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Weather Classification for PV System and its Validation in Real-world Conditions#

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Abstract

The integration of photovoltaic systems into the power grid is becoming increasingly important for sustainable energy production. The efficiency of PV systems is heavily dependent on weather conditions, making accurate weather classification crucial for system performance prediction and optimization. In this study, we utilize a threshold-based weather classification method for PV systems and compare it to K-means clustering classification. The effectiveness of both methods was evaluated using real-world data from a PV system in a temperate climate region. This comparative analysis highlights the strengths and limitations of each approach, demonstrating their combined utility in enhancing the accuracy and reliability of weather classification, thereby offering a comprehensive tool for optimizing PV system performance across diverse meteorological conditions.

Keywords: weather classification; threshold-based classification; photovoltaic output prediction; k-means clustering

Nonmenclature

Abbreviations	
PV	Photovoltaic
Symbols	
n	Year

1. Introduction

Photovoltaic (PV) technology has witnessed remarkable advancements over the past few decades, both in terms of technological innovation and global installation capacity. The inception of PV systems was characterized by high costs and limited efficiency, primarily catering to markets and specialized applications. However, technological advancements, coupled with significant reductions in manufacturing costs, have transformed PV systems into a mainstream energy source. This growth trajectory is evident in the exponential increase in installed capacity worldwide, making solar energy a pivotal component of the global renewable energy structure. The surge in installations is not only a testament to the technological maturity of PV systems but also reflects a global shift towards sustainable energy practices.

Different weather condition has varying impacts on the performance of PV systems. Weather classification is crucial to the prediction of PV power for several reasons. Firstly, it enables the optimization of energy output under varying environmental conditions. From clear skies to overcast conditions, different weather conditions may impact the amount of solar irradiance received by photovoltaic panels. Secondly, accurate weather classification contributes to predictive maintenance and operational planning, ensuring longevity and efficiency of the systems. Additionally, it assists in the accurate forecasting of energy production, which is crucial for grid stability and efficient energy distribution. As the integration of PV systems into the energy grid intensifies, understanding the interplay between weather conditions and PV performance becomes increasingly critical.

The existing body of literature on weather classification for PV systems presents a diverse range of methodologies and findings [1-4]. Early research primarily focused on the impact of basic weather conditions like solar irradiance and temperature on the efficiency of PV system. Recent studies delve deeper, exploring the effects of more variable conditions such as

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partial shading, snow, and dust accumulation [5-6]. Advanced predictive models have been developed, utilizing machine learning and artificial intelligence to forecast PV system performance under different scenarios. These models often incorporate data from local meteorological stations, satellite imagery, and sensor networks to enhance their accuracy [7-9]. Furthermore, recent literature also discusses the implementation of automatic generation control systems in PV installations, which adjust operational parameters in real-time based on weather data [10]. This comprehensive review highlights both the progress and the remaining challenges in the field, underscoring the necessity for further research and innovation.

This article is structured to provide a comprehensive overview of weather classification for PV systems and its practical implications. Following this introduction, the next section delves into the methodologies employed in weather classification, discussing both traditional approaches and innovative techniques emerging from recent research. The subsequent section evaluates the impact of different weather conditions on PV system performance, drawing on case studies and empirical data. This is followed by a discussion on the integration of weather classification models into PV system design and operation, highlighting best practices and technological innovations. It then discusses the challenges faced in this domain and pinpoints future research directions, highlighting areas that require additional exploration. The conclusion summarizes the main discoveries and their impact on renewable energy and sustainable development. Against the background, our study aims to offer a comprehensive insight into solar energy, addressing the interests of both academic researchers and professionals in this industry.

2. Weather classification

The classification of weather conditions is based on two metrics: total solar irradiance and the sum of irradiance fluctuations within a day, focusing on the categorization of sunny (clear sky), partly cloudy, and cloudy days. This approach allows for a more nuanced and precise categorization of weather conditions, which is critical for assessing and optimizing PV system performance.

2.1 Data collection

The data utilized in this study is sourced from a local meteorological station situated at the PV installation site. provides detailed meteorological data, including solar irradiance, total insolation, and ambient temperature, with readings taken at one-minute intervals. This high-resolution data is crucial for accurately capturing the nuances of solar irradiance fluctuations throughout the day.

2.2 Classification criteria

Sunny (Clear Sky): One day is classified as sunny if the total insolation exceeds 300,000 Wh/m² and the sum of irradiance fluctuation for the day is below 0.015. This category represents days with stable and high solar exposure, indicative of clear sky conditions.

Cloudy: A day is classified as cloudy if the total insolation is less than 120,000 Wh/m² and the sum of irradiance fluctuation is below 0.1 and over 0.015. These conditions suggest persistent cloud cover with minimal fluctuations in solar exposure.

Partly Cloudy: Days that do not meet the criteria for either sunny or cloudy are classified as partly cloudy. This category represents a transitional state with more variable solar exposure.

2.3 Processing and analysis

The collected data undergoes preprocessing to remove any anomalies and ensure consistency. The total daily insolation is calculated by summing the minute-wise irradiance values. The sum of irradiance fluctuations is determined by calculating the absolute differences between consecutive irradiance readings and summing these differences over the entire day.

2.4 Validation

The classification system is validated through a comparison with actual weather station records and satellite imagery, which ensures the accuracy and reliability of this classification methodology.

2.5 Implementation

The methodology is implemented using a combination of data processing software and custom scripts, designed to automate the classification process and handle large datasets efficiently.

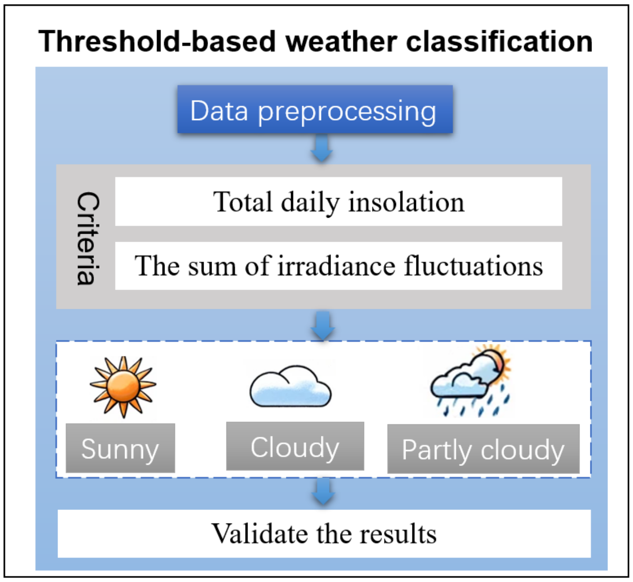

Fig. 1 The flowchart of method

3. Results

The results of this study are presented through the analysis of photovoltaic output curves under varying weather conditions, as depicted in the figures provided. These figures were derived from the collected and processed data, accurately representing the PV output under different weather conditions.

3.1 Sunny (Clear sky) days

The first figure illustrates the PV output curves on sunny days, characterized by a clear and pronounced bell shape. The solar irradiance begins to rise sharply in the early morning, reaching a peak at solar noon, and then gradually declines as the sun sets. The curves show minimal fluctuations, indicating stable conditions throughout the day. The high total insolation values, coupled with low fluctuation sums, confirm the classification criteria for sunny days as set forth in the methodology.

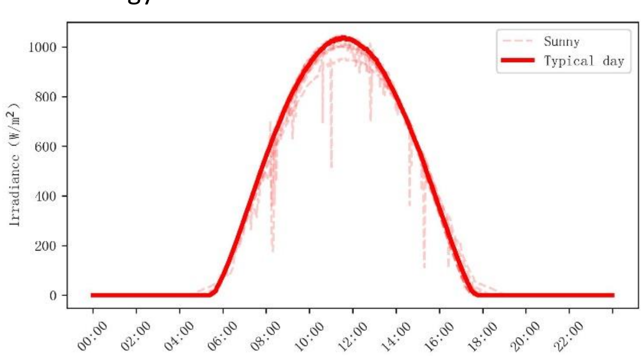

Fig. 2 The irradiance curve for sunny days

3.2 Partly Cloudy Days

Fig.3 presents the PV output curves for partly cloudy days. These curves display a greater variability, with numerous peaks and troughs, reflecting the transient nature of cloud coverage. The intermittent shading from passing clouds causes these fluctuations, which result in a lower overall insolation value compared to sunny days. Since the sum of fluctuations does not fall within the range classified as 'cloudy', it is categorized as 'partly cloudy'.

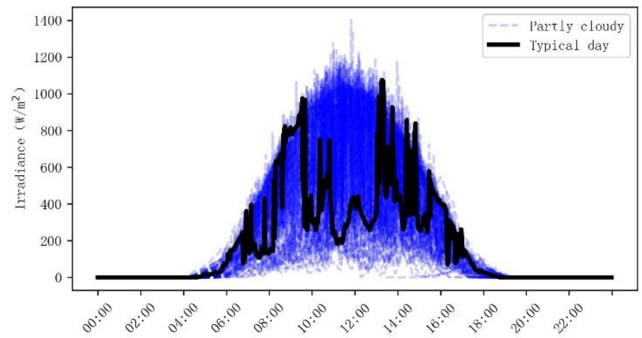

Fig. 3 The irradiance curve for partly cloudy days

3.3 Cloudy Days

The PV output curves on cloudy days are significantly flatter and lower in magnitude, with a much smoother profile than sunny or partly cloudy days. The total insolation is considerably reduced, and the curves lack the sharp fluctuations seen on partly cloudy days, which is consistent with the persistent overcast conditions typically observed on cloudy days.

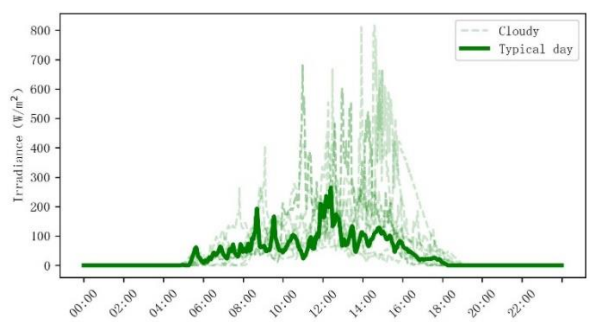

Fig. 4 The irradiance curve for cloudy days

3.4 Comparison of Weather Conditions

The fourth figure provides a comparative overview of the typical PV output curves across the three weather conditions. The contrast between the sunny, partly cloudy, and cloudy days is evident. Sunny days exhibit the highest and most consistent output, while cloudy days show the lowest. Partly cloudy days fall in between, with a high degree of variability.

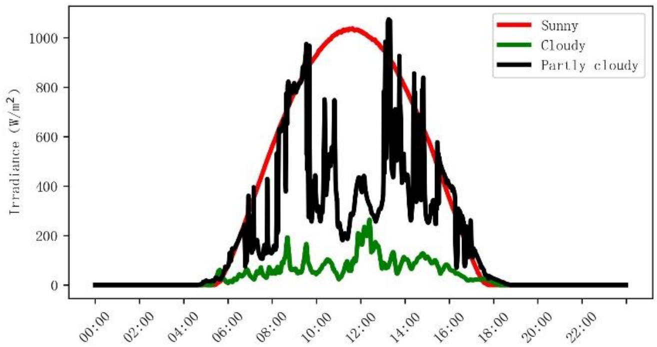

Fig. 5 Comparison of different weather irradiation curves

The consistency of these patterns across multiple datasets validates the robustness of the classification methodology. Furthermore, the clear distinctions between the different weather conditions underscore the importance of accurate weather classification for predicting and maximizing PV system performance. These results not only affirm the validity of the classification system but also provide valuable insights into the impact of weather on PV output, which can provide information for the design and operation of PV system to enhance its efficiency and reliability.

4. Discussion and conclusion

This article employs a method for weather classification based on specific thresholds of total solar irradiance and the sum of irradiance fluctuations, which are directly measured by a local meteorological station. In contrast, K-means clustering is an unsupervised machine learning algorithm that classifies data into a specified number (k) of clusters based on feature similarities. Here, we compare these two distinct methodologies with respect to their application in weather classification for PV systems.

The threshold-based classification method proposed in this article is deterministic, relying on predefined criteria to categorize weather conditions. This approach is straightforward and interpretable, as it directly relates physical measurements of insolation and irradiance fluctuations to specific weather categories. It allows for immediate classification without the training dataset, which can be advantageous in situations where historical weather data is limited or non-representative for future conditions. However, its rigidity can also be a limitation; it may not capture the subtleties of transition periods between different weather conditions, potentially leading to misclassification if the chosen thresholds do not accurately reflect the local climate.

Conversely, K-means clustering is a versatile approach that can adjust to accommodate the specific data presented. It does not require predefined thresholds; instead, it finds natural groupings in the data based on the features provided (e.g., irradiance and temperature values throughout the day). This method can potentially uncover more nuanced weather patterns and may be better at handling ambiguous conditions that do not fit neatly into the sunny, partly cloudy, or cloudy categories. However, K-means clustering requires a sufficiently large and comprehensive dataset to train the model. It also necessitates a criterion for selecting the appropriate number of clusters (k), which can be non-trivial and may require domain expertise or additional validation techniques such as the elbow method.

When comparing the two methods, one must consider the trade-offs between simplicity and adaptability. The threshold-based method is simpler to implement and interpret but may lack the sophistication to handle complex weather patterns. K-means clustering offers a more adaptable and data-driven approach but at the cost of increased complexity and the need for a substantial amount of training data.

In conclusion, the choice of method for PV systems may ultimately depend on the specific application requirements. For instance, a threshold-based classification could be more suitable for real-time monitoring systems where decisions need to be made quickly based on current measurements. K-means clustering might be more appropriate for retrospective analyses where there is enough data to understand historical patterns and trends. While the threshold-based method offers a clear and immediate classification system based on direct measurements, K-means clustering provides a more dynamic and potentially insightful analysis of weather conditions. The most effective approach for a given PV system depends on the feature of the data available and the specific operational requirements of the system. Further research and comparative studies could provide deeper insights into the advantages and limitations of each method and guide the development of more refined weather classification method for PV applications.

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