggests that a corresponding proportion of the PV panel's surface was obstructed in the previous sampling. Consequently, a theoretical lower bound $P_{\beta_{min}}$ narrows the sampling region around the current best particle to enhance local exploitation. This strategy ensures a dynamic balance between exploration and exploitation during tracking.

2.3. Tracking Termination

To prevent particle degeneration—where the weight distribution becomes excessively concentrated on a single particle—it is crucial to establish convergence conditions during the resampling process. The effective sample size N_{eff} is defined as:

$$N_{eff} = \frac{1}{\sum_{i=1}^N (\tilde{w}_k^i)^2}. \quad (4)$$

Convergence is assessed by comparing N_{eff} with a predefined threshold N_t . If N_{eff} falls below N_t , the sampling process continues. Otherwise, the algorithm is considered to have converged, and the estimated final maximum power position is given by $\hat{P} = \{(\hat{\theta}_A, \hat{\theta}_T)\}$, where

$$\hat{\theta}_A = \sum_{k=1}^N \tilde{w}_k^i \cdot \theta_{A,k}^i, \quad \hat{\theta}_T = \sum_{k=1}^N \tilde{w}_k^i \cdot \theta_{T,k}^i. \quad (5)$$

Figure 2 presents the full flowchart of the BPF solar tracking method, outlining its key procedural steps and decision-making processes.

3. Results

Simulations in MATLAB R2022a evaluated the performance of BPF under the Uniform Irradiance Condition (UIC) and PSC. A single PV panel consisting of 36 connected cells was used in the simulation. Under STC, the panel's maximum power, open-circuit voltage, and short-circuit current were 50 W, 21.6 V, and 2.9 A, respectively.

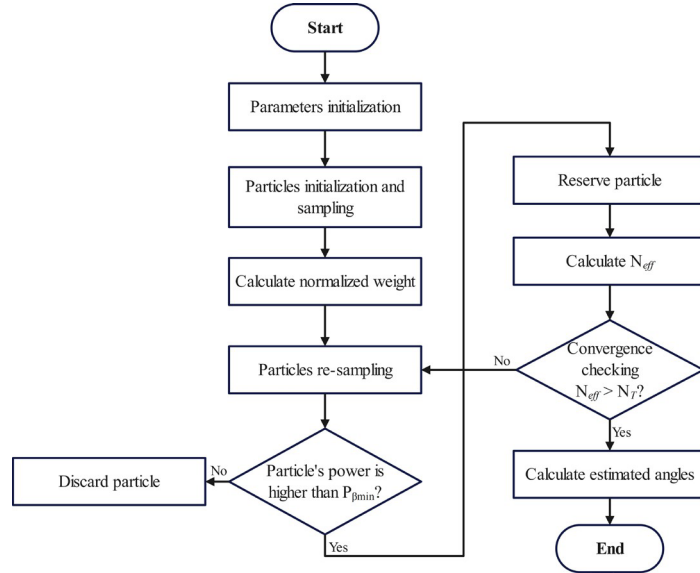


Figure 2: Flowchart of the proposed method.

To evaluate the tracking performance of the proposed method, comparative simulations were conducted against two existing approaches: the MPPT-based Solar Tracking Algorithm (MSTA) [7] and the PF method [4]. Both the PF and BPF methods utilized five particles, while MSTA operated with a step size of 2° . Each PV panel was modeled as three series-connected sub-panels, each comprising 12 cells and assumed to be bypass-diode-free. Environmental conditions for both UIC and PSCs were set according to [6], with the temperature fixed at 25°C . The UIC scenario, denoted as $\text{UIC} = [1000, 1000, 1000]$, represents a uniform irradiance of 1000 across all sub-panels before tracking. The shading pattern for the PSC is defined as $\text{PSC} = [600, 800, 1000]$, with an equivalent shading factor of 14.7%, which means 14.7% area of the panel is blocked.

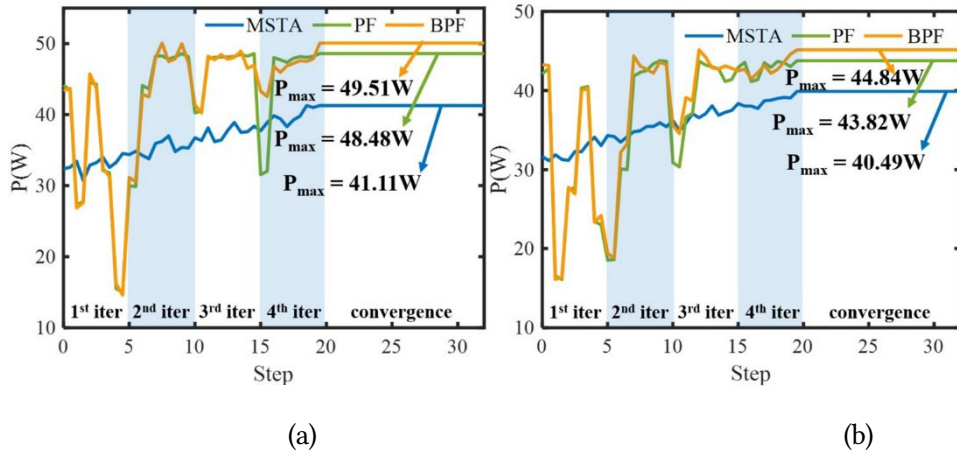


Figure 3: Simulation results of the three methods: (a) under UIC; (b) under PSC.

Figure 3 depicts the power variations of the three tracking methods across different scenarios. A quantitative comparison of their performance is provided in Table 1, which evaluates three key metrics: the maximum power P_{max} , the average power P_{avg} during tracking, and the power loss P_{loss} . The power loss is calculated as $P_{loss} = P_{max} - P_{avg}$, which quantifies the proportion of power lost during tracking relative to the theoretical maximum power.

As shown in Figure 3, the PF method experiences particle drift, with some particles converging into low-power regions after several iterations. In contrast, the BPF method effectively directs particles toward high-power regions by restricting the tracking interval.

Table 1

Simulation tracking performance comparison of the three methods

Parameters	Patterns	Methods		
		MSTA[7]	PF[4]	BPF
P_{\max} (W)	UIC	41.11	48.48	49.51
	PSC	40.49	43.82	44.84
P_{avg} (W)	UIC	37.87	44.69	46.12
	PSC	36.21	40.47	41.23
P_{loss} (%)	UIC	22.89	10.12	7.69
	PSC	21.73	11.35	7.13

Table 1 further confirms that the proposed method achieves the highest tracking power and the lowest power loss under both UIC and PSC scenarios. Notably, the improvement in power loss reduction compared to the PF method is more significant under PSC conditions than under UIC. Meanwhile, the MSTA approach struggles to reach the highest power within a limited number of steps due to its constrained global search capability, which is restricted by its small step size. Experiments were also conducted to validate the proposed method. A dual-axis solar tracker was tested under controlled shading. Halogen lamps simulated sunlight, while adjustable shields created PSC. Performance was compared against the fixed panel. The results are shown in Figure 4. Compared to a fixed panel, the proposed method boosts power generation by over 12% even under PSC.

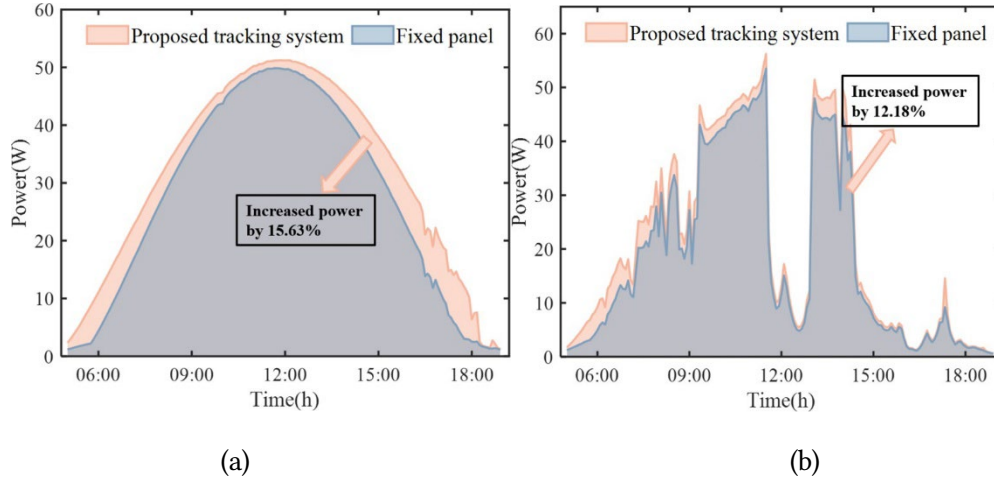


Figure 4: Experiment results of the proposed method: (a) under UIC; (b) under PSC.

4. Conclusion

This paper presented the BPF method, a sensorless solar tracking approach designed for PSCs. By leveraging the β parameter to define a constrained search interval, the method effectively prevents particles from converging into shaded low-power regions while eliminating the need for additional global searches. This targeted approach enhanced both tracking efficiency and overall power generation. Both simulation and experimental results validated the superior performance of the proposed method over conventional PF tracking under PSC. The results highlighted the method's ability to maintain robust performance even under complex shading scenarios, making it a promising solution for optimizing solar tracking efficiency. While the proposed BPF tracking method shows robust performance under partial shading, its effectiveness may degrade under extreme transient conditions due to delayed particle convergence. Future work will focus on integrating predictive models, such as deep neural networks, to guide particle initialization and reduce convergence time.

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Declaration on Generative AI

During the preparation of this work, the authors used GPT-4o in order to: Grammar and spelling check, improve writing style. After using the tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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