A Data Mining Approach Combining Fuzzy K – Means Clustering With Bagging Neural Network for Short-Term Wind Power Forecasting

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I. INTRODUCTION

Renewable energy in general and wind energy in particular have been growing rapidly in the last decade, becoming a more and more important component of the global energy supply. A catalyst for such growth has been growing energy demand, spiralling fossil fuel prices and an acute necessity to reduce carbon dioxide emissions. From the current perspective all the factors which led to the growth of wind energy in the last decades will continue advancing it in the future. Global energy demand is expected to keep growing, even under the declared intentions to increase energy efficiency (use energy wiser)[1]. Fossil fuel prices are expected (under a relatively optimistic scenario) to stay at least as high in the future [2]. Global warming continues calling for significant reductions in carbon dioxide emissions. In addition, the recent Fukushima disaster has lead to a new wave of serious debate on the safety of nuclear energy, making it somewhat undesirable in the forward-looking policies. All this makes wind energy a very attractive alternative, which is expected to keep growing significantly in the years to come

In recent years, wind speed and wind power prediction approaches are mainly categorized with respect tothe time horizon of the application [7]. These methods aremainly divided into three categories: 1) short-term windprediction estimates the wind data of several minutes to hoursahead. This type of prediction benefits electricity market clearing, real-time grid operations and regulation, economicdispatch, and operational security in the electricity market [8].
2) Medium-term forecasting focuses on time intervals in therange of several hours to a week. Unit commitment andreserve allocation decisions are made using this type ofpredictions. 3) Long-term forecasting refers to the predictionof wind velocity in the ranges of one week to a year or more.
Maintenance, expansion planning, and the feasibility studiesfor the design of wind farms are dependent on this task [9]
Generally, there are four types of wind speed forecastingmodels proposed in the recent literature: 1) Persistencemethods, which assume the wind data at a future time step has the same values as the current time instance. This assumptionis similar to the smoothness assumption know in Machine Learning, where a function approximation model outputs thesame results for two inputs close to each other in the inputspace. Although this assumption diminishes the future windspeed estimation precision for long time horizons, persistencemodels are accurate predictors for ultra-short horizons.
2) Physical methods, which are based on lower atmosphere ornumerical weather prediction (NWP) that uses weatherprediction data such as temperature, pressure, surfaceroughness, and obstacles. NWPs are generally executed onsupercomputers because of their high computational complexity. The computation burden limits the usefulness ofsuch methods for medium and long-term tasks [10].
3) Statistical methods, which are low-cost and easilyapplicable techniques to capture the mathematicalrelationships in the time series data. The prediction accuracy of such methods declines with the increase in the length of theprediction time horizon. Statistical approaches includeautoregressive (AR), autoregressive moving average (ARMA),and autoregressive integrated moving average (ARIMA) models. In [11], a hybrid ARMA model with wavelet transformation is introduced for short-term predictions. Theresearch work presented in [12] proposes several ARMAbasedapproaches for wind speed and wind direction dataprediction. An ARIMA with a regression

analysis approach isapplied to real-life short-term wind forecasting in [13].

Although AI approaches have recently obtained betterprediction results compared to statistical models, thesemethods have several drawbacks: 1) Shallow ANN models

have weak generalization capability; thus, they are not able toeffectively learn complex patterns from the highly varyingwind data. Although wind time series datasets contain largeamounts of data, these models cannot learn complex dataabstractions. SVM-based approaches, as well as linear models,

have the same problem because of the smoothness assumption.

2) Deep neural architectures proposed in the literature, i.e.DBM and SAE, do not consider the sequential characteristicsof the wind data. 3) The ANN-based approaches merely

capture wind patterns in the time-space and leverage temporalcorrelations to learn the temporal features from the time seriesdata. It is shown in the literature that neighboring wind siteshave high spatial correlations [27].

In this paper, a data mining approach consisting of the K-means clustering and bagging NN is proposed to predict the short-term wind power of individual wind turbine. The main contributions of this paper are summarized as follows. 1) To mitigate the impact of the diversity of training samples, the K-means clustering is utilized to classify the original data sets into several categories according to meteorological conditions and historical power. Pearson correlation coefficient is used to calculate the similarity between each category and the forecasting day.

II. RELATED AND EXISTING SYSTEM

Rajesh Kumar et al explores the usage of Markov Chains for forecasting wind speed during a short-term period (day-ahead hourly wind generation forecasts for an individual wind farm). The proposed prediction model depends on one variable factor - wind speed, for a specific wind turbine

Ning Li et al presents a kind of wind power forecasting method based on empirical mode decomposition (EMD) and random forest (RF). EMD is applied to this method to decompose wind power sequence into several intrinsic mode functions (IMF) and a residual component, and then RF is used to train each component. Finally, the predicting results of each component are summed together to obtain the wind power forecasting values.

Xiaodan Wang et al present model employes not only the small learning ability and simple calculation of SVM, but also strong global search ability of PSO. The addressed model was tested using real wind speed data. Experimental results show that, the proposed model has the best forecasting accuracy, comparing with classical SVM model and back propagation neural network model.

ArturasKlementavicius et al deals with the short-term forecasting of wind speed for the Laukžeme wind farm (Lithuania) using time series approach. The ARIMA model was selected and its best structure determined using the historical wind speed data (4 months) and varying both learning interval (3-5 days) of the model and the factual data averaging time (1-6 hours).

Jie Shi et al proposes a novel approach using autoregressive model (AR) and Hilbert-Huang Transform (HHT) to improve the accuracy of wind power forecasting. The input data is decomposed into several components, in every of which, the data satisfies the linear characteristic better than the one before transformation. Case study from a wind farm in Texas, U.S.A shows that the proposed approach performs better than the traditional linear forecasting method.

NatapolKorprasertsak et al investigate three widely-used forecasting models for short-term wind speed prediction from wind measurement data, that is persistence model, autoregressive moving average (ARMA) model, and artificial neural network (ANN). It is found that accuracy of persistence model dramatically decreases as time horizon increases; nevertheless, the persistence model is the simplest algorithm for implementation.

Ho-Chian Miao et al proposes an adaptive network-based fuzzy inference system (ANFIS) based forecasting method for short-term wind power forecasting. An accurate forecasting method for power generation of the wind energy conversion system (WECS) is urgent needed under the relevant issues associated with the high penetration of wind power in the electricity system

Zhong Fan et al propose a similar pattern matching technique for data pre-processing. The proposed technique is able to select the most appropriate segments from the available historical data for the forecasting. These segments are used for the training of parameters in the SVM model, which will then be able to provide the desired forecast

Proposed system

Data mining approaches have been widely used for classification and prediction problems. The proposed approach is based on data mining, which consists of the

K-means clustering and bagging NN. Fig. 1 shows the WPF model. First, data preprocessing is conducted on the vector space to clean unreasonable data, normalize the training samples, and select the most related variables as the inputs of the NN. Second, data after preprocessing are clustered by the K-means clustering to select the training set which is most similar to the forecasting day. Finally, the wind power is forecasted by the bagging NN, which is able to alleviate the instability and over fitting problems of the BPNN

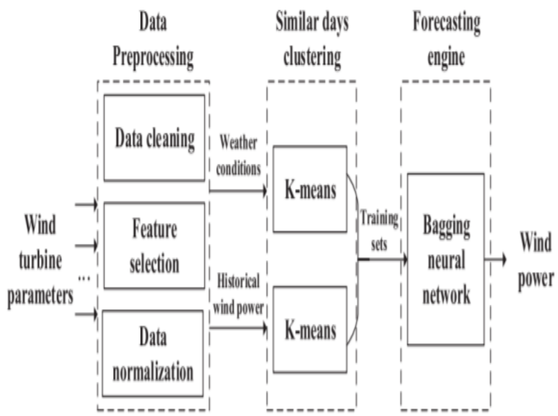

Figure 1 proposed system

A number of wind turbine parameters are collected as the training samples via the sensor unit. However, these samples may contain unreasonable data. Besides, using too many parameters as the training features would increase the computing complexity and obtain undesired results for the reason that some variables are irrelevant or redundant in this model. Selecting features which are most related to the wind power is able to improve the accuracy. Finally, data normalization has an effect on the convergence rate and accuracy of the training algorithm. Thus, in order to obtain accurate forecasting results, data preprocessing is necessary. 1) Data Cleaning: The original samples may contain data whose values of some characteristics are unreasonable. For example, the values of wind speed and wind power are less than zero. It is obvious that these data are notto fill the vacancy of the deleted data. The mean value method is applied, which makes use of the mean value ahead and back of the deleted data. 2) Feature Selection: In theory, more input variables can carry more discriminating power. But in practice, excessive variables are prone to cause many problems. Therefore, selecting a suitable set of input variables from the raw data has a great impact on the forecasting performance. Relief algorithm is a kind of feature weighting algorithms. The core idea is that the different weights are assigned to the corresponding features according to the correlation, and the feature whose weight is less than the threshold would be removed. The formulation of Relief algorithm is given by [18]. The running time of Relief algorithm increases linearly with the sampling times and original features so that this method has high operating efficiency. In addition, Relief algorithm can achieve the purpose of physical dimensions reduction compared with the principal component analysis (PCA). 3) Data Normalization: The aim of data normalization is to transform the raw data to the same orders of magnitude so that the convergence rate and forecasting accuracy can be improved. The min–max method is applied for normalization, which can be expressed as $x = (x - \min)/(\max - \min)$. In this equation, x is the original data, and max and min represent the maximum and minimum value of the training set. The result x is mapped to [0, 1].

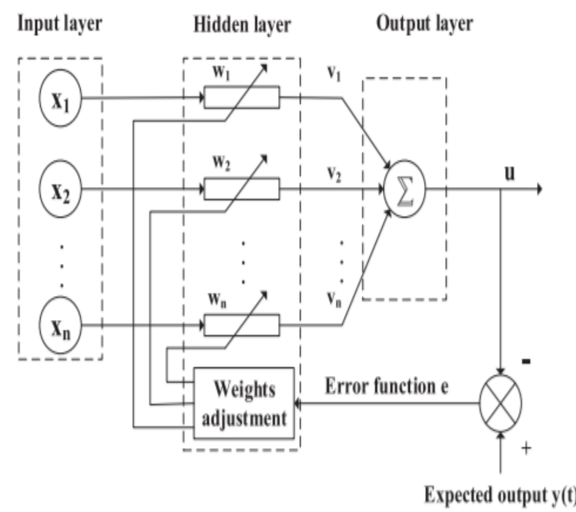

Fig. 2. Model of three-layers BPNN.

Bagging NN NN has been one of the most effective data mining approaches for prediction. NN can deal with nonlinear problems well without establishing complex mathematical model. BPNN as one of the most common NNs is usually used as the forecasting algorithm. The basic BPNN consists of three layers: 1) an input layer; 2) a hidden layer; and 3) an output layer. Fig. 2 shows the principle of the BPNN. The BPNN consists of two processes: 1) forward propagation of data stream and 2) BP of the error signal. In the process of forward propagation, the state of neurons in each layer only affect ones in the next layer. If the expected output could not be obtained in the output layer, the algorithm turns to the process of BP of the error signal.

The gradient descent method is conducted on the weights vector space. It is needed to dynamically search for a set of weights vector and minimize the error function. As for the hidden layer, the neural numbers of this layer is usually 2M + 1 according to the experience, where M represents the neural numbers of the input layer. However, different neural numbers have an effect on the results of the output layer so that the network is tested when M = [2, 3,..., 10] to find the best forecasting result.

III. SIMULATION RESULTS

In this section, the proposed forecasting approach has been simulated and compared with other approaches. The 10-min data obtained from the SCADA of a wind turbine are collected as research data. The six numbers for an hour are sum to obtain hourly data, which could avoid that 10-min data fluctuated greatly so that the forecasting accuracy could be improved. In order to evaluate the performance, two kinds of error calculation methods: 1) RMSE and 2) MAE are proposed

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y'_i)^2}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - y'_i|.$$

In the equations described above, yi is the actual power, y

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i is the predictive power, and N is the number of the test data.

IV. CONCLUSION

In this paper, a data mining approach for WPF has been proposed, which consists of the K-means clustering method and bagging NN. The historical data are clustered according to the meteorological conditions and historical power. Pearson correlation coefficient is used to calculate the distance between the forecasting day and the clusters. The input variables of the NN are selected by Relief algorithm to reduce the complexity and the Bagging algorithm is applied to optimize the stability and accuracy of the BPNN. To demonstrate the effectiveness, the proposed approach has been tested according to the actual data in the practical wind farm. The RMSE and MAE results show that the proposals have significant gains. Although the proposals are not specially designed for the individual wind turbine, the idea of clustering is still important and effective when a large-scale wind farm is built. Particularly, in a wind farm, the location of wind turbines may lie in one direction, then the wind speed of these wind turbines can be classified into one category. With this way, the proposal can be extended and widely used in all real wind farm, which not only increases the forecasting accuracy, but also reduces the computational complexity. To improve the forecasting accuracy, the effective meteorological forecasting should be researched, and the corresponding optimal method for the BPNN should be designed. Besides, the multidimensional clustering problem should be formed and the WPF model for wind farms should be researched.

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