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Comparative study of clustering methods for wake effect analysis in wind farm

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ABSTRACT

Wind energy poses challenges such as the reduction of the wind speed due to wake effect by other turbines. To increase wind farm efficiency, analyzing the parameters which have influence on the wake effect is very important. In this study clustering methods were applied on the wake effects in wind warm to separate district levels of the wake effects. To capture the patterns of the wake effects the PCA (principal component analysis) was applied. Afterwards, cluster analysis was used to analyze the clusters. FCM (Fuzzy c-means), K-mean, and K-medoids were used as the clustering algorithms. The main goal was to segment the wake effect levels in the wind farms. Ten different wake effect clusters were observed according to results. In other words the wake effect has 10 levels of influence on the wind farm energy production. Results show that the K-medoids method was more accurate than FCM and K-mean approach. K-medoid RMSE (root means square error) was 0.240 while the FCM and K-mean RMSEs were 0.320 and 1.509 respectively. The results can be used for wake effect levels segmentation in wind farms.

1. Introduction

Renewable energy sources have attracted lots of attention due to the technology development, their no dependence on fossil fuels and their friendliness to the environment. To increase efficiency of wind turbines, high number of turbines must be installed together in wind farm to obtain power station [1,2]. The wind farm efficiency is limited by spacing constraints owing to wind shadow or wake effect [3]. When one turbine is placed behind another turbine the total acquired energy by the downwind turbine will be less than the upper turbine due to wake effect [3,4]. In other words, the wind turbine layout determines the overall potential wind energy extraction of wind farm [5–8]. The wind turbine wake effect depends on several different factors such as the terrain morphology, the wind farm area, the wind turbine size, the wind speed, the wind direction and design of blades [9,10].

The wake effect is the key factor affecting the low efficiency of wind power production [11,12]. It is very important to predict the relationship between the wake wind speed (wake effect) for various wind turbine and wind farm parameters [13,14]. If there is a lot of interference or wake generated by the wind turbines, the possibility of mechanical failure would increase as well as the need for more maintenance actions, and an inevitable reduction in power output [15,16]. In addition, to consider the impact of turbines on the others, it is important to take into account the terrain, weather conditions and wind conditions in the region, such as speed and wind direction [17,18]. Several studies have been conducted in recent years in order to maximize energy production and the efficiency of the turbines [19,20].

To build a wind farm with the best features, it is desirable to select and analyze a subset of parameters that are truly relevant or the most influential to the wind turbine wake effect in order to minimize the effect [21,22]. In many traditional reliability and

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maintenance modeling studies, the states of the technical systems are categorized as fully successful or fully failure state [23,24]. This, so called “binary state model” or “birth and death model” is appropriate to represent random groups but it is not sufficient to reflect real working conditions of the system particularly in the case where system can still work while some of its parts degrade. Cluster algorithms could be applied for wake effects segmentation. Clustering process is discretization of the data into groups with following properties [25]:

(1) Homogeneity within the clusters and
(2) Heterogeneity between clusters.

A “clustering” is essentially a set of these clusters, usually contains all of the objects in the data set. Clustering large amounts of data is a difficult task because the objective is to find a suitable partition in an uncontrolled manner trying to maximize the similarity of objects belonging to the same cluster and minimize the similarity among objects in different clusters. Many different clustering approaches [26–33] have been applied in different technical arrears. For example K-means and FCM approaches are used for the water quality clustering [34]. FCM is used to determine clusters of zone structure distribution of aquifer parameters [35].

In this study, FCM, K-medoids and K-mean approaches were applied to identify levels of wake effect patterns in wind farm. The goal was to find the groups with the similar features. In the FCM methods, fuzzy membership values were assigned to each data point based on the relative distance of that point to the cluster centers. K-medoids make flat separation of the data with k non-overlapped groups.

2. Methodology

2.1. Wind farm efficiency model

Fig. 1 shows wake model which was analyzed in this study. The wake expands linearly with downstream distance. R_r is turbine radius and R_1 is the radius of the wake in the model. X is distance when the wake spreads downstream.

Following equation (Eq .(1)) estimates the wake wind speed (wake effect) after wind turbine rotor as shown in Fig. 1:

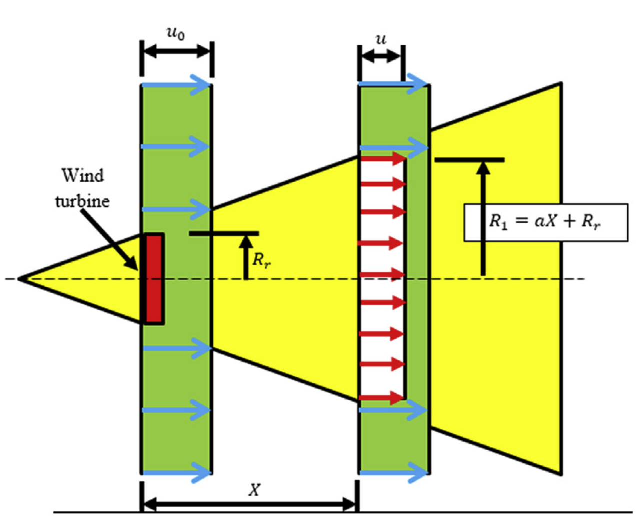

Fig. 1. Wake model scheme.

$$u = u_0 * \left(1 - \frac{2a}{1 + \alpha \left(\frac{X}{\left(R_r \sqrt{\frac{1-a}{1-2a}} \right)} \right)^2} \right) \tag{1}$$

where

- u_0 is the mean wind speed ($u_0 = 12$ m/s),
- a is axial induction factor which can be calculated from thrust coefficient C_T:

$$C_T = 4a(1-a)$$

- R_1 is related with R_r using following equation:

$$R_1 = R_r \sqrt{\frac{1-a}{1-2a}}$$

- α is the entertainment constant and can be obtained as follows:

$$\alpha = \frac{0.5}{\ln \frac{z}{z_0}}$$

where z denotes the hub height and z_0 is roughness of the surface. In this study, the used five variables are defined as in Table 1.

Table 1 shows wake downstream distance X is in the range of 100–500 m, wake or rotor radius is in range 10–40 m, axial induction factor is in range 0.2–0.4, hub height is in range 30–90 m. For parameter z_0 five roughness classes of the surface were analyzed as listed in Table 2:

The basic idea used in this paper was grouping wake effect data into homogeneous levels (clusters) using various statistical analysis techniques for clustering. The clustering approach should show wake effect level influence on the wind farm energy production. General aspects of clustering as well as a brief summary of three modeling techniques and corresponding algorithms are given in following section.

2.2. Clustering

The purpose of clustering is to distill natural groupings of data from a large data set, producing a concise representation of a system's behavior. The clustering of data produces a set of cluster centers, and each cluster center acts as a prototypical data point that describes a characteristic mode of the system.

As mentioned earlier, clustering algorithm assigns a large number of data points to a smaller number of groups such that data points in the same group share the same properties, while in different groups, they are dissimilar. They can be classified into four

Table 1
Wake effect parameters.

Inputs/Output	Parameters description
Input 1	X: wake downstream distance
Input 2	R_r: wake or rotor radius
Input 3	a: axial induction factor
Input 4	z: hub height
Input 5	z_0: roughness of the surface
Output	u: wake wind speed