Wind Power Forecasting in Short-Term using Fuzzy K-Means Clustering and Neural Network

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***Abstract*— Wind power forecasting is the large emerging field in research as it plays a vital role in wind power plant operation. Wind power is one of the fast-increasing sustainable power resources and it can be viewed as the additional substitute for traditional power produced from non-renewable energy. Wind power forecasting can reduce over-dependence on traditional source of electricity. Due to the random behaviour of the airstream, there will discontinuity in collecting of the wind data which is the major impact for forecasting accuracy. Last decade many researchers have applied data mining technique in different prediction system that produced good accuracy. So, this paper proposed, a hybrid method consist of Fuzzy K-Means clustering and Neural Network(NN) are used to improve the forecasting accuracy and also to reduce computational complexity for forecasting the wind power in short-term. Fuzzy K-Means clustering is used for selecting similar days and it consisting of information about the weather condition and historical power data. To avoid the volatility problems, a backpropagation algorithm is incorporated into the NN. In order to prove this efficiency, a hybrid approach can be evaluated in actual wind farm which can give better forecasting accuracy and also expected to reduce computational complexity when compared with other existing wind power forecasting approaches.**

Keywords—Neural Network (NN), Fuzzy K-means clustering, Wind Power Forecasting (WPF)

I. INTRODUCTION

Nowadays, the usage of sustainable resources plays a vital role in the world. The generation of wind power is widely adopted by many large-scale industries because of their cleanness and wide accessibility. Due to the characteristics of discontinuity and volatility of wind, it is difficult for collecting the training sample and also it is difficult to provide security for accessing the large-scale application. In order to solve this issue some data mining techniques are used. The wind power forecasting (WPF) approach has provided absolute and reliable forecasting result and also reduce the cost of spinning resources. In related works, the many wind power forecasting approaches are discussed for the proposed system. The wind power forecasting approaches are common categories into three types. They are 1) physical approach 2) statistical approach, and 3) combined approach [1]. The physical approach it provides a detailed information about the geographical location and weather conditions descriptions to the model wind farm at the particular location [2]. Then the numerical weather forecasting (NWF) approach which helps the wind speed to be converted in to wind power by wind turbine will produce the power graph. Only physical information helps as to improve the accuracy of this approach will greatly depend on it. The statistical approach to determine the similarity between the set of attributes and historical data such as wind temperature and the wind direction [3].

The combined approach it has the advantage of the physical approaches and the statistical approaches which is used to improve the forecasting accuracy results. The physical approach is used for determining the specific wind power forecasting design for the specific wind plant and it requires an only small amount of historical information for training these models. In order to obtain the accurate design, a detailed knowledge about the physical characteristic of the wind turbine is needed for this approach [4]. Therefore, the actual characteristic of the wind turbine is difficult for collecting the wind data in short-term.

When compared with physical approaches, the statistical approaches need a huge number of actual information to build a better design for forecasting. The approach consists of a time series model which is used for forecasting the accurate wind power. Within a very short time period, a better prediction accuracy can be obtained by the time series [5].

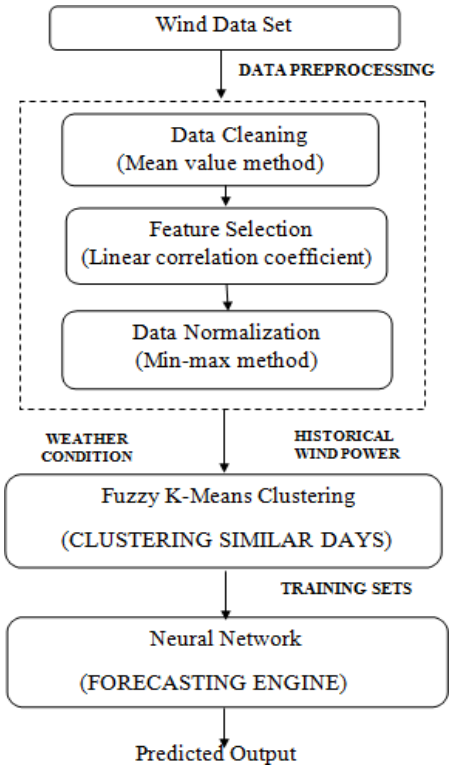

Fig. 1. Proposed System Architecture for Wind Power Forecasting Approach.

These approaches are capable for the continuous sequence and these data mining approaches are capturing the researcher's attention [6]. The neural network (NN) overtook the time series model and other approaches which are used in short-term prediction [7]. The neural network has the ability to design a composite mapping among meteorological conditions and actual data [8]. NN can provide better forecasting results but sometimes neural network may use actual information these become the larger impact on some of the variable such as speed of the wind, wind temperature, wind direction, wind pressure. Backpropagation neural network (NN) is used to train the data for providing accuracy for forecasting [9]. One of the major impacts for poor forecasting accuracy due to selecting the training sample.

For improving the forecasting accuracy, some clustering algorithm is used to select the correct training set [10]. The K-Means clustering which is used for clustering the sample into many categories based on their wind direction [11]. Neural Network (NN) will help in reducing the outfitting problem which also used to improve forecasting accuracy [12].

In this paper, fuzzy k-means clustering and the neural network can provide the forecasting with the wind power in the short time period.

II. PROPOSED MODEL WIND POWER FORECASTING

The data mining consisting of some of the following technologies are clustering, classification, a prediction soon. In these, the proposed system uses the Fuzzy k-means clustering and the Neural Network(NN) for providing the better forecasting results.

A. Data Preprocessing

Data pre-processing is a data mining technique that converts raw data into understandable data. In the real world, data are generally incomplete, inconsistent and noisy. For that, the data preprocessing consisting of three process. They are Data Cleaning, Feature Selection and Data Normalization

Data Cleaning

The original sample may consist of incomplete, inconsistent and noisy data. The unwanted data to be removed. In order to fill the empty space mean value method can be used.

Feature Selection

Feature selection will help in finding the important or most relevant feature. For selecting the best features linear correlation coefficient can be used. It help as to find the relationship between the two random sample. The value to bebetween±1 for correlation coefficient and other features are uncorrelated. With the help of linear correlation coefficient some features are selected. They are wind speed, wind temperature, and wind pressure.

Data Normalization

Data Normalization aims to convert raw data to some order which improve the accuracy of the forecasting. For normalizing the data min-max method to be applied. The formula used for expressing min-max method is X=(x-min)/(x-max). The x value to be between [0, 1]. Then x represent the original data, min and max value used for representing the minimum and maximum value of the data.

B. Clustering Similar Days

Generally, the wind turbine generates a large amount of data when it operates normally. However, it is difficult for obtaining the correct result while using the some incorrect of training data. For choosing the related days and to clustering the sample into many categories fuzzy k-means clustering will be considered to be the good method which also improving the forecasting accuracy. The role of the fuzzy will help in proper clustering of data and it also provide accurate prediction result.

Fuzzy k-means clustering is the extent of the K-Means clustering. The K-Means clustering helps in finding hard cluster (where each data points belongs to one cluster) whereas fuzzy k-means discovers soft cluster (where one data point to belong to two or more cluster) with certain probability towards each other[13] .

These algorithm calculates the membership values of each instance or data within the time series by making use of fuzzy sets. The fuzzy set value here corresponds to the cluster center the centroid. The number of fuzzy sets can be set to any value based on the need and this number is the same as the number of clusters the will be formed. The Fuzzy k-means clustering makes use of a fuzzification parameter called as m within the range [1, N] and this will determine the degree of fuzziness of the clusters. If the value of m is set to be 1, then the effect will be the crisp clustering of points into the clusters. As the value of m increases the degree of fuzziness between the points or data also increases.

The k-means clustering is similar to Fuzzy k-means clustering has the following process. 1)selects random cluster centres initially and then uses the Euclidean distance or Correlation measure to calculate the distance of each data or instance to each of the clusters.2) After this step, the Fuzzy k- means clustering will calculate the membership matrix that includes membership values of each instance with that or all the clusters. 3) The sum of membership of a single instance with all clusters will always be 1. 4) Then using these membership values of the instances or data, the new cluster centres are calculated and the algorithm keeps iterating till the optimal cluster split has been generated. They produced several clusters. The Euclidean distance will select the relevant class of future process.

C. Neural Network (NN)

Neural Network (NN) played a vital role in data mining approaches. It will provide a better prediction result. The most common network is the neural network (NN). Basically, the BPNNs will consist of 3 layers. They are i) input layer, ii) hidden layer, iii) output layer.

The back propagation neural network (BPNN) contains two processes. The first process is the forward propagation of the data. In each layer the state of the neuron only 1 to be affected in the second layer. So that output layer cannot be obtained the expected outcome. The second

process is the backward propagation process. In these process, the gradient descent method is used. This method is based on the weight vector space.

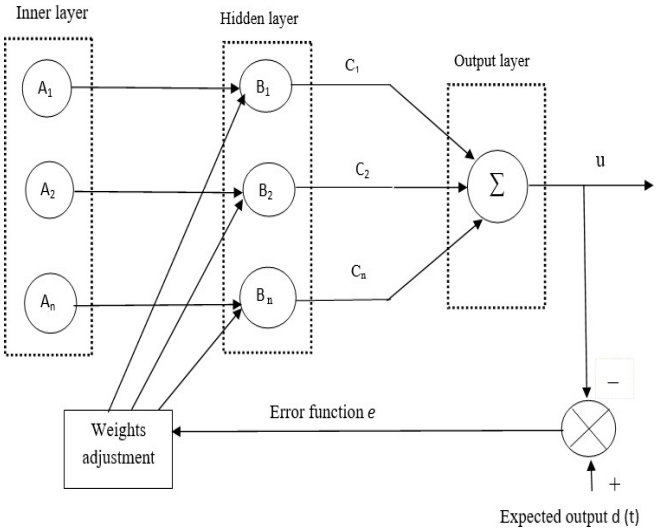

Fig. 2. Back Propagation Neural Network Model

It actively searches for a form of weight vector and helps in reducing the error signal. In *fig.2*: [a_1, a_2, a_3……a_n] be the input [b_1, b_2, b_3…..b_n] be the weights that is between the first layer and the second layer, and [c_1,c_2,c_3…..c_n] be the weights that is between the second layer and the third layer. D (t) be the third layer. The nonlinear problems are handled by general sigmoid function which can be expressed as

$$d = f(a) = \frac{1}{1+e^{-a}} \quad (1)$$

The hidden layer output *g* can be formulated as

$$g = f_1(b_i \quad (2)$$

The output layer output u can be formulated as

$$u = f_2(\sum c_k z_k) \quad (3)$$

Thus, the forward propagation process is finished.

The is the error signal which is generated by using the function d (t) and u.

$$e = \frac{1}{2}\sum (y_i(t) - u_i)^2 \quad (4)$$

The method used is the gradient descent which helps in changing the value of bi and also helps in reducing the error. This method will also help to update the weights and ci. It will continue till the value will be equivalent to 0. Because of these process weight value is subsequently change and lots of time to be consumed.

The Back propagation will get better forecasting results while comparing with the other algorithm like support vector machine and linear regression. Besides, these overfitting problem will arise in the back propagation. So that neural network to be used for reducing the overfitting problem. The process of the neural network is that, first select the training set initially. Secondly, the trained set is divided in to subset and then the subset to be trained on the individual network. Finally, the results will be obtained. The neural network will give the better forecasting. It also improves the accuracy of forecasting.

D. Experimental Results

In this, the proposed forecasting approach has been compared with the existing approaches. The performance of these approach to be calculated by using two method

1) RMSE, 2) MAE.

$$\text{RMSE} = \sqrt{\frac{1}{A}\sum^2} \quad (5)$$

$$\text{MAE} = \frac{1}{A} \quad (6)$$

In above equation describes b_i is the actual power, is the predicted power, and A is the number of data.

TABLE I: RESULT OF THE PROPOSED SYSTEM

Forecasting approach	**RMSE(kW)**	**MAE(kW)**
NN with Fuzzy k-means clustering	323.285	236.256

The result in Table I, shows the forecasting accuracy of the proposed system.

TABLE II: COMPARISON WITH OTHER EXISTING APPROACHES

Forecasting approach	**RMSE(kW)**	**MAE(kW)**
NN with PLSR	956.363	834.321
ANN with k-means clustering	433. 721	320.286
NN with Fuzzy k-means clustering	420.285	306.256

Table II shows the comparison with existing approaches. The first approach in [9] use Partial Least Squares Regression and Neural Network, and the second approach in [11] use principle component analysis and artificial neural network. The proposed approach has obtain better forecasting result when compared with other approaches

III. CONCLUSION

In this paper, Fuzzy k- means clustering is combined with Neural Network (NN) used to forecast the wind power. By applying this technique, the historical data are clustered based on weather condition and historical powered data. It can improve the forecasting accuracy and also reduce the computational complexity.

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