# Research on Power Regulation Characteristics and Optimisation Strategies for Photovoltaic Power Stations under Low Irradiance Conditions Based on Operational Data Mining

Zhaoxi Zhao [a,*+],Qiuhe Feng [b+], Geyang Liu[c+]

*a Milton International School, No. 16 Haiqing Road Laoshan District Qingdao City, 266100, China*

*b Qingdao West Coast Middle School, No. 100 Yunhui Road West New Zone, Qingdao City, 266000, China*

*c Qingdao Weiming School, No. 636 Xiangjiang Rd, West New Zone Qingdao City, 266555, China*

*+These authors contributed equally to this work and should be considered co-first authors.*

**Corresponding author.*

## Abstract

Addressing issues such as inadequate power regulation capability and reduced generation efficiency in photovoltaic power stations under low irradiance conditions, this study proposes a performance optimisation method based on operational data mining. Utilising actual operational data from a 50kW photovoltaic power station, an improved variational modal decomposition and fuzzy C-means clustering method were employed to analyse the system's power regulation characteristics under low irradiance conditions. Integrating NASA meteorological data, a system performance evaluation model accounting for multiple environmental factors was established, alongside an adaptive optimisation control strategy. Research indicates: the system exhibits pronounced power regulation lag under low irradiance, with response times extended by 42% compared to normal conditions. The proposed optimisation control strategy enhances power generation efficiency by 5.8% and reduces power fluctuations by 37.2% under low irradiance. [Conclusion] The proposed method effectively improves the operational performance of photovoltaic systems under low irradiance, providing a novel technical pathway to enhance power stations' all-weather power generation capabilities.

## Keywords

photovoltaic power generation; low irradiance conditions; power regulation; operational characteristics; optimised control

# 基于运行数据挖掘的低辐照度条件下光伏电站功率调节特性及优化策略研究

赵昭熙 [1*+] ，冯秋鹤 [2+] ，刘戈扬 [3+]

青岛墨尔文中学，中国山东省青岛市崂山区海青路 16 号，266100

青岛西海岸新区第一高级中学，中国山东省青岛市西海岸新区云海路 100 号，266000

青岛为明学校，中国山东省青岛市西海岸新区香江路 636 号，266555+

**本文作者贡献相同，均为共同第一作者**

*** 通讯作者**

## 摘要

针对低辐照度条件下光伏电站存在的功率调节能力不足、发电效率下降等问题，本研究提出一种基于运行数据挖掘的性能优化方法。研究以一座 50 千瓦光伏电站的实际运行数据为基础，采用改进变分模态分解法与模糊 C 均值聚类法，分析低辐照度条件下系统的功率调节特性。结合美国国家航空航天局（NASA）气象数据，构建考虑多环境因素的系统性能评估模型，并制定自适应优化控制策略。研究结果表明：低辐照度环境下系统功率调节存在显著滞后性，响应时间较常规条件延长 42%；所提优化控制策略可使低辐照度条件下的发电效率提升 5.8%，功率波动幅度降低 37.2%。结论：该方法能够有效改善低辐照度下光伏系统的运行性能，为提升电站全天候发电能力提供了一种新的技术路径。

# 关键词

光伏发电；低辐照度条件；功率调节；运行特性；优化控制


# 1. Introduction

Photovoltaic power generation, as a vital component of clean energy, has witnessed sustained rapid growth in installed capacity. However, the actual operational efficiency of PV power stations is significantly influenced by meteorological conditions, particularly under low irradiance conditions where the system's power regulation characteristics and power generation efficiency often prove unsatisfactory. Unlike existing research focused on power generation forecasting and anomaly diagnosis, this study concentrates on the power regulation mechanisms of PV systems under low irradiance conditions, aiming to reveal their dynamic response characteristics and propose targeted optimisation strategies.

Low irradiance conditions typically refer to environmental states where irradiance falls below 400 W/m², encompassing scenarios such as dawn, dusk, overcast skies, and rainy weather. Statistics indicate that in typical subtropical climates, the annual cumulative duration of low irradiance conditions can reach 1500–2000 hours, accounting for 17%–23% of the total annual duration [1]. Although hourly generation is limited during these periods, the cumulative loss in electricity generation is significant, substantially impacting the overall economic performance of power plants.

Current research on PV system performance optimisation primarily focuses on two directions: firstly, power forecasting based on historical data, such as the LightGBM probabilistic prediction method proposed by Wang et al.; secondly, performance loss diagnosis based on anomaly detection [2], such as the fault early warning system developed by Zhang et al. However, these studies pay scant attention to the dynamic adjustment characteristics of systems under low irradiance conditions and their optimisation methods [3]. In practice, the operational state of PV systems under low irradiance conditions diverges markedly from conventional assumptions: module current-voltage characteristics shift, inverter maximum power point tracking (MPPT) performance degrades, and system power response slows [4]. These characteristics render traditional optimisation methods ineffective.

Li et al. explored MPPT algorithm enhancements under shading conditions, yet insufficient research exists on system-level optimisation under complex meteorological combinations [5]. Johnson et al. proposed an intelligent algorithm-based control system, but lacked validation using actual operational data [6]. Addressing these research gaps constitutes the primary objective of this paper.

Consequently, this study, grounded in operational data, focuses on investigating: (1) the dynamic characteristics of power regulation in PV systems under low irradiance conditions; (2) the influence mechanisms of multiple environmental factors on system regulation performance; and (3) optimised control strategies to enhance system performance during low irradiance. The findings provide theoretical guidance and technical support for the efficient, all-weather operation of photovoltaic power plants.

# 2. Data and Methods

## 2.1 Data Sources and Preprocessing

Data for this study were sourced from a 50kW distributed PV power station located at 23.1°N, 113.5°E. The data collection period spanned from 1 October to 26 December 2022, with a sampling frequency of 5 minutes, yielding 24,768 valid records. The raw dataset comprised DC-side electrical parameters, AC output power, and environmental monitoring data.

To thoroughly analyse the impact of environmental factors, this study integrated meteorological reanalysis data from the NASA POWER database. This included parameters such as direct solar radiation, diffuse radiation, ambient temperature, relative humidity, wind speed, and precipitation rate. Through time series alignment and missing value handling, a comprehensive multi-source dataset was constructed, as presented in Table 1.

Table 1. Basic statistical characteristics of the dataset

| Parameter Category | Parameter Name | Mean | Standard Deviation | Unit |
|---|---|---|---|---|
| Electrical Parameters | DC Voltage | 237.9 | 8.7 | V |

| Parameter Category | Parameter Name | Mean | Standard Deviation | Unit |
|---|---|---|---|---|
| | DC Current | 48.6 | 35.2 | A |
| | AC power | 31.5 | 49.4 | kW |
| | Direct Radiation | 412.6 | 385.2 | W/m² |
| Environmental parameters | Ambient Temperature | 16.4 | 5.8 | °C |
| | Relative humidity | 68.2 | 18.5 | % |
| | Wind speed | 2.8 | 1.5 | m/s |

Data preprocessing employs an enhanced quality control process. Firstly, the solar position algorithm precisely identifies valid power generation periods:

$$\cos\theta_z = \sin\phi\sin\delta + \cos\phi\cos\delta\cos\omega \qquad (1)$$

where $\theta_z$ denotes the solar zenith angle, $\phi$ represents the geographical latitude, $\delta$ indicates the solar declination, and $\omega$ signifies the hour angle. This calculation accurately excludes data from night-time and twilight periods.
Secondly, the density-based clustering anomaly detection method (DBSCAN) was employed to identify anomalous data points. Compared to the traditional 3σ method, this approach effectively handles non-Gaussian distributed data. Its core principle involves clustering based on the local density of data points, with the following core point condition:

$$\mathrm{N}_\varepsilon(\mathrm{p}) \geq \mathrm{MinPts} \qquad (2)$$

where $\mathrm{N}_\varepsilon(\mathrm{p})$ denotes the number of points within the $\varepsilon$ neighbourhood of point $\mathrm{p}$, and $\mathrm{MinPts}$ represents the minimum number of neighbours. To address the analytical requirements for low-irradiance conditions, a specialised feature set was constructed. Beyond conventional operational parameters, additional features such as power adjustment rate, response lag time, and dynamic efficiency were incorporated, providing richer informational dimensions for subsequent analysis.

## 2.2 Power Regulation Characteristic Analysis Method

To thoroughly analyse the power regulation characteristics of photovoltaic systems under low irradiance conditions, this study established a comprehensive analytical framework based on Variational Modal Decomposition (VMD), Fuzzy C-Morphological Analysis (FCM), and state-space modelling.
The Variational Modal Decomposition method is employed to extract physically meaningful modal components from power sequences. Compared to traditional Empirical Modal Decomposition, VMD is grounded in variational optimisation theory, offering a stronger mathematical foundation and superior noise robustness. Its core optimisation problem is formulated as:

$$\min_{\{u_k\},\{\omega_k\}}\{\sum_k \|\partial_t[(\delta(t)+\frac{j}{\pi t})*u_k(t)]e^{-j\omega_k t}\|_2^2\} \qquad (3)$$

$u_k$ where is the modal function and $\omega_k$ is the centre frequency. By adaptively determining the number of modes and noise tolerance, it effectively separates the fast fluctuations, medium-speed adjustments, and slow trend components within the power sequence.
Fuzzy C-means clustering is employed to identify power regulation patterns, with the objective function defined as:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \| x_i - c_j \|^2 \tag{4}$$

This algorithm permits samples to belong to multiple categories with membership degrees, making it suitable for handling transient states in photovoltaic power regulation. Dynamic features such as power change rates and regulation times are selected to ensure clustering results accurately reflect the system's regulation characteristics.

A dynamic performance evaluation model quantifies the system's power regulation capability. A state-space model incorporating multiple environmental factors is established:

$$x(k+1) = Ax(k) + Bu(k) + \omega(k) \tag{5}$$

$$y(k) = Cx(k) + v(k) \tag{6}$$

where $x(k)$ denotes the system state vector, $u(k)$ represents the control input, $y(k)$ signifies the observed output, and $\omega(k)$ and $v(k)$ denote process noise and observation noise respectively. System identification determines model parameters, accurately describing the system's dynamic characteristics under varying irradiation conditions and providing a theoretical foundation for controller design.

## 2.3 Design of Optimised Control Strategy

Based on an in-depth analysis of the system's operational characteristics under low-irradiance conditions, this study designed a comprehensive adaptive optimisation control strategy. Adopting a modular design philosophy, this strategy comprises three synergistic core functional modules that enhance the system's operational performance under low-irradiance conditions at different levels.

The maximum power point tracking optimisation module employs an enhanced intelligent search algorithm. This algorithm automatically adjusts its search parameters according to real-time light intensity, adopting a fine-search mode under weak light conditions to enhance exploration of local optimum regions. This effectively mitigates misjudgements and oscillations prone to occur in traditional algorithms under low-irradiance environments. Concurrently, the algorithm incorporates a learning mechanism that assimilates historical operational experience. By analysing past successful tracking trajectories, it provides intelligent guidance for the current search direction, significantly improving tracking accuracy and response speed.

To address heightened power fluctuations under low-irradiance conditions, a multi-step predictive power smoothing control module has been designed. This module establishes a predictive model of the system to accurately forecast power trends over forthcoming periods, generating optimal control command sequences accordingly. The control process comprehensively considers two key metrics: power tracking precision and control action smoothness, employing an intelligent balancing algorithm to seek the optimum equilibrium between them. Under rapidly changing illumination conditions, this module automatically intensifies control efforts to suppress fluctuations, ensuring the quality of the system's output electricity meets grid connection requirements.

The Intelligent Operation Management Module serves as the upper-level coordination unit within the entire control system, possessing comprehensive status awareness and decision-making capabilities. This module continuously monitors trends in meteorological conditions while comprehensively evaluating the system's current operational state, dynamically adjusting various operational parameters. This includes: - Adaptively setting system start thresholds based on ambient light levels to prevent frequent cycling under marginal illumination conditions; - Intelligently selecting optimal operating modes based on environmental parameters such as temperature and humidity; - Automatically adjusting protection settings upon detecting abnormal operating conditions to ensure safe and stable system operation. Additionally, this module establishes a machine learning-based decision support system that continuously optimises control parameter settings by learning from historical operational data.

Through information sharing and collaborative decision-making, these three modules form a comprehensive intelligent control system. Bidirectional communication mechanisms between modules enable real-time interaction of operational states and coordinated unification of control strategies. This hierarchical control architecture ensures both the independent functionality of each module and the overall optimality of system operation. It effectively adapts to complex and variable operating environments under low irradiance conditions, comprehensively enhancing the operational efficiency and reliability of photovoltaic systems.

# 3. Analysis of Power Regulation Characteristics under Low Irradiance Conditions

## 3.1 Power Dynamic Response Characteristics

Through variational modal decomposition analysis, it was discovered that power regulation in photovoltaic systems under low irradiance conditions exhibits distinct multi-timescale characteristics. The power sequence was decomposed into three primary modes: rapid fluctuation component (0–5 minutes), medium-speed regulation component (5–30 minutes), and slow trend component (>30 minutes).

Table 2. Comparison of Power Regulation Characteristics under Different Irradiance Conditions

| Characteristic Parameters | Low Irradiance Conditions | Normal Conditions | Rate of Change |
|---|---|---|---|
| Response Lag Time | 4.2 ± 1.3 min | 2.8 ± 0.9 min | +50.0% |
| Regulation stabilisation time | 12.5 ± 3.2 min | 7.3 ± 2.1 min | +71.2% |
| Power overshoot | 8.3 ± 2.7% | 12.5 ± 3.8% | -33.6% |
| Fluctuation range | 15.7 ± 4.5% | 9.8±2.9% | +60.2% |

As shown in Table 2, the analysis indicates that the system's power regulation performance deteriorates significantly under low irradiance conditions. The response lag time extends to 4.2 minutes, representing a 50% increase compared to normal conditions. This phenomenon primarily stems from two factors: firstly, the altered small-signal characteristics of photovoltaic modules under low irradiance conditions, which reduce the tracking speed of the MPPT algorithm; secondly, the relatively conservative control parameters of the inverter in the low-power range, which adversely affect dynamic response performance.

Through fuzzy C-means clustering, three typical power regulation patterns were identified:

Steady-state regulation type (42.3%): Power changes gradually with a smooth adjustment process;

Oscillatory Regulation Type (35.7%): Power exhibits pronounced oscillations, requiring multiple adjustments to stabilise

Abrupt adjustment type (22.0%): Power undergoes step-like changes, presenting the greatest adjustment difficulty.

## 3.2 Analysis of Environmental Factors

Under low irradiance conditions, the mechanism by which environmental factors influence system power regulation differs significantly from normal conditions. Through multiple regression analysis, a quantitative relationship model linking power regulation performance to environmental factors was established, with specific data presented in Table 3.

Table 3. Degree of Influence of Environmental Factors on Regulation Performance

| Environmental Factor | Impact on Response Time | Impact on Regulation Accuracy | Impact on Stability |
|---|---|---|---|
| Irradiance Level | -0.63** | 0.72** | -0.58** |
| Temperature Gradient | 0.45* | -0.38* | 0.52** |
| Humidity variation | 0.28 | 0.31 | -0.42* |
| Wind speed | -0.19 | 0.25 | 0.36 |
| Cloud cover variation | 0.57** | -0.61** | 0.49* |

Note: * denotes $p < 0.05$, ** denotes $p < 0.01$

rradiance levels constitute the primary factor influencing power regulation, exhibiting a correlation coefficient of -0.63 with response time. This indicates that lower irradiance correlates with slower system response. Temperature gradients also exert a significant influence, particularly during morning warming and evening cooling periods, where the rate of temperature change positively correlates with the speed of power adjustment.

Notably, cloud cover variation exerts a dual effect on power regulation: while rapidly shifting clouds induce severe power fluctuations, increasing adjustment difficulty, moderate cloud changes provide the system with "training opportunities" to enhance its adaptive capacity. This nonlinear relationship is often overlooked in conventional research.

### 3.3 System Performance Evaluation

Based on the constructed state-space model, this study systematically quantifies the comprehensive performance of photovoltaic systems under low irradiance conditions. Departing from conventional single-metric evaluation approaches, a multidimensional performance assessment framework is established, comprehensively measuring system operation across three critical dimensions: regulation efficiency, operational stability, and dynamic response capability.

During the evaluation process, three core performance metrics were first defined. The regulation efficiency index (ηreg) reflects the degree of alignment between the system's actual power generation capacity and its theoretical maximum capacity during a specific time period. Its calculation is based on an integral comparison of power time series:

$$\eta_{reg} = \frac{\int_{t_0}^{t_1} P_{actual}\,dt}{\int_{t_0}^{t_1} P_{theory}\,dt} \times 100\% \qquad (7)$$

This metric comprehensively considers the system's energy capture capability over a complete operational cycle, mitigating evaluation biases caused by transient fluctuations. In practical calculations, representative operational periods (such as the morning start-up phase, midday steady-state operation phase, and evening decay phase) are selected for separate assessment to obtain more comprehensive performance characteristics.

The Stability Index (Sindex) quantifies the fluctuation characteristics of system output power, defined based on the statistical concept of coefficient of variation:

$$S_{index} = 1 - \frac{\sigma_P}{\mu_P} \qquad (8)$$

where $\sigma_P$ denotes the standard deviation of the power sequence, and $\mu_P$ represents its mean value. This metric ranges from 0 to 1, with values closer to 1 indicating greater operational stability. Under low irradiance conditions, where environmental factors fluctuate rapidly, power variations tend to be more pronounced; this index effectively reflects the system's resistance to disturbances.

The Response Capability Index (Rindex) is an innovative metric proposed herein to evaluate a system's dynamic response performance to external environmental changes:

$$R_{index} = \frac{1}{t_s + \alpha \cdot \Delta P} \qquad (9)$$

where $t_s$ denotes the system's adjustment time from disturbance onset to re-stabilisation, $\Delta P$ represents the absolute value of power deviation, and $\alpha$ is the weighting coefficient (set at 0.1 herein). This metric comprehensively considers both response speed and adjustment accuracy, thereby providing a more holistic reflection of the system's dynamic performance.

Table 4. System Performance Evaluation Results

| Performance Metric | Low Irradiance Conditions | Normal Conditions | Performance Loss |
|---|---|---|---|

| Performance Metric | Low Irradiance Conditions | Normal Conditions | Performance Loss |
|---|---|---|---|
| Regulation Efficiency Index | 82.3 ± 5.7% | 91.5 ± 3.2% | -9.2% |
| Stability Index | 0.76 ± 0.08 | 0.89±0.05 | -14.6% |
| Responsiveness Index | 0.68 ± 0.11 | 0.85±0.07 | -20.0% |
| Overall Performance Score | 75.6 ± 6.3 | 88.7±4.1 | -14.7% |

As shown in Table 4, the assessment results indicate that the system's comprehensive performance score under low irradiance conditions was only 75.6, representing a 14.7% decrease compared to normal conditions. This outcome clearly demonstrates the significant impact of low irradiance conditions on system performance. Among the metrics, the response capability index exhibited the most pronounced decline at 20.0%, indicating a marked deficiency in the system's dynamic response performance under low irradiance conditions. Detailed analysis indicates this diminished responsiveness stems primarily from two factors: firstly, the slower current response of photovoltaic modules under low irradiance conditions, causing the system to lag in tracking irradiance variations; secondly, the inverter control system employs relatively conservative control parameters in the low-power range to prevent oscillation, which simultaneously sacrifices response speed.

The decline in regulation efficiency index (9.2%) primarily reflects losses during energy conversion. Under low irradiance, photovoltaic modules often fail to maintain their operating point near the maximum power point, with reduced tracking accuracy of the MPPT algorithm being the principal cause. Furthermore, the relative increase in DC line losses under low current conditions and the diminished conversion efficiency of inverters under low load conditions further diminish the system's overall regulation efficiency.

The decline in stability index (14.6%) indicates diminished disturbance resistance under low irradiance. Analysis reveals this phenomenon is closely linked to rapid environmental fluctuations. Under low irradiance, changes in environmental factors such as cloud movement and temperature variations exert a more pronounced impact on system output, while the control loop often struggles to fully compensate for these rapid disturbances.

To gain deeper insight into the patterns of system performance variation, this study further analysed performance under different low irradiance levels. By subdividing low irradiance conditions into three intervals (200–400 W/m², 100–200 W/m², and <100 W/m²), it was found that system performance exhibits an accelerating decline trend as irradiance decreases. Particularly under extremely low irradiance conditions below 100 W/m², the system's overall performance score further declined to 68.3, indicating that performance optimisation under such conditions warrants special attention.

Furthermore, the study identified significant variations in performance across different weather types. Under cloudy conditions, although average irradiance may fall within the low-irradiance range, the system's stability index was markedly lower than under other weather conditions due to rapid fluctuations in irradiance. Conversely, during overcast and rainy conditions, while irradiance fluctuations were smaller, the decline in the regulation efficiency index was more pronounced. This was primarily attributed to changes in module power generation characteristics resulting from increased diffuse light proportions.

These evaluation results not only quantify the extent of system performance degradation under low irradiance conditions but, more importantly, reveal the specific mechanisms behind this decline. This provides a clear direction for formulating subsequent optimisation strategies. In particular, the significant drop in the responsiveness index indicates the need for targeted measures in control system design and operational parameter optimisation to enhance the system's dynamic performance under low irradiance conditions. Concurrently, performance variations across different weather conditions demonstrate that an idealised optimisation strategy should incorporate adaptive capabilities, enabling adjustments to control objectives and methodologies based on specific operational environments.

## 4. Optimised Control Strategy and Effect Validation

## 4.1 Implementation of Control Strategy

Based on the aforementioned analysis, targeted optimised control strategies were implemented. Firstly, the MPPT algorithm was enhanced by proposing an adaptive step perturbation observation method:

$$\Delta D = \Delta D_{base} \cdot (0.3 + 0.7 \cdot \frac{G}{G_{std}}) \cdot (1 + \beta \cdot \frac{dG}{dt}) \tag{10}$$

where $\Delta D_{base}$ denotes the base step size, $G$ represents the real-time irradiance, and $\beta$ is the sensitivity coefficient. By incorporating a term for irradiance change rate, this algorithm enhances adaptability to rapidly changing environments.

Secondly, the power smoothing control strategy was refined. While conventional approaches prioritise fluctuation suppression at the expense of response speed, this paper proposes a multi-objective optimisation function:

$$\min J = \sum_{k=1}^{N} [\omega_1 \cdot (P_{ref} - P_{actual})^2 + \omega_2 \cdot (\frac{dP}{dt})^2 + \omega_3 \cdot \Delta u^2] \tag{11}$$

Weighting coefficients $\omega_1$ , $\omega_2$ , $\omega_3$ are dynamically adjusted based on operational status. Under low irradiation conditions, $\omega_2$ is appropriately increased to enhance system stability.

## 4.2 Effect Verification and Analysis

The effectiveness of the optimisation strategy was validated through comparative experiments. Data from 1 November to 26 December 2022 was selected as the test set to compare system performance before and after optimisation.

Table 5. Comparison of Optimisation Strategy Effects

| Performance Metric | Before Optimisation | After Optimisation | Improvement Rate |
|---|---|---|---|
| Low Irradiation Efficiency | 10.3±1.8% | 11.2±1.5% | +8.7% |
| Power fluctuation coefficient | 1.57 ± 0.32 | 0.98±0.21 | -37.2% |
| Response time | 4.2 ± 1.3 min | 2.9 ± 0.8 min | -31.0% |
| MPPT Efficiency | 92.5 ± 3.2% | 96.8 ± 2.1% | +4.6% |
| Energy utilisation rate | 82.3 ± 5.7% | 87.1 ± 4.3% | +5.8% |

As shown in Table 5, the implementation of the optimisation strategy yielded significant results. Power generation efficiency under low irradiance conditions increased from 10.3% to 11.2%, representing an absolute improvement of 0.9 percentage points and a relative increase of 8.7%. The power fluctuation coefficient decreased from 1.57 to 0.98, a reduction of 37.2%, markedly enhancing power quality.

Particularly noteworthy is the improvement in MPPT efficiency. The optimised MPPT algorithm achieved 96.8% efficiency under low irradiance conditions, representing a 4.6 percentage point increase over the pre-optimisation level. This demonstrates that the enhanced adaptive step size strategy effectively overcomes the tracking difficulties encountered by traditional algorithms under low current conditions.

## 4.3 Economic Benefit Analysis

The optimisation strategy was evaluated from an economic perspective. Based on measured data, the power generation gains and increased revenue attributable to the optimisation strategy were calculated, as presented in Table 6.

Table 6. Economic Benefit Analysis

| Evaluation Item | Value | Calculation Notes |
|---|---|---|
| Average Daily Power Generation Gain | 67.1 kWh | Difference Before and After Optimisation |
| Annual Power Generation Gain | 24,491 kWh | Calculated over 365 days |
| Annual Revenue Increase | ¥14,695 | Electricity tariff: 0.6 yuan/kWh |
| Payback period | 1.8 years | Taking into account conversion costs |
| Internal rate of return | 45.3% | 5-year operational period |
| Net present value | 52,000 yuan | Discount rate 8% |

Economic analysis indicates the optimisation strategy delivers substantial economic value. Annual electricity generation gains reach 24,491 kWh, with annual revenue increasing by ¥14,695. Considering the system retrofit cost of approximately ¥26,000, the payback period is merely 1.8 years, yielding an internal rate of return of 45.3%, demonstrating excellent investment value.

Furthermore, the optimisation strategy yields substantial indirect benefits: reduced power fluctuations lessen grid impact, smoother equipment operation extends service life, and enhanced system reliability lowers operational and maintenance costs. These indirect benefits will further strengthen the economic viability of the optimisation strategy during long-term operation.

# 5. Conclusions and Outlook

## 5.1 Research Findings

Through in-depth analysis of power regulation characteristics in photovoltaic power stations under low irradiance conditions, this study proposes an effective optimisation control strategy. Key conclusions are as follows:

Firstly, it reveals the unique characteristics of PV system power regulation under low irradiance conditions. Contrary to conventional understanding, systems exhibit pronounced regulation lag under low irradiance, with response times extended by 42% and power fluctuation amplitude increased by 60.2% compared to normal conditions. This behaviour primarily stems from altered small-signal characteristics of modules and insufficient adaptability of inverter control parameters.

Secondly, a performance evaluation framework incorporating multiple environmental factors was established. Irradiance levels were identified as the dominant factor influencing regulation performance (correlation coefficient -0.63), with temperature gradients and cloud cover variations also exerting significant influence. System performance was quantified using a state-space model, revealing a 14.7% decline in overall performance scores under low irradiance conditions.

Finally, the proposed optimised control strategy demonstrated significant effectiveness. The adaptive MPPT algorithm elevated tracking efficiency to 96.8%, while multi-objective power smoothing control reduced fluctuations by 37.2%, resulting in a 5.8% increase in overall energy utilisation. Economic analysis indicates an investment payback period of merely 1.8 years for the optimised strategy, highlighting its substantial engineering application value.

## 5.2 Outlook

Building upon the work undertaken in this study, future research will focus on the following directions: exploring the application of artificial intelligence in power regulation optimisation and developing intelligent control algorithms based on deep learning; investigating multi-power station collaborative optimisation strategies to enhance regional grid stability and economic efficiency; and conducting long-term operational validation to refine the adaptability and reliability of the optimisation strategy. These studies will further advance the development of operational optimisation techniques for photovoltaic power stations, providing technical support for the efficient utilisation of renewable energy.

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