Analysis of Factors Influencing Mountain Wind Power Generation Based on Grey Relational Analysis

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Abstract. With the growing demand for renewable energy, mountain wind farms have attracted significant attention as an important clean energy generation method. However, the rapid changes in mountainous meteorological data and the complexity of terrain pose challenges for wind power forecasting in these areas. This paper aims to analyze the characteristics of mountain wind farms and the key factors involved in predicting wind power. Based on the grey relational analysis method, this study explores the factors influencing the power generation of mountain wind farms.By collecting and preprocessing data such as wind speed, wind direction, temperature, air pressure, and air density, the grey relational analysis method is employed to calculate the correlation between the influencing factors and wind power generation. By comparing the impact weights of different terrains and meteorological elements on power prediction, suitable meteorological elements for wind power generation in high-altitude mountainous regions are determined. The results indicate that wind speed is the primary factor determining wind power output, while wind direction plays a secondary role. In mountainous scenarios, air density also emerges as one of the influencing factors affecting wind power generation.

Keywords: Mountainous wind farm · Grey relational analysis · Meteorological elements · Wind power

1 Introduction

In recent years, with the rapid development of new energy, wind power has become one of the important alternative energy sources. In high-altitude mountainous regions, wind resources are abundant, and the application of wind power generation technology is increasingly widespread. However, due to the complex terrain and variable meteorological conditions in this area, wind power generation exhibits significant fluctuations. Therefore, in-depth research on the diurnal variation of wind power in this region and exploration of the factors influencing wind power generation are of great significance for improving the utilization efficiency of wind power. Thus, a comprehensive study of the power influencing factors in mountain wind farms is crucial for enhancing power generation efficiency and optimizing operational strategies [1, 2, 3, 4, 5].

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2 Analysis of Mountain Wind Power Characteristics

The rapid and irregular changes in meteorological data and the complex terrain in mountainous regions are significant challenges in the prediction of wind power generation in mountain wind farms. Currently, the accuracy of numerical weather forecast data in China is relatively low. To minimize reliance on such data, it is necessary to select a minimal set of meteorological elements as input for wind power prediction systems. These essential meteorological elements are defined as the minimum set of meteorological elements for wind power generation. The following will compare the impacts of different meteorological elements from different terrains on power prediction and ultimately select the minimum set of meteorological elements for wind power generation in high-altitude mountainous regions through correlation analysis. There are many factors that influence wind power generation, and we will focus on the following four aspects [6, 7, 8, 9, 10, 11, 12].

2.1 Wind Speed

The power of wind energy generated by wind passing through the rotor area F of a wind turbine in a unit time, represented by velocity v, is given by the formula:

$$W = \frac{1}{2}\mu F v^2 \tag{1}$$

where μ is the air density (kg/m3), and F represents the area swept by the rotor blades in one rotation m2. The magnitude of the surface wind speed directly determines the wind power output.

2.2 Wind Direction

Wind direction is usually represented by azimuth angles and described using wind direction frequency to indicate the frequency of occurrence in a specific direction. By calculating the wind direction frequency, the predominant wind directions and relatively weaker wind directions in a certain area can be determined. Although wind direction tends to maintain a certain direction over a period of time, it constantly changes from moment to moment. Therefore, real-time tracking of wind direction by wind turbines is challenging. Changes in wind direction can lead to frequent start-ups and braking of the yawing motor in the nacelle, resulting in mechanical component wear.

2.3 Temperature

In the mountainous regions of the western Sichuan plateau, one of the causes of wind speed variation is the high temperature difference caused by the flow of high-altitude air. This directly affects the power generation of wind turbines. The region also experiences icing phenomena, where water droplets in fog collide with the blades and freeze at or below 0 °C, causing harm to the turbines. Icing can result in failures or increased data errors in wind speed sensors and wind direction indicators, subsequently affecting power output and safety. Although heating devices can alleviate this phenomenon, data deviations may still occur. Wind speed and wind direction data are crucial for turbine control.

2.4 Air Pressure and Air Density

The high altitude of the western Sichuan plateau results in low air pressure due to the thinning of the air with increasing altitude. The decrease in air density, along with higher altitude, causes a general decrease in air pressure at a rate of around 10 kPa/km within the range of 1–5 km. The low air density reduces wind turbine output and decreases the overall efficiency of power generation. Reduced air density also lowers the external insulation strength of electrical equipment. Furthermore, the large diurnal temperature range and relatively high humidity in the region increase the presence of free electrons, making electrical components and equipment more susceptible to condensation and corona discharge phenomena.

3 Grey Relational Analysis Method

Grey relational analysis method uses mathematical methods to study the geometric correspondence between data of relevant factors by forming sequences. This method can determine the weights of various factors and compare their magnitudes. The larger the weight, the higher the degree of correlation, and vice versa. There are many factors that influence wind power prediction. By applying grey relational analysis method to analyze the data, factors closely related to wind power generation can be selected as the final prediction inputs [13, 14, 15].

The steps of grey relational analysis method are as follows:

Determine the reference sequence and other comparative sequences. Let the reference sequence be $X_0 = \{X_0(k)|k = 1, 2, \cdots, n\}$ and the comparative sequence be $X_i = \{X_i(k)|k = 1, 2, \cdots, n\}, i = 1, 2, \cdots, m$.

Process the original data to make it dimensionless. The data dimensions of different factors may cause unnecessary complications when comparing. Therefore, it is necessary to process the data to make it dimensionless. In this study, the following method is used to process the data:

$$x_i(k) = X_i(k) \big/ X_i(1) \;\; k = 1, 2, \cdots, n; i = 1, 2, \cdots, m \tag{2}$$

select the optimal samples from each major factor as the reference sequence, and compare the comparative sequence with the reference sequence. The greater the similarity, the closer the relationship with the target.

Calculate the grey relational coefficient δ_i between $x_0(k)$ and $x_i(k)$:

$$\xi_i(k) = \frac{\min\limits_i(\Delta_i(\min)) + 0.5 \max\limits_i(\Delta_i(\max))}{|x_0(k) - x_i(k)| + 0.5 \max\limits_i(\Delta_i(\max))}, \; k = 1, 2, \cdots, n; i = 1, 2, \cdots, m \tag{3}$$

Calculate the correlation degree of each factor. After calculating the grey relational coefficient between the reference sequence $x_0(k)$ and the comparative sequence $x_i(k)$, calculate the average value of the correlation coefficients of each factor. The average value $\overline{X_i}$ represents the degree of correlation between the reference sequence $x_0(k)$ and the comparative sequence $x_i(k)$:

$$\overline{X_i} = \frac{1}{n} \sum_{k=1}^{n} \delta_i(k), k = 1, 2, \cdots, n \tag{4}$$

Sort the correlation degrees. The degree of correlation between factors cannot be determined solely based on the magnitude of the correlation coefficient. The order of correlation degrees is also a major aspect. If $\overline{X_1} < \overline{X_2}$, it means that the reference sequence X_0 is more similar to the comparative sequence X_2.

Calculate the weights of each factor:

$$\overline{X_j}' = \frac{\overline{X_j}}{\overline{X_1} + \overline{X_2} + \cdots + \overline{X_n}}, \; j = 1, 2, \cdots, n \tag{5}$$

4 Simulation Analysis

Based on the aforementioned research, this section will utilize the Grey Relational Analysis method to analyze the factors that influence wind power generation, such as wind speed, wind direction, temperature, humidity, air pressure, and air density. The analysis will be based on the measured wind power characteristics data from a mountainous wind farm in the western Sichuan plateau. The data was collected during the latter half of February 2021 with a sampling interval of 5 min. By calculating the correlation weights of the mountainous wind power characteristics data, the main factors affecting wind power generation will be analyzed.

A total of 4,320 training data samples from a single turbine's main factors will be selected for Grey Relational Analysis. The analysis will determine the factors influencing wind power generation. The results are shown in Fig. 1.

From Fig. 1, it can be observed that wind speed is the primary factor determining wind power generation, while wind direction is a secondary factor. In high-altitude mountainous regions, air density has a more significant impact on wind power generation compared to other factors. Therefore, in plateau areas, it is crucial to consider the influence of air density, especially in high-altitude locations where air density is lower, resulting in a decrease in turbine output power.

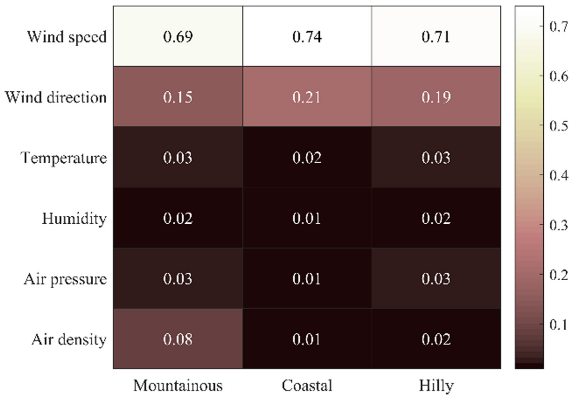

Fig. 1. Heatmap of Factors Influencing Wind Power Generation.

5 Conclusion

This paper starts by examining the mechanisms of different meteorological factors and thoroughly analyzes the factors influencing the power output of mountainous wind farms using the Grey Relational Analysis method. Through the calculation and analysis of the correlation between factors such as wind speed, wind direction, temperature, air pressure, and air density, and wind power generation, the following conclusions are drawn: in mountainous wind farms, wind speed is the primary factor determining the power output, as the magnitude of wind speed directly determines the wind power generation. Different wind directions may result in varying degrees of airflow impact on the turbines, making wind direction a secondary factor influencing power generation. Analyzing the relative importance of these factors on wind farm power generation helps accurately predict wind power output, optimize wind farm scheduling strategies, and improve overall efficiency.

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