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Very Short Term Wind Speed Forecasting Using Multivariable Dense Data with WLS-MARMA Model

Tansu Filik[a]*, Ümmühan Başaran Filik[a]

[a]Department of Electrical and Electronics Engineering, Anadolu University, Iki Eylül Kampusu, Eskişehir, 26555, Turkey

Abstract

In this study, very short-term wind speed forecasting problem, which is quite important for the future's electricity market –wind forecasting control algorithms, is investigated. Recently, the multi-channel (spatial) methods which uses neighboring (from different locations) wind measurements are become popular. But it is not always possible to collect spatially distributed neighboring wind speed values around target location simultaneously. In this study, previously proposed multichannel autoregressive moving average (MARMA) model is applied to local multiple sensor measurements such as wind speed, direction, temperature, pressure, solar radiation etc. instead of neighboring (distributed) wind speed measurements. It is shown that weighted least squares solution based MARMA model (WLS-MARMA) can give more accurate wind speed estimation results according to other well-known benchmark methods (such as Persistence, AR, VAR) with real data set.

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Keywords: wind energy, very short-term wind speed forecasting, multivariable data, autoregressive moving average, weigted least squares

1. Introduction

In order to use wind energy in optimum power system operations, it is required to accurately determine the three or less hours ahead (short-time) wind power generation values. This problem is known as short-term wind speed forecasting and widely studied in literature [1-2]. For the future's electricity market –wind forecasting control

* Corresponding author. Tel.: +90-222-335-0580/6460; fax: +90 2223239501.
E-mail address: tansufilik@anadolu.edu.tr

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algorithms [3], it is also required to predict (forecast) very-short term wind speed values (less than an hour) with computationally efficient and accurate ways.

In this study, we used a multi-variable (multi-channel) Autoregressive Moving Average (MARMA) linear model to accurately estimate the very-short term wind speed values with using multiple local measurements at the same time. MARMA models are commonly used for blind identification of the unknown systems in communications and source localization [4]. MARMA model is first used in [5] for short-term wind speed forecasting, and model uses geographically distributed wind speed measurements around the target wind farm for better results. It is shown that despite limited correlations between measurement stations, MARMA model serve better performance than all other known linear benchmark methods (persistence, AR and VAR). The distinguishing point of MARMA model than VAR, is to add multichannel white noise random processes to the model which improves the overall forecasting performance. But it is not always possible to collect spatially distributed neighboring wind speed values around target location [6]. Instead, it is always cheap and possible to collect local multiple sensor measurements such as temperature, pressure, wind speed and direction etc. In this study, we used modified MARMA model which is called as weighted least square MARMA (WLS-MARMA) with local multivariable measurements instead of spatial measurements. It is shown that using very dense local multi variable measurements; wind speed, direction, pressure, temperature and global radiation together with MARMA model quite improves the very-short term wind speed prediction performance.

Nomenclature

$x_1[n]$	wind speed values (m/s), n is the time index
$x_2[n]$	wind direction values
$x_3[n]$	temperature values (Celsius)
$x_4[n]$	pressure values
$x_5[n]$	global solar radiation values
$w[n]$	Gaussian white noise for wind speed data (for model deviations)
$s_i[n]$	multivariable white noise process, i is the local variable index number
M	total number of the local variables
N	number of previous observations
P	total number of autoregressive coefficients
Q	total number of moving average coefficients
a	autoregressive model coefficients
b	moving average coefficients
d	ARMA coefficients
AR	autoregressive model
ARMA	autoregressive moving average model
VAR	vector (multivariable) autoregressive model
WLS	weighted least squares

2. Multivariable linear model for very-short term wind speed prediction

MARMA model, which uses spatially distributed multiple wind speed measurements, is first used in [5] for the short-term wind speed forecasting. It is shown that proposed model gives better performance than the vector (multichannel) autoregressive (VAR) method. In this study, we modified the considered MARMA model to apply the local multivariable dense data sets for better very short-term wind speed forecasting performance. MARMA model for Δ hour forecast lead-time wind speed output is

$$\hat{x}_1[n+\Delta] = \sum_{i=1}^{M}\sum_{p=1}^{P} a_{i,p} x_i[n-p] + \sum_{i=1}^{M}\sum_{q=1}^{Q} b_{i,q} s_i[n-q] + w_1[n] \quad (1)$$

where $s_i[n]$ are multi-channel spatially and temporally white noise inputs of the model. P and Q are the model orders.

M is the total number of the used variables. In this study, we used five local variables (M=5), namely wind speed (x_1), wind direction (x_2), temperature (x_3), pressure (x_4) and global radiation (x_5). In order to accurately solve the unknown model coefficients (a and b), N previous samples can be used. It is possible to put all equations for N number previous observations in matrix form as,

$$\begin{bmatrix} x_1[n+\Delta] \\ \vdots \\ x_1[n-N+1+\Delta] \end{bmatrix} =$$

$$\begin{bmatrix} x_1[n-1] \ldots x_1[n-P]\; s_1[n-1] \ldots\; s_1[n-Q] & \cdots & x_M[n-1] \ldots x_M[n-P]\; s_M[n-1] \ldots\; s_M[n-Q] \\ \vdots & \ddots & \vdots \\ x_1[n-N] \ldots x_1[n-N-P+1]\; s_1[n-N] \ldots\; s_1[n-N-Q+1] & \cdots & x_M[n-N] \ldots x_M[n-N-P+1]\; s_M[n-N] \ldots\; s_M[n-N-Q+1] \end{bmatrix} \begin{bmatrix} a_{1,1} \\ \vdots \\ a_{1,P} \\ b_{1,1} \\ \vdots \\ b_{1,Q} \\ \vdots \\ b_{M,Q} \end{bmatrix} +$$

$$\begin{bmatrix} w_1[n] \\ \vdots \\ w_1[n-N+1] \end{bmatrix} \tag{2}$$

It is possible to write above equations as,

$$\widehat{\boldsymbol{x}}_1 = \boldsymbol{H}_{N\times M(P+Q)}\, \mathbf{d}_{M(P+Q)\times 1} + \mathbf{w}_{N\times 1} \tag{3}$$

where **H** is the multivariable observation matrix which contain all previous multivariable data (x_i) and multivariable white noise processes (s_i). **d** is unknown model coefficient vector which contains all a and b coefficients. **w** is model deviation vector which is modelled as white Gaussian random vector. The details of these compact matrix from can be seen in [5]. In order to accurately estimate Δ ahead wind speed values, the above coefficient vector **d** should be estimated accurately. The optimum least squares solution for unknown prediction coefficient is

$$\widehat{\boldsymbol{d}}_{LS} = (\boldsymbol{H}^T\boldsymbol{H})^{-1}\boldsymbol{H}^T\,\mathbf{x}_1 \tag{4}$$

In this study, local multivariable data with a very small intervals (seconds) are collected for very-short term (in minutes) wind speed forecasting. In order to achieve more exact solution for the above dense data set weighted least square (WLS) solutions is proposed which can be called as WLS-MARMA. In WLS-MARMA, weighted production of the error is minimized as,

$$\widehat{\boldsymbol{d}}_{WLS} = (\boldsymbol{H}^T\boldsymbol{W}^{-1}\boldsymbol{H})^{-1}\boldsymbol{H}^T\boldsymbol{W}^{-1}\,\mathbf{x}_1 \tag{5}$$

where **W** is the N by N weighting matrix which should minimize $\boldsymbol{w}^T\boldsymbol{W}^{-1}\boldsymbol{w}$ where **w** is the error vector in equation (3). For the optimum result, $\boldsymbol{W}$ matrix is selected as the covariance matrix of the residual noise $\boldsymbol{w}$.

3. Multivariable dense data acquisition setup

The data acquisition system, which is shown in Fig. 1, is capable of collecting multiple local outdoor measurements such as wind speed, direction, temperature, pressure, global and diffuse radiation, and real solar power production values. These measurements can be recorded very dense in 1 milliseconds intervals.

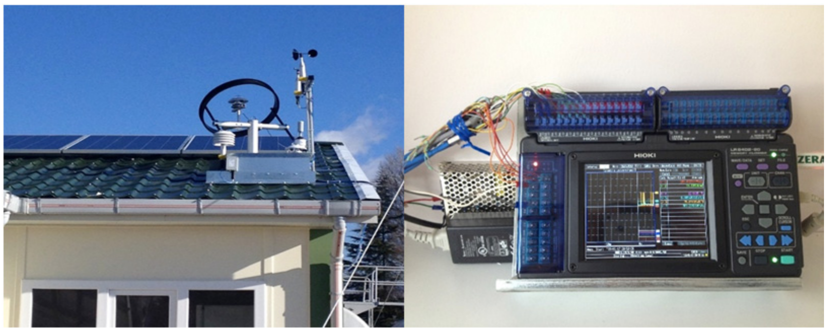

Fig. 1. (a) Local measurement sensors; (b) Multichannel data recording system which can record in 10 millisecond resolution.

In this study, five different local variables are recorded with 20 seconds intervals between 2 March and 2 April 2016. Fig. 2a shows wind speed and temperature values versus time data in 4th March. Similarly, Fig. 2b shows global radiation and wind direction values of the same example day.

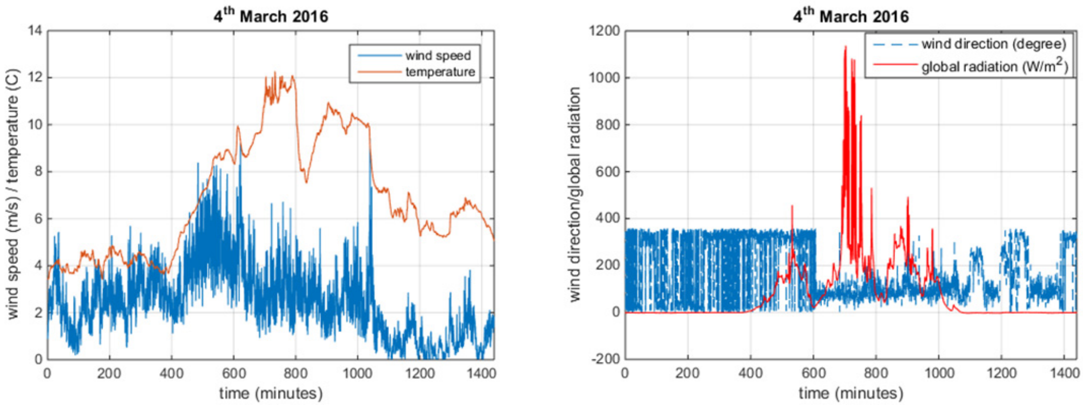

Fig. 2. (a) Daily wind speed and temperature values; (b) Wind direction and global radiation values.

Fig. 3 shows the Auto and Cross-correlation coefficient values of the local variables with the wind speed values for different time delays. All the correlations demonstrate a decline with time delay, except for maximum at diurnal periods (multiples of 24 h). This is an expected case; all these local variables (wind speed, temperature, solar radiation etc.) have a similar diurnal pattern. Fig. 3 also shows that cross-correlations between wind and other local variables are very limited. It is also shown that the auto-correlation value of wind (wind-wind) is rapidly decreasing after a small time delay.

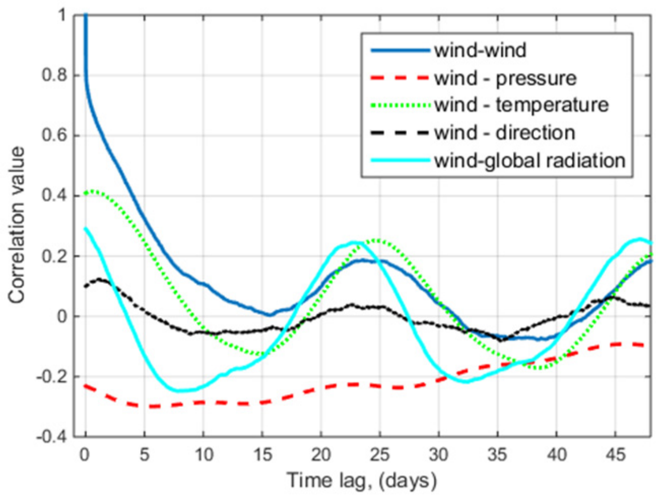

Fig. 3. Auto and Cross-correlation coefficient values of wind speed and all other local measurements for different time delays.

4. Test results and conclusion

In this part, the proposed WLS-MARMA model is tested with real multivariable dense local data set, which is introduced in previous section, for very short-term wind speed forecasting. Fig. 4 show**s** the root mean square error

(RMSE) and mean absolute error (MAE) performance of WLS-MARMA model. It is shown that over the 3 minutes look ahead time MARMA gives quite better results according the well-known persistence, linear method AR and multivariable VAR.

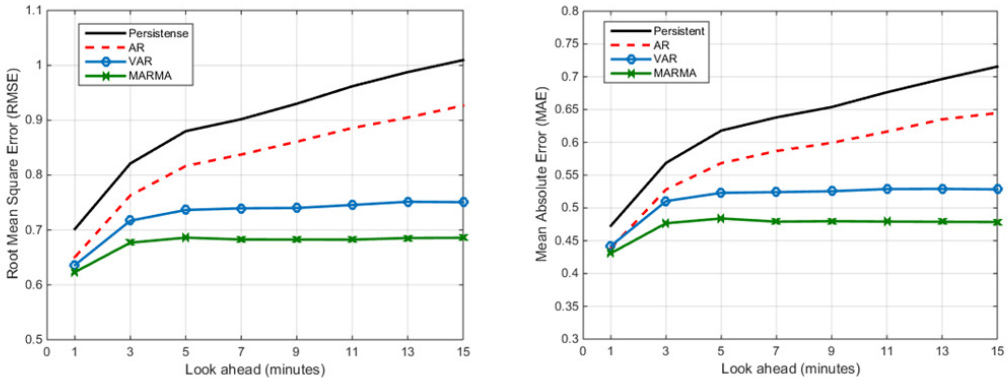

Fig. 4. (a) Root mean square error (RMSE) values versus look ahead time; (b) Mean absolute error (MAE) values versus look ahead time.

Finally, Table 1 shows the RMSE percentage improvements of the proposed WLS-MARMA with respect to persistence model. As it is shown the proposed WLS-MARMA model gives more accurate results than VAR methods which uses the same amount of local data. It can be concluded that using only the past temporal wind speed values, different local sensor measurements can quite improve the forecasting accuracy with a suitable model and solution (WLS-MARMA).

Table 1. Percentage forecasting improvements with respect to persistence model.

Forecasting lead time (Δ)	AR	VAR	WLS-MARMA
Δ = 1 minute	7,29 %	9,36 %	11,18 %
Δ = 3 minute	7,08 %	12,69 %	17,56 %
Δ = 15 minute	8,24 %	25,67 %	32,10 %

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