SHORT TERM WIND SPEED FORECASTING USING LINEAR PREDICTION FILTERS

[1]EMRAH USTUNDAG, [2]FATIH O. HOCAOGLU, [3]EMRE AKARSLAN, [4]FATIH SERTTAS

[1]Institute of Science, Afyon Kocatepe University, 03200, Afyonkarahisar, Turkey
[2,3,4]Electrical Engineering Department Afyon Kocatepe University, 03200, Afyonkarahisar,Turkey
[2]Solar and Wind Research & Application Center, Afyon Kocatepe University, Afyonkarahisar, Turkey
Email: [1]ustundag_emrah@hotmail.com, [2]fohocaoglu@gmail.com, [3]e.akarslan@gmail.com, [4]serttasf@gmail.com

Abstract: Increasing energy demand has increased the need for different sources and renewable energy sources have gained great importance. Wind energy is an important resource among the renewables. Electricity generation from a wind turbine is strongly related to wind speed on its area. Therefore accurate forecasting of wind speed is important for planning issues. In this study the performance of the Linear Prediction Filters on wind speed forecasting is investigated. Wind speed values collected in a short period from Afyonkarahisar region is used and the performances of different filters templates are examined. Using only past samples of wind speed, eight different filter templates are formed. Each filter template utilize from the different number of data which are belong the different time instances. The experimental results show that Linear Prediction Filters are suitable for wind speed modeling and the data belong to different time carry different level of information on next wind speed.

Keywords: Wind Speed, Short-term prediction, Linear Prediction Filters.

I. INTRODUCTION

Nowadays, environmental pollution is a global issue that is receiving significant attention. Increase on the use of renewable energy sources to reduce pollution is a problem that must be solved. As a renewable resource, wind power has attracted broad attention, both at home and abroad, and a large number of wind farms have been built [1]. Wind energy can have a significant impact on power grid security, power system operation, and market economics when connected with a power grid, due to its intermittent nature [2, 3]. Wind speed is necessary to assess wind energy potential of the possible installation sites since wind energy is proportional to the cube of wind speed and that makes it important to obtain the characteristics of the wind speed [4,5]. The utilization and operation of wind power would be challenging due to the intermittency and stochastic fluctuation of wind. Accurate short-term wind speed forecasting plays a significant role in meeting the challenges [6]. There are a lot of studies in the literature on wind speed forecasting.

[7] proposed a procedure based on hidden Markov models (HMMs). To model the wind speed data, they use a dependent process of atmospheric pressure in the form of HMMs. The experiments on data obtained from recordings of hourly atmospheric pressure and wind speed values for two cities in Turkey, namely Izmir and Kayseri, are showed that the proposed algorithm provide successful results. [8] presented three new hybrid methods consist of Wavelet Packet Decomposition (WPD), Empirical Mode Decomposition (EMD) and Extreme Learning Machine(ELM) for wind speed multi-step predictions. In the approach, WPD is chosen to decompose the actual wind speed series into several sub-layers while the EMD is adopted to further decompose the obtained Low Frequency sub-layers, the obtained High Frequency sub-layers and all the obtained sub-layers into a number of Intrinsic Mode Functions, respectively. To complete the wind speed predicting computation for the decomposed wind speed sub-layers, ELM is employed. [9] proposed a hybrid approach which uses a feature selection process and an artificial neural network optimized by a modified bat algorithm with cognition strategy for wind speed forecasting. Experiments on data of the city of Penglai in China showed the success of the method. [10] developed a hybrid model which combine a data preprocessing technique, forecasting algorithms, an advanced optimization algorithm. This combination provides to overcome some limitations of the individual forecasting models and improves the accuracy. Successful forecasting results are obtained on experiments with 10-min wind speed data from the wind farm in Peng Lai, China.

[11] developed a model by combining a data pre-processing, modified optimization algorithms, three neural networks and an effective deciding weight method. The model is developed for short-term wind speed forecasting and to improve the forecasting capacity, a modified optimization algorithm is employed. Ten-minute wind speed data from a wind farm in Penglai, China are used and the experimental results show that a significant improvement on forecasting accuracy is obtained with the algorithm. [12] proposed a new hybrid model which combines the wavelet packet decomposition, density-based spatial clustering of applications with noise, and the Elman neural network (WPD-DBSCAN-ENN) for short term wind speed prediction. The promising results are obtained in the experiments on the wind speed data from the Sichuan Province, China. [13] proposed a new method which uses nonlinear-learning ensemble of deep learning time series

prediction based on LSTMs (Long Short Term Memory neural networks), SVRM (support vector regression machine) and EO (extremal optimization algorithm). Ten minutes ahead and one hour ahead wind speed predictions are performed on two case studies data collected from a wind farm in Inner Mongolia, China and good results are obtained.

In this study Linear Prediction Filters (LPFs) are employed for short term wind speed forecasting. Wind speed data in a ten minute period are measured and collected from a meteorological station placed on campus are of Afyon Kocatepe University on Afyonkarahisar region. To predict the wind speed values in short term, different prediction filter templates are built. Each template utilize from the different number of data which are belong the different time instances. The performance of the different filter templates are evaluated. The organization of the paper is as follow: The data used in the study is presented in Section 2. The linear prediction filters are introduced in Section 3 and the experimental results are presented in Section 4. Finally, conclusions are given in Section 5.

THE DATA USED

In this paper, measured and recorded wind speed data in a ten minute period from the main campus of Afyon Kocatepe university are studied. The data collected from a meteorological station located on main campus area of Afyon Kocatepe University in the period between 23th March and 4th May 2018. For measurements, Davis trademark meteorological station was used which is capable to measure temperature, wind speed and direction, air pressure, humidity etc. In this study only past samples of wind speed are used for predict the ten minutes later wind speed value. The variation of the wind speed data is shown in **Fig.1**.

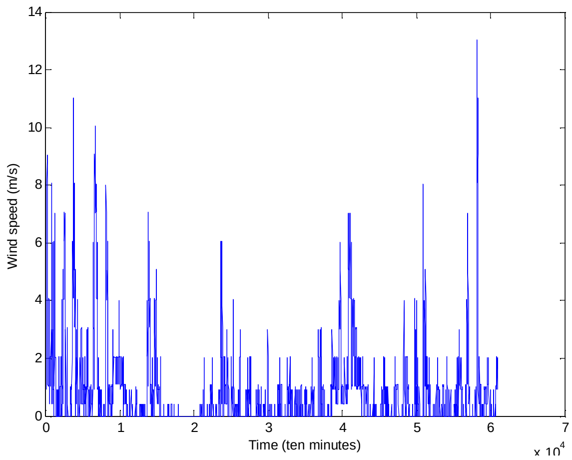

Fig.1. The variation of wind speed in the period between 23th March and 4th May 2018

As seen in Figure 1, wind speed is highly variable and to model it is a big challenge. In this study, the performance of the linear prediction filters is investigated. To perform the linear prediction filter, the time series data converted into 2-D image and this image is used instead of time series data itself.

LINEAR PREDICTION FILTERS

In this study 2-D linear prediction filters are employed to predict next wind speed value. Linear prediction filters scan whole 2-D data image and determine the optimal filter coefficients and next value of data is calculated by using these coefficients [14]. The number of coefficient depend on the filter template. The filter coefficients are calculated as follow for the filter template seen in **Fig. 2**.

$Z_{i,j}$	$Z_{i,j+1}$
$Z_{i+1,j}$	$\check{Z}_{i+1,j+1}=?$

Fig.2. A sample filter template

In this template there will be 3 filter coefficients and if we call these coefficients as a_1, a_2 and a_3, the next value ($\check{Z}_{i+1,j+1}$) is calculated with equation 1;

$$\check{Z}_{i+1,j+1} = a_1 Z_{i,j} + a_2 Z_{i,j+1} + a_2 Z_{i+1,j} \quad (1)$$

The filter coefficient is calculated with an optimization algorithm and then the error in prediction is calculated with equation 2;

$$e_{i+1,j+1} = \check{Z}_{i+1,j+1} - Z_{i+1,j+1} \quad (2)$$

The energy of the error will be as follow;

$$\varepsilon = \sum_{i=1}^{m} \sum_{j=1}^{n} e_{i,j}^2 \quad (3)$$

where m,n represent the size of the data image. The filter coefficients which minimize the error are calculated with following [15];

$$\frac{\partial \varepsilon}{\partial a_1} = \frac{\partial \varepsilon}{\partial a_2} = \frac{\partial \varepsilon}{\partial a_3} = 0 \quad (4)$$

From equation 4, the following equation is obtained;

$$\begin{bmatrix} R_{11} & R_{12} & R_{13} \\ R_{21} & R_{22} & R_{23} \\ R_{31} & R_{32} & R_{33} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix} \quad (5)$$

The solution of the equation 5 will provide the optimal filter coefficients. The equation also can be compactly written as ***R.a=r***. Finally, the optimal filter coefficients can be obtained as

$$a = R^{-1} r \quad (6)$$

where a is a vector containing the filter-tap coefficients, r includes the correlation values of the target pixel to the pixels in prediction template, and R includes correlation values within the prediction template [18]. Then by using these coefficients, the future values according the filter templates are calculated.

EXPERIMENTAL RESULTS

Pre mentioned data measured and recorded from the main campus of Afyon Kocatepe University are converted into 2D form andseveral 2-D linear prediction filters are built for forecasting. The prediction performances of each template on prediction of 10 minutes later wind speed are tested. To evaluate the performance, root mean square error (RMSE) and coefficient of determination (R^2) are selected. The RMSE is a commonly used measure of the differences between the modeled and the observed values and lower RMSE indicates better performance [16,17]. The coefficient of determination is used to analyze how differences in one variable can be explained by a difference in a second variable. In this scope, totally 5 different filter templates (**Fig. 3**) are built.

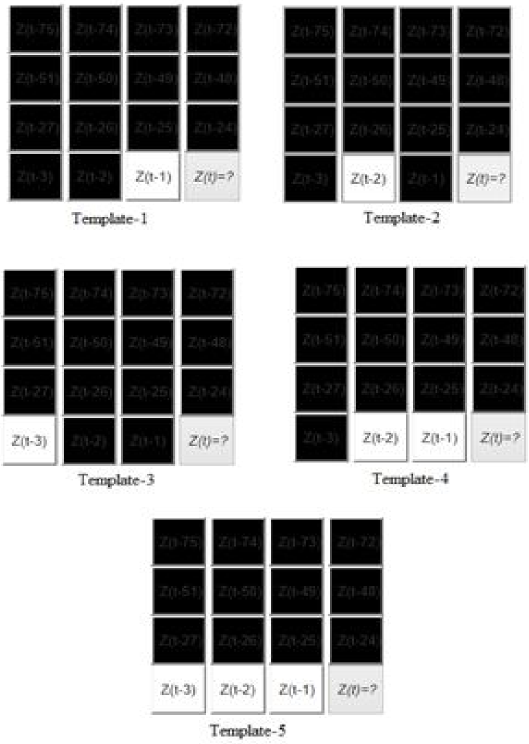

Fig.3. The different filter templates used in this study

The filter template determine which data will be used in prediction. In Template-1, to predict actual value of wind speed, ten minutes before wind speed is used and this template uses only one coefficient while prediction. Template-2 utilizes from the twenty minutes before data while Template-3 uses thirty minutes before data in prediction. Template-4 utilizes from ten minutes and twenty minutes before data together to predict next value while Template-5 uses ten-twenty-thirty minutes before data. The performances of each template on short term wind speed prediction are shown in **Table 1**.

Table 1. The performances of each filter template

Template	RMSE(m/s)	R^2
Template-1	0,6041	0,8474
Template-2	0,8015	0,7339
Template-3	0,9246	0,6485
Template-4	0,6026	0,8479
Template-5	0,6011	0,8485

It is obvious from the results that, the usage of linear prediction filters it is possible to obtain successful results in short term wind speed prediction. The best result is obtained with Template-5 that utilize from ten-twenty-thirty minutes before data to predict actual value of wind speed. It can be seen from the results that the data in the recent time period carry more information for next value of wind speed. To illustrate the efficiency of the method, the measured and predicted data for Template-5 are drawn in same graph as presented in **Fig. 4**. As seen in **Fig. 4**, predictions are close the measured values and it indicates successful predictions.

Different filter templates which utilize from much more data can be selected to improve the prediction accuracy however please consider that more data means more complicated calculations. Therefore, it will be more sense to use reasonable filter size. Even if larger filter templates are used the computational cost will be less than non-linear or artificial intelligence methods.

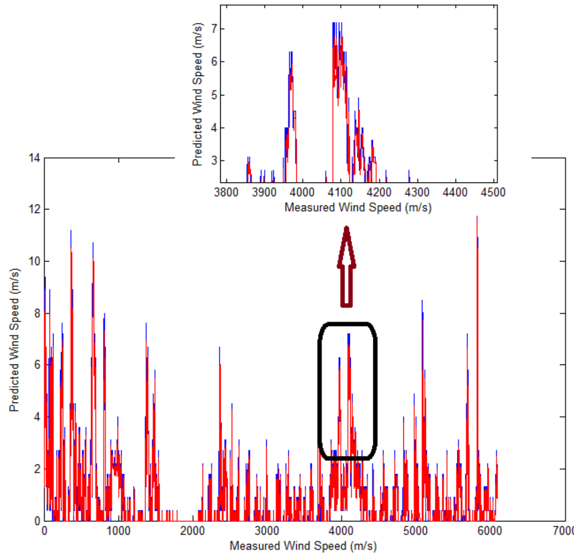

Fig.4. The comparison between the measured and predicted data

CONCLUSIONS

In this study, the performance of the Linear Prediction Filters on short term wind speed forecasting is investigated. The wind speed data collected in ten minutes period from a meteorological station placed at the main campus area of Afyon Kocatepe University are studied. Different filter templates are built and their performances are tested and compared. Considerably accurate results show that, linear prediction filters can be used for short term wind speed prediction. The filter template which utilize from the previous three data provide the best results among the others. In comparison, it is obvious that the recent data carry more information for next value of wind speed.From the results of Template-5 and Template-1, the importance of recent data can be seen obviously. The prediction accuracy increases when the Template-5 is used however the accuracy is improved, slightly. Developing different filter templates and usage of different data together with wind speeds can be regarded as future works.

ACKNOWLEDGMENTS

This study is supported by a project from Afyon Kocatepe University Scientific Research Project Department which is numbered 17.FEN.BIL.72.

REFERENCES

[1] P. Jiang, Y. Wang, and J. Wang, "Short-term wind speed forecasting using a hybrid model," Energy, vol. 119, pp. 561–577, Jan. 2017.
[2] Q. Han, F. Meng, T. Hu, and F. Chu, "Non-parametric hybrid models for wind speed forecasting," Energy Convers. Manag., vol. 148, pp. 554–568, Sep. 2017.
[3] Z. Guo, J. Wu, H. Lu, and J. Wang, "A case study on a hybrid wind speed forecasting method using BP neural network," Knowledge-Based Syst., vol. 24, no. 7, pp. 1048–1056, Oct. 2011.
[4] L. Xiao, Y. Dong, and Y. Dong, "An improved combination approach based on Adaboost algorithm for wind speed time series forecasting," Energy Convers. Manag., vol. 160, pp. 273–288, Mar. 2018.
[5] S. Sun, H. Qiao, Y. Wei, and S. Wang, "A new dynamic integrated approach for wind speed forecasting," Appl. Energy, vol. 197, pp. 151–162, Jul. 2017.
[6] C. Li, Z. Xiao, X. Xia, W. Zou, and C. Zhang, "A hybrid model based on synchronous optimisation for multi-step short-term wind speed forecasting," Appl. Energy, vol. 215, pp. 131–144, Apr. 2018.
[7] F. O. Hocaoğlu, Ö. N. Gerek, and M. Kurban, "A novel wind speed modeling approach using atmospheric pressure observations and hidden Markov models," J. Wind Eng. Ind. Aerodyn., vol. 98, no. 8–9, pp. 472–481, Aug. 2010.
[8] H. Liu, X. Mi, and Y. Li, "An experimental investigation of three new hybrid wind speed forecasting models using multi-decomposing strategy and ELM algorithm," Renew. Energy, vol. 123, pp. 694–705, Aug. 2018.
[9] T. Niu, J. Wang, K. Zhang, and P. Du, "Multi-step-ahead wind speed forecasting based on optimal feature selection and a modified bat algorithm with the cognition strategy," Renew. Energy, vol. 118, pp. 213–229, Apr. 2018.
[10] J. Song, J. Wang, and H. Lu, "A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting," Appl. Energy, vol. 215, pp. 643–658, Apr. 2018.
[11] P. Jiang and C. Li, "Research and application of an innovative combined model based on a modified optimization algorithm for wind speed forecasting," Measurement, vol. 124, pp. 395–412, Aug. 2018.
[12] C. Yu, Y. Li, H. Xiang, and M. Zhang, "Data mining-assisted short-term wind speed forecasting by wavelet packet decomposition and Elman neural network," J. Wind Eng. Ind. Aerodyn., vol. 175, pp. 136–143, Apr. 2018.
[13] J. Chen, G.-Q. Zeng, W. Zhou, W. Du, and K.-D. Lu, "Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization," Energy Convers. Manag., vol. 165, pp. 681–695, Jun. 2018.
[14] E. Akarslan, F. O. Hocaoğlu, and R. Edizkan, "A novel M-D (multi-dimensional) linear prediction filter approach for hourly solar radiation forecasting," Energy, vol. 73, pp. 978–986, 2014.
[15] F. O. Hocaoğlu, Ö. N. Gerek, and M. Kurban, "Hourly solar radiation forecasting using optimal coefficient 2-D linear filters and feed-forward neural networks," Sol. Energy, vol. 82, no. 8, pp. 714–726, Aug. 2008.
[16] E. Akarslan, F. O. Hocaoglu, and R. Edizkan, "Novel short term solar irradiance forecasting models," Renew. Energy, vol. 123, pp. 58–66, Aug. 2018.
[17] P. T. Nastos, A. G. Paliatsos, K. V. Koukouletsos, I. K. Larissi, and K. P. Moustris, "Artificial neural networks modeling for forecasting the maximum daily total precipitation at Athens, Greece," Atmos. Res., vol. 144, pp. 141–150, Jul. 2014.
[18] R. C. Gonzalez and R. E. (Richard E. Woods, Digital image processing. Prentice Hall, 2008.

★★★