Self-adaptive Wind Speed Forecasting Method for New Wind Farm

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Abstract:

As a green and renewable energy resource, wind energy has been growing rapidly all over the world. However, the stochastic and uncontrollable characteristics of wind would affect the safety and stability of power grid. Therefore, wind speed has to be accurately forecasted, for optimizing the schedule of wind farm maintenance and electricity reserves.

Many approaches have been proposed, most of which need several months' local historical data for model training, which is a major obstacle for newly built wind farms: there is no or little historical operational data collected yet. To solve this problem, a self-adaptive method based on Gaussian Processes is proposed, which could operate without any local historical wind data for new wind farm.

The proposed method, named as O-GP (on-line training GP) model, includes several parts: 1) Appropriate method for choosing dataset from other long-term run wind farms is designed, to provide proper data for initial model training; 2) Gaussian processes is adopted to build wind prediction model; 3) New operational data of measured wind speed and NWP (Numerical Weather Prediction) data from new wind farm is obtained each day, and the training set is updated by new data under certain rules to update the forecasting model accordingly.

Three years field data from a commercial wind farm is used to validate the model, and the experimental results proved that the proposed method can achieve higher accuracy for wind forecasting, with about 20% improvement comparing to the persistent method, and 15% improvement comparing to normal GP method.

1. Introduction

Wind energy has been developed rapidly all over the world [1]. In China, the accumulated capacity of wind farms has reached 145.1 GW, with a growth rate of 26.6% in 2015 [2]. However, the integration of wind farm into power grid can challenge its safety and stability, considering the instability of wind power [3]. Therefore, accurate prediction of wind speed is urgently needed for better scheduling wind farm maintenance and electricity reserves [4].

Most research focus on short-term wind power forecasts, which means predict wind in 1 hour to several days and is critical to grid reliability. Broadly speaking, there are two related approaches: statistical models using only historical data or with physical information like weather prediction. The former uses historical measured wind data to build models, based on methods such as autoregressive integrated moving average (ARIMA) [5], Kalman filter [6], artificial neural network [7] and support vector machine [8], etc. These models are effective only for hours-ahead forecasts, since wind varies quickly with time. On the other hand, models with meteorological information added, have advantages over longer multi-hour horizons (from several hours to dozens of hours) [9-10], but normally need to be corrected using local measured wind speed.

Nevertheless, straightforward application of the mentioned methods in new built farms is

impeded by a major obstacle: there is no or little historical operational data for these methods to build forecasting model. To solve this problem, an online learning method based on Gaussian Processes (O-GP model) is proposed in this paper. This method could operate with very limited or no historical information at the beginning of a new built wind farm.
Compared with former works, contributions of this paper are listed below:

1) On-line learning system using Gaussian process is adopted to build wind speed forecasting model. The O-GP method can operate at the very beginning of a new wind farm, without any locally measured wind data.

2) A selection method is designed to choose the most suitable dataset from long-term run wind farms as the initial training set for the new built wind farm. The method of choosing the initial dataset is presented in this paper.

3) The training set updating rule is determined, to update the forecasting model everyday with new operational data obtained in the new wind farm, including real wind speed, wind power and NWP data.

Real-world wind dataset from a large commercial wind farm in China is used to validate the proposed method. The results show that the O-GP model performs better than several classic wind forecasting methods.
Section 2 firstly describes the overall modeling process of O-GP method, including both training set selection/adjusting process and the wind speed correction model based on GP using NWP data. Section 3 presents the principle of the related mathematical methods: selection method for choosing the initial training dataset, training dataset adjustment rule and principle of Gaussian Processes used in regression problem. Experimental results on field wind farm data are presented and analyzed in Section 4. Finally, Section 5 includes the overall conclusion.

2. Modeling Process

Since there is no or little historical data for new wind farm, the first step of building forecasting model in this paper is to choose an appropriate existing dataset from other wind farm as the initial training dataset. Then with daily operation of new wind farm, training set can be updated reasonably using newly collected data every day. When data in the initial training dataset is finally all substituted by data from new farm, precise wind speed forecasting model could be built. A brief description of the training set initialization and updating process is shown in Fig 1.

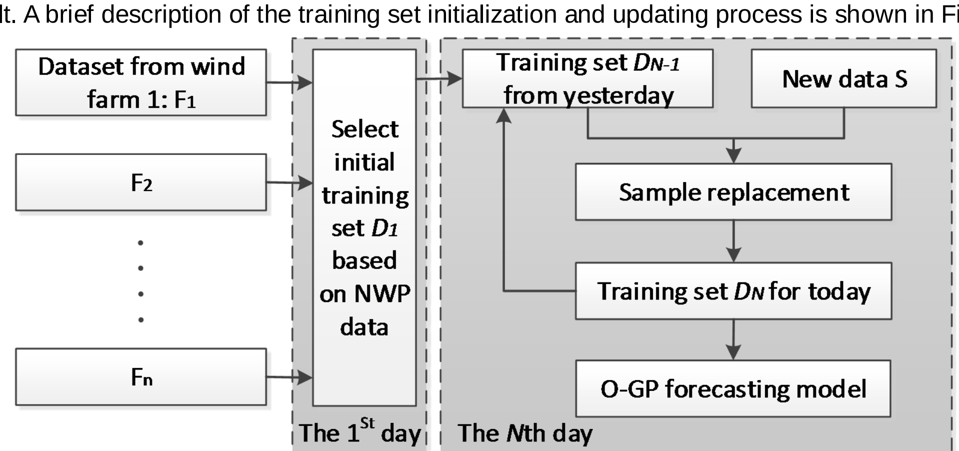

Fig 1. Schematic of training set initialization and updating for wind prediction model

As shown in Fig 1, suppose n historical datasets $F_1, \cdots F_n$ are available, including NWP data, measured wind speed and measured wind power, from n wind farms. Choose the dataset from the wind farm that has the most similar meteorological situation with target new wind farm, based on the similarity calculated as described in section 3.1. Forecasting model can be built using the chosen dataset as initial training dataset D_0, that is the model used at the first operational day of new wind farm. Denote the operational data (including NWP data, measured wind speed and measured wind power) from new wind farm at the Nth day as S, training dataset D_N can be obtained by substituting data in D_{N-1} which is the closest to new data from dataset S. The rule for data substitution is simply using new operational data to replace closest data in training set, as described in Section 3.2.

With training set ready, wind speed forecasting model can be built to learn the relationship between NWP data and the locally measured wind speed. NWP data is the weather forecast for next several days that is published timely online, which usually includes several kinds of meteorological information: wind speed, wind direction, temperature, air pressure, and humidity. GP is used to build the relationship between these NWP data and measured wind speed, as shown in Fig 2.

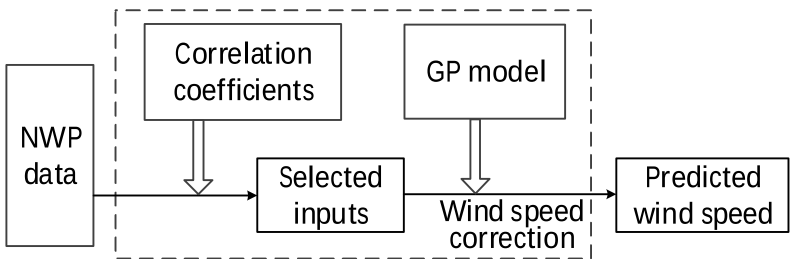

Fig. 2 Wind speed prediction model based on GP

As shown in Fig.2, firstly, correlation coefficients are calculated to select the features in NWP that are strongly relevant to measured wind speed as inputs to forecasting model. Then a wind speed correcting model between the chosen NWP variables and measured wind speed is obtained using Gaussian process. Finally, predicted wind speed in NWP is corrected by the trained speed correcting model to a more accurate value, which is the final predicted wind speed of the proposed O-GP model.

3. The mathematical methods

3.1 Selection method of initial training dataset

The first key step of the proposed O-GP method for forecasting wind speed is to select the most suitable training set for new farm from other available wind farm datasets. Among M old wind farms, the training set is chosen in such a way that the trend of NWP data of selected farm should be more similar than other farms to the new farm. In this paper, similarity is defined by the Euclidean distance between two datasets. Considering two objects $x_i = \left(x_{i1}, x_{i2}, ..., x_{ip}\right)^T$ and $x_j = \left(x_{j1}, x_{j2}, ..., x_{jp}\right)^T$, the Euclidean distance between them is given by,

$$d\left(x_i, x_j\right) = \left[\sum_{k=1}^{p} \left|x_{ik} - x_{jk}\right|^2\right]^{\frac{1}{2}} \quad (1)$$

Suppose M wind farm datasets $F_1, \cdots F_M$, for each dataset F_i, find its NWP data $x_i(t_{ij})$ that is the nearest to NWP data $x_0(t)$ from new wind farm at time point t. Then calculate Euclidean distance of two data at next time point, that is $d\left(x_0(t+1), x_i(t_{ij}+1)\right)$, abbreviate as d_{ti}. The distance represents differential between meteorological variation of new wind farm and wind farm i at time point t. Considering NWP data of length N from new farm, we can obtain a matrix of meteorological variation differential between new farm and other M farms:

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1M} \\ d_{21} & d_{22} & \cdots & d_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N1} & d_{N2} & \cdots & d_{NM} \end{bmatrix} \tag{2}$$

Where the i^{th} row represents meteorological variation differential array between new farm and wind farm F_i. Average difference between new farm and M old farms is obtained after calculating average of each row:

$$V = \left[d_1, d_2, ..., d_M\right] \tag{3}$$

Where d_i represents the difference in meteorological average variation trend between NWP data from new farm and wind farm F_i.

In this paper, dataset from wind farm with the minimum difference in average meteorological variation is selected as the initial training set.

2.2 Updating rule of training set

From daily operation of new wind farm, measured data $S = \{(x_i, y_i), i = 1, \ldots, n\}$ can be obtained everyday, where x_i is NWP data at time point i, y_i is supervised data from SCADA (Supervisory Control And Data Acquisition) system. Training dataset D is updated using S in O-GP method. To be more specifically, training set is updated by substituting data which is the closest to new data from dataset S, with the closeness also defined as Euclidean distance presented in last section. In this way, data in initial training dataset is substituted by the data from new wind farm every day, until all the data in training set is purely from new farm.

2.3 Gaussian Process

In this paper, Gaussian Processes is used to build a regression model reflecting the relationship between NWP data and measured wind speed in wind turbine SCADA system. Therefore, in application, NWP data can be inputted into the trained GP model, to forecast the wind speed in the future.

A Gaussian process $f(x)$ can be completely specified by its mean function and covariance function, written as $(x) \sim GP(m(x), k(x, x_0))$, where the mean function $m(x)$ and covariance function $k(x, x_0)$ are defined as

$$\begin{gathered} m(x) = E[f(x)] \\ k(x, x_0) = E[(f(x) - m(x))(f(x_0) - m(x_0))] \end{gathered} \tag{4}$$

Usually, the mean function is assumed to be zero. Consider the GP in a classic regression problem: assume we have a training set D of n observations: $\{D = f(x_i, y_i) | i = 1, \cdots, n\}$, where x denotes an input vector of dimension M and y denotes a scalar output. Collect inputs in a matrix X and targets in a vector y, we can write $D = (X, y)$. The key point of the regression problem is to model the relationship between inputs and targets, that is to build a function to satisfy,

$$y_i = f(x_i) + \varepsilon_i \tag{5}$$

where the observed values y differ from the function values $f(x)$ by additive noise ε_i, which is assumed to be an independent, identically distributed Gaussian distribution with zero mean and variance σ_n^2, i.e. $\varepsilon \sim N(0, \sigma_n^2)$. Note that y is a linear combination of Gaussian variables and hence is itself Gaussian [11]. The prior on y becomes

$$\begin{aligned} E[y] &= E[f + \epsilon] = 0 \\ cov[y] &= K(X, X) + \sigma_n^2 I \end{aligned} \tag{6}$$

where K is a matrix with elements $k_{ij} = k(x_i, y_j)$.

Given a training set$D = (X, y)$, our goal is to make predictions of the target variable f_* on a new input x_*. The distribution with new input can be written as

$$\begin{bmatrix} y \\ f_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X,X) + \sigma_n^2 I & k(X, x_*) \\ k(x_*, X) & k(x_*, x_*) \end{bmatrix}\right) \tag{7}$$

where $k(X, x_*) = k(x_*, X) = [k(x_1, x_*), \ldots, k(x_*, x_1)]$, which we will abbreviate as k_*. Then according to the principle of joint Gaussian distributions, the prediction result for the target is given by

$$\begin{aligned} \overline{f_*} &= k_*^T (K + \sigma_n^2 I)^{-1} y \\ V[f_*] &= k(x_*, x_*) - k_*^T (K + \sigma_n^2 I)^{-1} k_* \end{aligned} \tag{8}$$

Now, the whole regression model based on Gaussian process is completed.

The GP toolbox in Netlab [12] is used to train and model and calculate results for testing set in this paper.

4. Simulation Results

4.1 Selection of initial training set

The performance of the designed training set selection method is validated in this section. Totally five candidate datasets are collected from five wind farms locate in different parts of China. Turbine type in the five wind farms is same with that in target wind farm (new farm). Wind turbine of same type has similar working behavior, therefore the key comparison among these wind farms are the different meteorological condition, which can be expressed by historical NWP data. Note that historical NWP data for every wind farm is available – easily by downscaling online NWP data to the location of wind farm.

To evaluate the performance of training set selection method, firstly Farm-1 is assumed as the target farm, which is the new built farm. The datasets from five farms can be used as the initial training set to predict wind speed of Farm-1 respectively, and the accuracy of forecasting models built on different training set can be compared. Data measured in Farm-1 from July 1st to December 31st is used as test set, while data from January 1st to June 30st from the five farms are used as training set respectively. Wind speed forecasting accuracy for Farm-1 based on different training sets are shown in Fig 3.

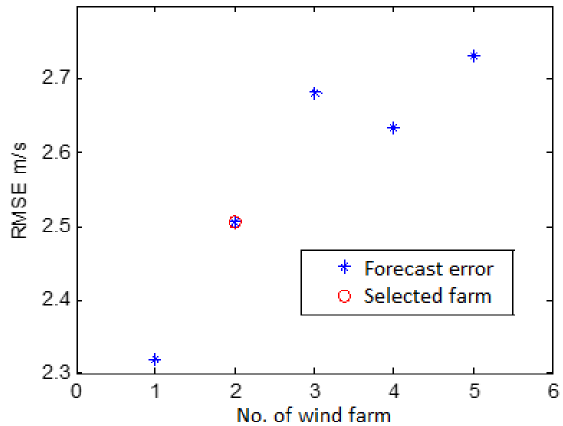

Fig. 3 Influence of different training sets on forecast error

From Fig 3, it is obvious that the minimum wind speed forecasting error is achieved when data from Farm-1 is used as the training set. Fair forecasting could also be realized when using training set from other wind farms, but with a relatively larger forecasting error. Fortunately, the chosen dataset by the selection method designed in this paper, which is dataset from Farm-2 as shown in Fig 3, leads to a second best forecasting result. Therefore, the selection process successfully chose the most suitable training set from other available wind farm data.

According to the same procedure, Farm-2, Farm-3, Farm-4 and Farm-5 is assumed as the target farm sequentially. When Farm-i is used as the target farm, data from Farm-i from July 1st to December 31st is used as test set, while data from the rest farms from January 1st to June 30st are used as training sets respectively.

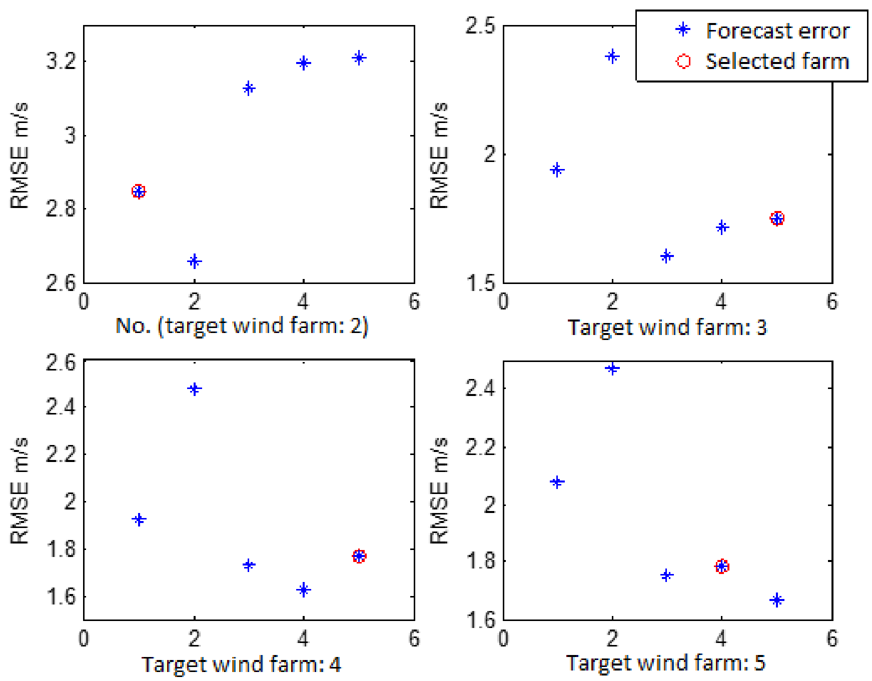

Fig. 4 Selection of initial training set

As shown in Fig. 4, for each target wind farm, wind speed forecasting error is the minimum while dataset from itself is used as the training set. Hence it is necessary to use the dataset from Farm-i to forecast wind speed for Farm-i, if possible. Since historical data from new wind farm itself is not available, the initial training set need to be selected from the rest of the datasets. As marked in the red circle, the initial training set chosen by the proposed selection method in some cases give the optimal choice from available datasets, or at least the suboptimal one, while the forecasting error using the optimal and suboptimal one is close to each other. The result shows that the selection method is effective in choosing appropriate initial training dataset for new built wind farm.

Length of initial training set should also be considered. Short dataset may lead to poor performance of initial model, while long dataset need a long time to be substituted completely by the data from new wind farm. In this paper, training dataset including 900 hours data is used, which is the training data needed for convergence of GP model in wind speed forecasting problem, according to experience. This way, forecasting model with high accuracy could be built using relatively small dataset.

4.2 Case study

To validate the performance of O-GP model, i.e. the necessity and advantage of selecting an initial training set and substituting training data with new wind farm data, the experimental result on a real case is presented in this chapter. With Farm-3 assumed as the target wind farm, two forecasting models are built for comparison: 1) Forecasting model based on Gaussian process by data collected only from Farm-3 itself (since it's not possible to build forecasting model with too little data, this model is built since the 6-th day); 2) The proposed O-GP model for wind speed forecasting. The dataset from Farm-5 is chosen as the initial training set, while the training data is substituted by the data from Farm-3 every day, and daily wind speed is predicted based on the updated training set.

Long testing set could better validate the performance of forecasting model. One whole year dataset of 2012 from Farm-3 is used as the testing set in this paper. Suppose Farm-3 began operating at January, 2012, and data of last 900 hours of 2011 from Farm-5 is used as the initial training set, forecasting error of two models are shown in Fig. 5.

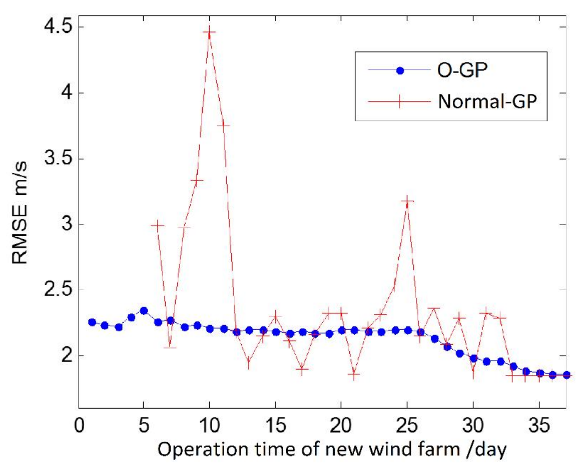

Fig. 5 Comparison of two models on wind speed forecasting

As shown in Fig. 5, the proposed O-GP method could achieve a high prediction accuracy at the beginning of new wind farm, plus the forecasting performance keeps improving gradually with the operation of wind farm as the new operational data changes the training set. The forecasting performance of the model built by dataset only from Farm-3 is also improving with operation of new farm but presents significant oscillations, indicating the unreliability of this forecasting model.

4.3 Statistical forecasting results

In this paper, actual measured wind speed data from Farm-J, supposed as new built farm, through 3 years from April 2010 to April 2013 is applied in experiment to illustrate the performance of the proposed O-GP method. Data from April 1st 2011 to April 1st 2013 from Farm-J is used as the test set, and Farm-J is assumed as in operation from April 1st 2010. Daily wind speed of Farm-J is forecasted by two models: 1) forecasting model based on Gaussian process using only operational data in new wind farm; 2) O-GP model proposed in this paper.

Persistence method is used as benchmark too, which simply uses the current value as the forecast, and is a very classical benchmark in wind forecasting area. Wind speed forecasting error for Farm-J of the three models is shown in Table 1.

Table 1. Comparison of three forecasting models

Model	RMSE (m/s)	MAE (m/s)	MAPE (%)
Persistence	2.56	1.77	34.8
Normal GP	2.32	1.62	31.8
O-GP	1.97	1.39	27.2

As shown in Table 1, the forecasting error of the proposed O-GP method is relatively low, under several criteria. Compared with other two models, the proposed model presents the highest wind speed prediction accuracy, with about 20% improvement comparing to the persistent method, and 15% improvement comparing to normal GP method.

5. Conclusion

Short-term wind speed forecasting strongly impacts the safety and economics of the electricity grid and has received great attention for the past decade. However, application of the existing approaches in new wind farm is impeded by lack of local operational data.

A online learning wind speed forecasting method is proposed in this paper for new wind farm based on Gaussian process, with certain parts designed to improve the forecasting accuracy: selection method for choosing appropriate data from a long term operation farm of similar meteorological condition as initial training dataset; updating process for replacing data in initial training set by daily operational data from new wind farm; wind speed prediction model built on GP using NWP data as inputs.

Performance of the proposed O-GP method has been validated by experimental results on field wind farm data. The forecasting error of O-GP method is only 1.97 m/s (RMSE), which achieves about 20% improvement comparing to the persistent method, and 15% improvement comparing to normal GP method.

6. References

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