Research Paper

Application of Support Vector Machine for Wind Speed Forecasting

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ABSTRACT

As the whole world is facing problem of global warming and energy crisis, technologists are looking for the renewable energy sources for better present and future of the next generation. Many countries pay more attention to the development of wind power, which will play an important role in meeting the target of electricity generation from renewable sources. The utility-scale generation of electricity from the wind has a number of desirable attributes such as no air pollution and low operating costs. Despite these attributes, operators of electric power systems remain concerned that wind, as an intermittent resource, can harm system reliability and raise operating costs. There is no doubt that the addition of large amounts of wind generation to respond to changes in wind generation. Recent studies have indicated that accurate wind speed forecasts bring significant cost savings. Forecasts of wind speed are becoming critical as interest grows in wind as a clean and renewable source of energy, in addition to wide range of other usages. Support Vector Machine [LIBSVM] with MATLAB platform is used in the present work for the wind speed forecasting. Encouraging results are obtained on the data measured at the two different locations in Mumbai.

Keywords: Support Vector Machine, Artificial Intelligence, Wind Speed, Forecasting.

INTRODUCTION

Human efforts to harness wind for energy date back to the ancient times, when he used sails to propel ships and boats. Later, wind energy served the mankind by energizing his grain grinding mills and water pumps. During its transformation from these crude and heavy devices to today's efficient and sophisticated machines, the technology went through various phases of development.

Numerous methods are reported in literature for the wind speed forecasting.^[1-5] SVM is also applied by Patil^[6] for wind speed prediction. She used 1584 samples of 22 days of October 2006, 2007, 2008 and

used 70% for training and 30% for testing. She evaluated the performance of the feed forward back propagation neural network by comparing predicted speed values with actual speed values. It was observed that the Mean Absolute Percentage Error (MAPE) by SVM method was around 7% and correlation coefficient was close to 1.

This paper presents an application of Support Vector machine for wind speed forecasting using the real data of Mumbai city of Maharashtra.

MATERIALS AND METHODS

The Support Vector Machine (SVM) is a supervised learning method that generates

input-output mapping functions from a set of labeled data. Its development followed in the reverse order to the developments of neural networks. SVMs evolved from the sound theory to the implementation and experiments, while the neural networks followed more heuristic path, from applications and extensive experimentation to the theory.

Support Vector Regression (SVR) is the natural extension of large margin kernel methods used for classification to regression analysis.^[7] It retains all the properties that characterize maximal margin SVM. SVR has already become a powerful technique for predictive data analysis with many applications in varied area of study. The problem of regression is that of finding a function which approximates mapping from an input domain to real numbers on the basis of training samples, i. e. instead of attempting to classify new unseen variables **x**'into one of the two categories $y' = \pm 1$, we have to predict a real valued output for y' so that our training data is of the form:

{x_i, y_i}, where, i = 1....l, $y_i \in \Re$, $\mathbf{x}_i \in \Re^N$ $y_i =$ $\mathbf{w} \cdot \mathbf{x} + b$

(1)

The support vector regression uses a more sophisticated penalty function than before, not allocating a penalty if the predicted value y_i is less than a distance ε away from the actual value t_i , i. e. if $|t_i - y_i| < \varepsilon$.

For proper and efficient utilization of wind power, the forecasting of wind speed is very important. It is needed for site selection, performance prediction, planning of wind mills and the selection of an optimal size of the wind machine for a particular site.

The proposed algorithm for wind speed forecasting using Support Vector Machine (SVM) based regression is described as follows:

Step 1: Data Acquisition: Three sources of wind data are available namely IMD data,

CWET data and NCEP/NCAR reanalysis data. CWET data is usually far from the site. Big extrapolations are needed to convert the data from mast height to hub height. Therefore, it is not used in the present work. NCEP/NCAR reanalysis data does not capture accurately local effects. Consistency of the data difficult to track, hence it is not used in the present work. IMD data consists of synoptic observations from over 400 stations. It consists of balloon observations at a height of 10 m. The data of 1998 to 2007 (10 years) at the two stations located at Mumbai is used in the present problem of wind speed forecasting. Each data recording represents an instantaneous wind speed. Fig.1 shows instantaneous wind speed recorded at 10 meter height and the corresponding daily average wind speed variation at station A is displayed in Fig. 2.

Step 2: Data Preprocessing

IMD data consists of mean hourly wind speed in km/hr round the clock for all the days of the year 1998 to 2007. It is first converted into daily mean hourly wind speed in km/hr. For the best results all the data is normalized between 0 and 1.

Step 3: Design of SVM model for Wind Speed Forecasting

The available wind speed data of 10 years is divided into two parts: training data and testing data. By conducting the series of experiments, different SVM models are developed and compared. During training an SVM model, there are some parameters to choose along with the kernel function. The selection of the parameters influences the performance of the SVM model. Some important parameters are cost of error C, the width of *\varepsilon*-insensitive tube, mapping function φ , and the size of training and testing data. To evaluate the performance of the model mean squared error (MSE) and squared correlation coefficient (R^2) is calculated.

Step 4: Different models using different kernel functions and various kernel parameters are developed in the present

work and their performance is compared. The best model is can be used for the wind speed forecasting.



Fig 1 (a) Instantaneous wind speed recorded at 10 m height at Station A during January 1998



Fig. 2 Daily average wind speed variation at 10 m height at Station A during January 1998

IMPLEMENTATION USING LIBSVM

Implementation of SVM for the present problem of wind speed forecasting is done by using LIBSVM software.^[8] LIBSVM is an integrated software package for support vector classification, regression and distribution estimation. The main objective of the present work is to develop various models for wind speed forecasting so that the best model can be adopted. In this, the data is divided into five subsets of equal size. Sequentially one subset is tested using the SVM model trained on the remaining subsets. The available wind speed data cover a period of 10 years between 1998 and 2007.

The performance measure adopted in the present work is the mean square error (MSE) and the squared correlation coefficient R^2 . R^2 is a statistical coefficient that will give information about the goodness of fit of a model. In regression, the R^2 coefficient of determination is a statistical measure of how well the regression curve approximates the real data points. An R^2 of 1.0 indicates that the regression line perfectly fits the data.

An epsilon-SVR model with radial basis function kernel is developed in the present work. The validation data is used to optimize the kernel parameters C and gamma. Several trials were carried out to find the reasonably good values of these parameters for wind speed forecasting of station_A and station_B. The value of C=1 and gamma=2 are found to be the best for the present problem of wind speed forecasting. The results obtained by using various forecasting models with their forecasting capability are presented in the next section.

RESULTS AND DISCUSSION

The results of the various models developed for station_A and station_B are presented in Table 1 and Table 2 respectively. Fig. 3 and Fig. 4 displays graphical results of wind speed forecasting for station_A. It is seen that the observed values of the wind speed are closely equal to the forecasted wind speed by the SVM.

Table 1 Results of the Different Models for Station_A									
S. No	Training Data	Testing Data	Model Name	Mean Square Error (MSE)	Squared Correlation Coefficient (R^2)				
1	1234	5	A_1234	0.0002968	0.9879				
2	1235	4	A_1235	0.0001383	0.991661				
3	1245	3	A_1245	0.0003197	0.989746				
4	1345	2	A_1345	0.0002152	0.9922				
5	2345	1	A_2345	0.001441	0.9681				

Table 1 Results of the Different Models for Station_A

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163

S. No	Training Data	Testing Data	Model Name	Mean Square Error (MSE)	Squared Correlation Coefficient (R ²)
1	1234	5	B_1234	0.00164	0.9728
2	1235	4	B_1235	0.00189	0.963
3	1245	3	B_1245	0.00398	0.9513
4	1345	2	B_1345	0.0022	0.956
5	2345	1	B_2345	0.00286	0.972119

Table 2 Results of the Different Models for Station B



Model A_1234



Model A_1235

CONCLUSION

The present work serve as an introduction to wind speed forecasting mainly for wind power companies operating in electricity wholesale markets. Given a set of existing wind power resources, wind power operators want to use them as efficiently and profitably as possible. In this pursuit, predicting the future output is one of their key interests. On the other hand, it is also a major challenge as wind forecasting in general is one of the most arduous forecasting problem. An attempt is made in

this work to forecast the wind speed by using SVM based regression.

Very encouraging and consistent results are obtained for both the stations A and B in Mumbai. The best model obtained for station_A gives MSE of 0.0002968 and squared correlation coefficient of 0.9879 out of the various models developed. Similarly, the best model obtained for station B gives MSE of 0.00164 and squared correlation coefficient of 0.9728. From the analytical and graphical results, it is observed that the predicted wind speed is nearly equal to the observed wind speed.

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