Research on Wind Power Prediction Algorithm Based on Fusion Model

Angru Li1,2,∗, Dechao Ma1,2, Qi Liu1,2, Kun Ji1, Shaoliang Ling1,2 and Jiajia Chen1,2
1NARI Group Corporation (State Grid Electric Power Research Institute), Nanjing, China
2NARI Research Institute Xi’an R & D Center, Xi’an, China

*Corresponding author email: liangru@sgepri.sgcc.com.cn

Abstract. Wind power generation is currently one of the most promising power generation technologies. It is particularly important to improve the prediction accuracy of wind power output, which can effectively reduce the impact on the grid when wind power is connected to the grid. Based on the fractal model, this paper integrates it with the wind power prediction model, and combines the custom K nearest neighbor algorithm to evaluate the prediction effect using multi-dimensional indicators. Finally, taking the data of a wind farm in northwest China as an example, compared it with the prediction model of random forest, support vector machine and gradient boosting decision tree prediction model to verify the effectiveness of the prediction algorithm in this paper.

Keywords: Fractal model; knn; Machine learning; Wind power prediction.

1. Introduction
The fossil energy on the earth is gradually being exhausted, and the development and utilization of new energy is imperative. Among them, wind energy resources have many advantages, such as a wide range, almost no pollution, and reusability. It has become one of the most potential new energy sources. However, natural wind is characterized by strong randomness and intermittent [1]. When large-scale centralized grid connection, it will bring certain threats to the stable operation of the power grid. Accurately predicting wind power for a period of time in the future is of great significance to power dispatching and safe operation.

Physical method and statistical method are commonly used in wind power prediction. Among them, the physical method does not rely on the historical data of the wind farm [2]. It is mainly based on numerical weather forecasting, according to the wind direction, air humidity, air pressure, etc. as the input of the prediction model, the data is used to model and analyze the location of the wind farm, but in different locations, different moments, environmental factors have bigger difference, which make the practicability of the physical method poor and difficult to promote. The statistical learning method is to use a large amount of historical wind power generation data [3], wind speed, wind direction, air pressure and other data of the wind turbine hub to obtain the mapping law between the input data such as numerical weather parameters and the actual power of the wind power from a large amount of historical data, and establish the input and output relationship. The commonly used methods include support vector machine and artificial neural network.

The other is the similar day method [4]. After years of gradual research, this method has been applied to wind power forecasting [5] and photovoltaic power forecasting [6]. The author combine neural
network, fuzzy inference research and similar day method, and integrate the advantages of each other to predict the wind speed of a day [7]. Zhang Yiyang [8] and other researchers subdivided similar days into "similar periods", "reference segments" and "prediction segments", predicting from different levels, but ignoring the mutual influence between reference power and meteorological characteristics. In literature [9], the clustering method was first used to select similar days to avoid hard division of clustering. However, the unsupervised method also has obvious shortcomings, such as high requirements for original samples and sensitivity to outliers, which can easily lead to excessive classification and the final accuracy is difficult to guarantee. Some researchers considered the change law of wind speed within a certain period of time, and proposed a method based on continuous time clustering and combined with SVM algorithm to predict wind power. However, this method is difficult to reflect the difference between historical data and forecast data. Zhao Ting [11] and other scholars studied the power curve of the previous K days, taking the characteristics of the power change curve into account in the model, but did not analyze the correlation trend relationship before and after. Li Hui [12] et al. first extracted similar days, and then used principal component analysis to reduce dimensionality and computational complexity, but the prediction accuracy was not high and the model could not be explained.

In this paper, a hybrid K-nearest neighbor algorithm based on fractal model is proposed for wind power prediction. Drawing on the fractal model, considering the reference power curve problem and meteorological characteristic values, the use of fractal interpolation can effectively obtain the local information of adjacent samples, and then combine with the custom KNN algorithm to generate a prediction model. Finally, based on the historical measured data of a certain wind farm, and compared with some existing prediction models, the fusion model proposed in this paper has high prediction accuracy, reduced complexity and better performance.

2. Fractal Theory Model and K-nearest Neighbor Algorithm Description

2.1. Fractal Lemma

Lemma 1[12]: In a certain complete distance space $(X, d)$, the mapping set with compression factor $0 \leq s_i < 1$ is defined as $\{\omega_i: X \rightarrow X, i = 1,2,\ldots,M\}$, which constitutes an iterative function system (IFS). When $W$ is a compressed mapping cluster with compression ratio $c$ on $(X, d)$, then $W$ can generate a complete metric space $(H, h)$ compressed mapping cluster $F: H(X) \rightarrow H(X)$, $F(A) = \bigcup_{i=1}^{M} W_i(A)$, $A \in H(A)$, and the compression ratio is $c$, that is $h(W(A), W(B)) \leq ch(A,B), A,B \in H$.

Lemma 2[13]: Suppose the hyperbolic iterative function system $(X, W)$ on the complete metric space $(X, d)$, the compression factor is $s$, and $A$ is the attractor, then $h(L, A) \leq \frac{1}{1-s^L} h(L, \bigcup_{i=1}^{M} W_i(L))$ for any $L \in H(X)$. The collage theorem gives the approximate similarity between a set and an invariant set, and it is sufficient to select an appropriate IFS Well, similarly, a set of iterative function systems can be generated by continuously constructing interpolation nodes.

2.2. Fractal Interpolation Theory

The IFS [14] satisfies Lemma 1 and Lemma 2 above. Determine the data set $\{(x_i, y_i): i = 0,1,\ldots,M\}$, Where the attractor $A$ is the graph of a continuous function $F: [x_0, x_M] \rightarrow R$, The following constructs an IFS on $R^2$.

IFS $\{R^2; \omega_m, m = 1,2,\ldots,M\}$, Where $\omega_m$ is the affine transformation of formula (1):

$$\omega_m \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a_m & 0 \\ c_m & d_m \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} e_m \\ f_m \end{bmatrix}$$

(1)

Where $b_m = 0$ is made so as not to intersect with the function between the cells.

$$\omega \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} x_{m-1} \\ y_{m-1} \end{bmatrix} \text{ and } \omega \begin{bmatrix} x_M \\ y_M \end{bmatrix} = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix}$$
Each transformation must satisfy the following equation (2), so that the left and right endpoints of the large interval can be mapped to the left and right endpoints of the subinterval:

\[
\begin{align*}
    a_m x_0 + e_m &= x_{m-1} \\
    a_m x_M + e_m &= x_M \\
    c_m x_0 + d_n y_0 + f_m &= y_{m-1} \\
    c_m x_M + d_n y_M + f_M &= y_M
\end{align*}
\]

The vertical scaling factor of \( a_m \) is \( d_m \) [15], choosing the free variable as \( d_m \) and \( d_m < 1 \), so makes IFS converge. Let \( L = x_M - x_0 \) to solve the above equations, we can get the following expression (3):

\[
\begin{align*}
    a_m &= L^{-1}(x_m - x_{m-1}) \\
    e_m &= L^{-1}(x_M x_{m-1} - x_0 x_M) \\
    c_m &= L^{-1}[y_m - y_{m-1} - d_n (y_M - y_0)] \\
    f_m &= L^{-1}[x_M y_{m-1} - x_0 y_m - d_n (x_M y_0 - x_0 y_M)]
\end{align*}
\]

It is difficult to reflect the local features between two adjacent known information points in the traditional method, but the fractal interpolation method has its unique advantages. It can make better use of the local information of samples, so that most features of the original sampling curve can be effectively supplemented and retained [16].

### 2.3. KNN Algorithm Description

For a set of training data, the KNN algorithm finds K closest instances in the training set, and finds these K instances as candidate classes [17]. Then take the similarity between them as the weight and substitute the preset threshold value to basically determine the classification of the sample [18]. The algorithm flow chart is as shown in Figure 1.

**Figure 1.** KNN algorithm flow chart

**Figure 2.** Framework diagram of wind power short-term prediction model
3. Prediction Algorithm of Hybrid KNN Algorithm Based on Fractal Model

The wind power generation time series have periodic characteristics. The daily power generation curve has self-similarity on the time scale, and there are also very similar fractal dimensions [19], and a period of power generation time series is also relevant. The historical data and the power generation curve can be fitted into a similar period, and the fractal interpolation method can make good use of the characteristics of the local information of the adjacent known points [16], and the algorithm can quickly converge to the true value. In the traditional KNN algorithm, the historical sample set needs to be searched every time to obtain n similar historical sample sets [20]. When the set K value increases, the number of searches continues to increase, and the repeated samples of the search continue to appear, which not only consumes extra the storage space will greatly reduce the operating speed of the system.

In order to make up for some shortcomings of traditional algorithms, this paper designs a hybrid custom KNN algorithm based on fractal models. The algorithm is based on the fractal dimension of self-similarity in the fractal theory, combined with the related theory of the KNN algorithm, to improve the search method of similar historical sample sets, which not only reduces the memory space consumed, but also reduces the time complexity of the algorithm.

The main process of the prediction model is as follows:

- The prediction day is set as the starting point, which is used to split the fractal dimension data, part of which is used for training and part of the data is used for verification.
- Take the horizontal axis as the time coordinate of the fractal dimension point collection, and then analyze the power curve characteristics of the reference day to find the main characteristic points of the curve. In this example, we mainly consider the three main characteristics of weather, temperature, wind speed, and wind direction, and select the power value of nine integral points.
- Establish the power curve IFS on the base day. The iterative function system is established by the set of interpolation points in step 2). It can be known that when \( d_m \) is set to 0.9~0.95, the prediction error is the smallest, and the formula used for calculation is equation (3).
- Establish the power curve IFS. The set of interpolation points is obtained by the reference time coordinate of step 2) and the power value corresponding to each similar point. The iterative functions are established separately, where the value of \( d \) remains unchanged.
- After the calculation, the fractal dimension of wind speed, wind direction and temperature are saved in memory. KNN algorithm does not search all the historical sample sets any more, but searches from the fractal dimension of main features, which greatly reduces the search amount of the algorithm.
- According to the test set date specified in the current data set, find out the observations of the latest 9 time points and combine them into a data frame, and calculate the fractal dimension of the three characteristics of wind speed, wind direction and temperature in this data frame. Figure 2 above is the Prediction model diagram of hybrid KNN algorithm based on fractal model.

4. Case Analysis

Taking a wind farm (20 units) as an example, the data of 334 days from January 1, 2019 to December 1, 2019 were selected as the sample data, and the data of the first 290 days were used as the training sample set. The test object set of the following 44 days was predicted by using the training sample set. Set the forecast time interval to 15 minutes, forecast 24 hours in advance, calculate the average power of each forecast time point in the next 44 days, and compare it with the actual power value in the next 44 days. At the same time, it is compared with Random Forest (RFR), SVM, Gradient Boosting Decision Tree (GBDT), and calculates the Root Mean Square Error (RMSE) and prediction accuracy rate of each algorithm, to verify whether the hybrid KNN algorithm prediction model based on fractal theory proposed in this paper has higher accuracy and effectiveness.

In the prediction model of the hybrid KNN algorithm based on the fractal model, this article sets the K value twice, the first time the K value is 3, mainly to find the fractal dimension cache value in the time range of the nearest neighbor, the second time K value 5. Mainly to find the nearest weighted average
power value, and then compare the actual power with the predicted power. The result is shown in Figure 3, the abscissa is the predicted time axis and the ordinate is the power value.

![Figure 3. Comparison of predicted power and actual power of hybrid KNN algorithm model based on fractal model](image1)

![Figure 4. Comparison of predicted power and actual power based on RFR model](image2)

The predicted power curve of the RFR model is shown in Figure 4. Through the random search method combined with the grid global search for optimal parameter tuning, it is determined that \( n_{\text{estimators}}=100, \text{max\_depth}=10 \). In Figure 5, the kernel skills in SVM adopt Linear kernel function, degree=3, and the penalty coefficient adjustment model is adopted to prevent over-fitting. The predicted power curve of the GBDT model is shown in Figure 6. Through hyperparameter tuning, constantly modify the model, determine learning_rate=0.1, \( n_{\text{estimators}}=500, \text{max\_depth}=3 \). Table 1 shows the root mean square error (RMSE), time consumed by training model data (CT) and goodness of fit (SCORE) of the prediction model after hyperparameter tuning of the four models.

|       | H-KNN | RFR  | SVM  | GBDT |
|-------|-------|------|------|------|
| RMSE  | 7.673 | 11.295 | 34.677 | 12.857 |
| SCORE | 0.962 | 0.947 | 0.544 | 0.928 |
| CT    | 2.611 | 24.164 | 558.356 | 13.346 |
As can be seen from the above table, the performance of the SVM prediction model is the worst. When low-dimensional data is mapped to a high-dimensional space, the model training consumes a long time, and the RMSE does not decrease. After continuous hyperparameter tuning of GBDT, the time consumed for model training has been reduced, but the increase in RMSE and model fit value is not obvious. After the RFR prediction model is adjusted for a series of hyperparameters, the goodness of the model fit is improved significantly, but at the same time the model training time has increased. The hybrid KNN wind power prediction model based on fractal model proposed in this paper has better performance in root mean square error, model goodness of fit and training consumption time, which fully verifies that this model can be used to predict wind power well.

5. Conclusion
At present, the grid-connected capacity of wind power is still increasing, and large-scale wind power grid-connected has a great impact on the operation of the grid. In order to cope with the challenges brought by the strong randomness of wind power, the accuracy of wind power forecasting has received great attention. A series of studies conducted in this article are aimed at improving the accuracy of wind power forecasting. Fractal model related theory with the custom of KNN algorithm, the combination of several important characteristics of sample first fractal dimension calculated and stored in memory, after interpolation combining KNN algorithm search twice, one is the nearest neighbor time within the scope of the fractal dimension of the cache, another is to find the weighted average power value of the nearest neighbor. At the same time, compared with the existing wind power prediction methods, in each index has a better performance. By introducing the fractal idea, the local information of samples can be guaranteed, the model is simple and the complexity is low, especially for a large number of samples, the algorithm performance is still good. The selection of the optimal value of the specific fractal dimension still needs further research, which will also be the main direction of the follow-up research in this article.

References
[1] Huang Jiaming. Discussion on the development status and prospects of wind power generation [J]. Applied Energy Technology, 2015(04):51-54.
[2] Sun Na. Forecast and Analysis of Wind Farm Output Power [J]. Science & Technology Information, 2014, 000(034):94-94.
[3] Xue Y, Zheng Y, Bose A. Proceedings of 2020 International Top-Level Forum on Engineering Science and Technology Development Strategy and The 5th PURPLE MOUNTAIN FORUM (PMF2020)[J]. Lecture Notes in Electrical Engineering, 2021.
[4] Li Shenghu, Dong Wangchao. Reliability sensitivity of wind power system to forecast error using NSTPNT method[J]. System Engineering Theory and Practice, 2019, 039(005):1340-1350.
[5] Zhang Xinlei, Li Gen. Multi-step prediction method of short-term wind power based on the IEEMD and LS-SVM[J]. Electrical Measurement & Instrumentation, 2020(6):52-60.
[6] Yang Xiyun,Liu Huan,Zhang Bin,et al. Similar day selection based on combined weight and photovoltaic power output forecasting [J]. Electric Power Automation Equipment, 2014, 34(9):118-122.
[7] Haque A U , Mandal P , Kaye M E , et al. A new strategy for predicting short-term wind speed using soft computing models[J]. Renewable and Sustainable Energy Reviews, 2012, 16(7):4563-4573.
[8] Zhang Yiyang,Yan Huan. Multi-Step Wind Power Forecasting Based on Subsection and Layer Searching for Similar Day and Adaptive Ridgelet Neural Network[J]. Power system and clean energy, 2015, 031(004):124-131.
[9] Li X , Li C , Cong L , et al. Short-term load forecasting based on dynamic weight similar day selection algorithm[J]. Power System Protection & Control, 2017, 45(6):1-8.
[10] Ding Zhiyong, Yang Ping, Yang Xi, et al. Wind Power Prediction Method Based on Sequential Time Clustering Support Vector Machine [J]. Automation of Electric Power Systems, 2012, 36(14):131-135.
[11] Zhao Ting, Wang Haixia, Lv Quan et al. Short-Term Wind Power Forecasting Based on Trend-Similar Days and Chaotic Time Series [J]. Power system and clean energy, 2013, 029(003):74-79.

[12] Feng Yi, Liu Huiwen, hang Baoping. Short-term Wind Speed Forecasting Using Ensemble Empirical Mode Decomposition and Extreme Learning Machine with Feature Selection [J]. Smart Power, 2018(12).

[13] Cui Herui. Research Characteristic of Power Load Based on Fractal Theory [J]. Journal of Electric Power, 2012,(03):181-185.

[14] Bansley, M F. Fractals Everywhere[M]. New York: Academic Press Inc, 1993, 56-63.

[15] Liang Ping, Fan Fumei, Lv Yukun. Fractal forecasting and R/S analyses of electric power consumption [J]. Journal of North China Electric Power University(Natural Science Edition), 2004, 31(004):32-35.

[16] Zhang Yujuan, Bao Fangxun. Bivariate Rational Cubic Spline Fractal Interpolant for Monotone Data Visualization [J]. Journal of Computer-Aided Design & Computer Graphics, 2017(5):882-894.

[17] Yang Mao, Jia Yunpeng, Mu Gang, et al. Wind power real-time prediction research based on the improved KNN algorithm [J]. Electrical Measurement & Instrumentation, 2014(24):44-49.

[18] Wu XiaoLi, Zheng Yifeng. Noise type recognition and intensity estimation based on K-nearest neighbors algorithm [J]. Journal of Computer Applications, 2020, 040(001):264-270.

[19] Li Rui, Zhu Hongliang, Xin Yang, et al. Study on the Self-Similarity of P2P Traffic Behavior Based on Fractal Method [J]. Journal of Beijing University of Posts and Telecommunications, 2010(04):39-42+62.

[20] Liu Ruiyang, Zheng Jiangfan, Liu Zhi. Research of Parallel KNN Algorithm Based on CUDA [J]. Journal of Chinese Computer Systems, 2019(6):1197-1202.