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 in the wind farm 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. This wind speed prediction method could operate with very limited or no local historical wind speed data for new wind farm.

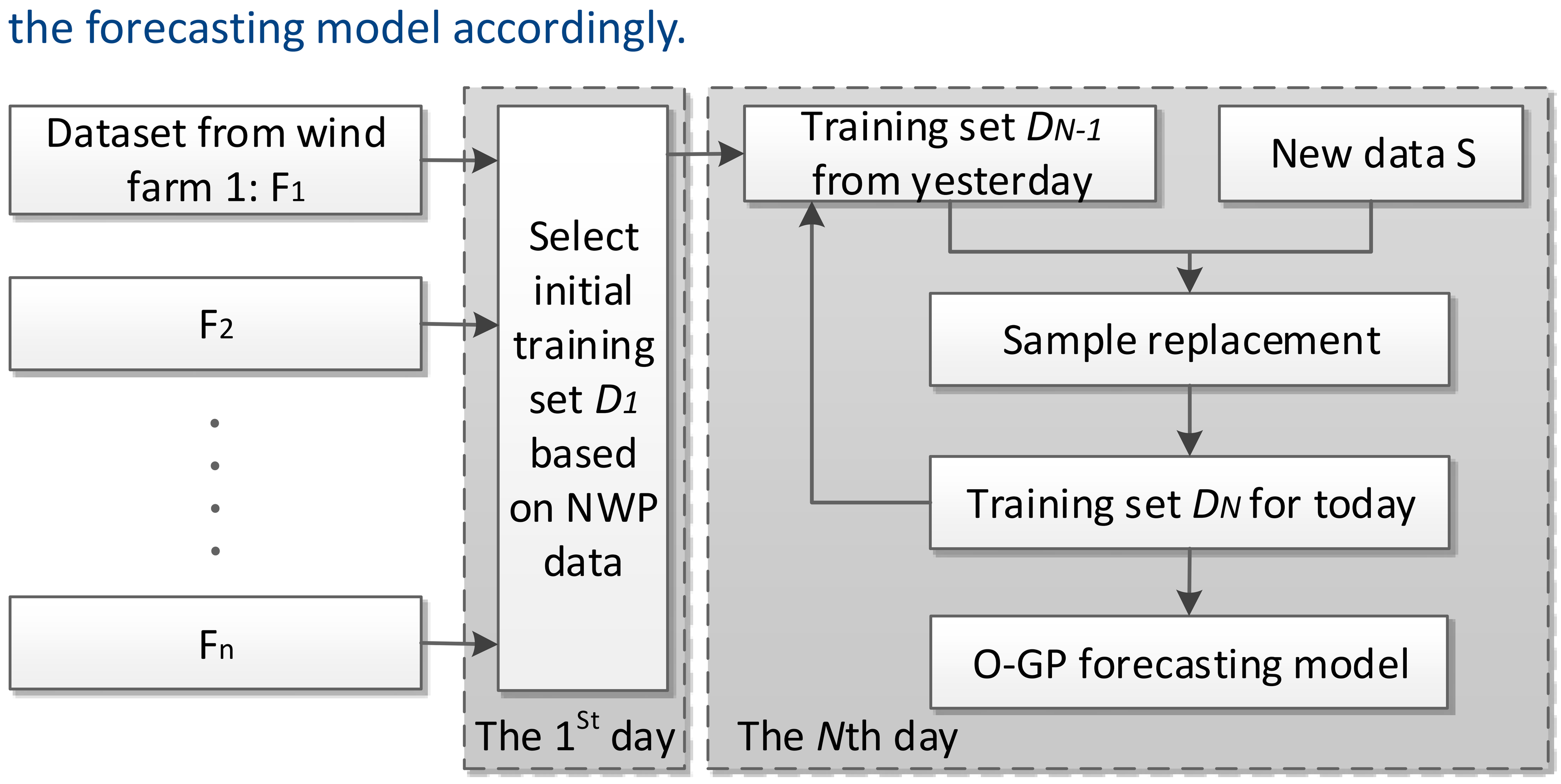
Three years real-world data from a wind farm in China is used to validate the model, and the experimental results proved that the proposed method can achieve higher accuracy for wind forecasting, with about 20% improvement comparing to the persistent method, and 15% improvement comparing to normal GP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

Objectives

Design an accurate wind speed forecasting method for new wind farm, which has no historical wind speed data. The method can automatically choose the most suitable data from other wind farm to build a prelim model, and update itself with new coming data from the daily operation of new wind farm.

Methods

The whole self-adaptive wind speed forecasting method for new wind farm based on Gaussian processes, named as O-GP (on-line training) 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 prediction model – Gaussian processes is a stable regression method, which only need small training set; 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.



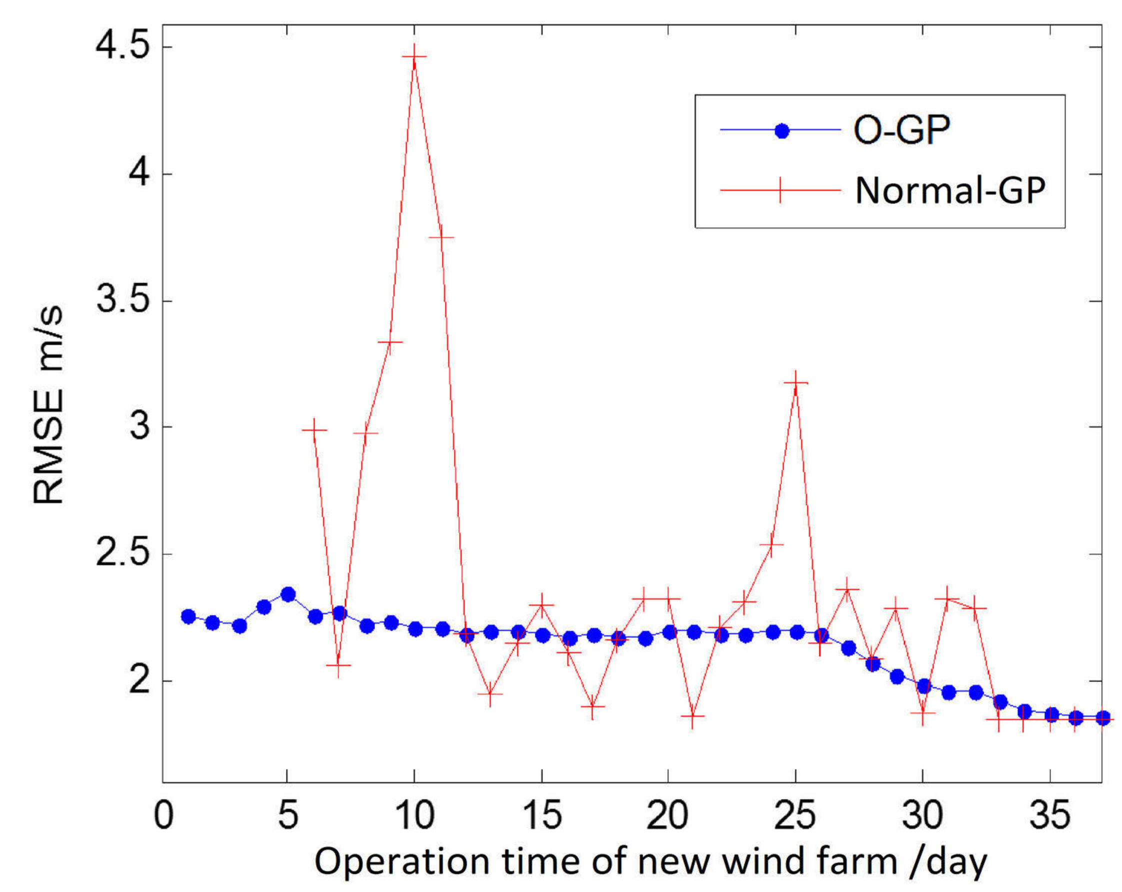
As shown in the figure, there are several datasets from existing wind farms, a selector is designed to choose the most suitable initial training set from existing data, based on the principle of selecting the wind farm which has the NWP data that is the closest to new wind farm. Forecasting model built by the initial training dataset D_1 is the model used in the first operational day of new farm. Then as new data can be collected through daily operation, the training set can be updated everyday – any old sample which is the closest to one new sample is replaced.

With training set ready, for time point *t*, both the historical wind speed data $S_{t-n}…S_t$ and NWP forecasting data S_{t+i}' are set as inputs, while future wind speed S_{t+i} is set as output, the model can be built using Gaussian Processes, to reflect the relationship between historical/NWP data and future wind speed. Therefore in application, with historical speed data and NWP data, the future wind speed can be calculated by the trained model.

Results

Actual measured wind speed data from Farm-J, with a duration of 3 years (April 2010 to April 2013) is applied to illustrate the performance of the proposed O-GP method. The data from April 1st 2011 to April 1st 2013 is used as the test set, while Farm-J is assumed as in operation from April 1st 2010. Chosen from 5 other wind farms, data of last 900 hours of 2011 from one farm is used as initial training set, as the corresponding NWP data is the closest to new wind farm – that indicates there are similar pattern in meteorology.

Two models are built: 1. one model by the proposed method; 2. another model based on Gaussian process trained by data only from Farm-J, that is denoted as Normal-GP (this model is available from the 6th day, since it's not possible to train a model with too little data). Daily forecasting error of two models are shown in the figure below.



As shown in the figure, the proposed O-GP method guarantees a relatively high prediction accuracy at the beginning phase, and has its accuracy improving gradually with the new data added, while performance of the Normal-GP is also improving but presents significant oscillations, thus is unreliable.

With persistence model added as a benchmark, 24-hour-ahead wind speed forecasting error for Farm-J in 2 years of 3 models is shown in the table below.

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

Compared with other two models, the proposed O-GP model has the highest wind speed prediction accuracy. The forecasting accuracy of O-GP method is 20% better than the classical persistent method, and is about 15% better than normal GP method, in terms of RMSE criterion.

Conclusions

A self-adaptive forecasting model is proposed in this paper for new wind farms which are lack of historical operation data. Certain techniques were employed to improve the forecast accuracy: selector is designed to choose the most suitable dataset from several long-term farms with similar meteorological condition, so it can be used as the initial training dataset; initial training set is updated reasonably using operational data from new farm every day; both historical wind speed data and NWP data are used as model inputs due to forecast horizon to achieve better prediction for future wind speed.

The experimental results show that the proposed method is very effective for short term wind speed forecasting in new wind farm, the accuracy of which is 20% better than the classical persistent method, and is about 15% better than normal GP method.

References

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