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Short-term wind speed estimation based on weather data

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Abstract

For accurate and efficient use of wind power, it is important to know the statistical characteristics, availability, diurnal variation, and prediction of wind speed. Prediction of wind power permits the scheduling of the connection or the disconnection of wind turbines to achieve optimal operating costs. In this paper, a simple and accurate method for predicting wind speed based on weather-sensitive data is presented. The proposed wind speed prediction system is cost-effective and only needs wind speed data at 40 m and weather data to forecast wind speeds at 50 m and 60 m for the current and next months. Hellman coefficients are first estimated by using a feed-forward backpropagation neural network and wind speeds at different heights are predicted. The autoregressive moving average algorithm is used for forecasting the short-term wind speed and is compared to in situ measurements. The predicted results are then compared to a powerful estimation algorithm known as the Mycielski algorithm.

Key Words: *Wind speed/power forecasting, Hellman equation, autoregressive moving average algorithm, Mycielski, artificial neural network*

1. Introduction

The renewable energy technology that is experiencing the fastest growth is wind power, which is becoming an important business sector. The use of wind energy has developed considerably throughout the world in hopes of achieving the ideal of a future with environmentally friendly electrical generation. However, wind is considered to be one of the weather variables that are more difficult to predict.

Wind speed prediction is very important in power systems due to the fact that knowledge of wind speed is needed for predicting the energy output of a wind speed energy conversion system. Wind speed is also fundamental to power system security, planning, and management. Wind speed is often considered one of the

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most difficult parameters to forecast because of its intermittence, although much effort has been dedicated to wind speed prediction. It is a key step in obtaining a correct precision of wind speed via an operational approach.

When the wind speed fluctuation is not predicted or is incorrectly predicted, it is essential to use extra reserves, generally expensive backup generators in low efficiency states, in order to quickly compensate the unbalance between generation and load and, therefore, make the system reliable [1,2]. It is also accepted that wind power forecasting should be based on the actual wind signal prediction rather than on the output of the wind aerogenerators.

The rest of the paper is organized as follows: Section 2 reviews previous work. The techniques and methodology used are discussed in Section 3. Short-term prediction techniques are explained in Section 4. Simulation results and comparisons are given in Section 5, and conclusions are drawn in Section 6.

2. Previous work

Wind forecast models are usually divided into 2 main categories. The first group is based on physical models and the second on statistical models.

The first group of forecasting is based on numerical weather prediction models, which use equations governing the motions and forces affecting the motion of fluids. From the information of the atmosphere's actual state, the system of equations allows the estimation of the progress of state variables such as temperature, velocity, relative humidity, and pressure at a series of grid points. These models calculate how the atmosphere will change over time and how each grid point will affect its neighbors, thus building a forecast of upcoming events. Information related to the terrain effect, such as the terrain features, height, roughness, and obstacles, can be included in the physical equations. More information on these studies can be found in [2-5].

The second group of forecasting approaches is based on statistical models. These models concentrate on capturing the relationship between historical measurements and future outputs with statistical models, whose parameters have to be estimated from available data. These models rely on the previous wind patterns over time and extrapolate the future patterns. Statistical models can also be divided into 2 groups: linear and nonlinear. Many statistical models have been proposed in recent years, such as autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) algorithms [6,7], and the persistence approach [8], time series analysis [9], artificial neural networks (ANNs) [10,11], wavelets [12,13], Kalman filters [14,15], and the Mycielski algorithm [16,17].

This study presents a simple approach for predicting wind speed by means of short-term prediction. The proposed hybrid algorithm uses the Hellman equation [18] and a neural network to predict Hellman coefficients and wind speed. The ARMA algorithm is then used for short-term wind speed and power prediction. The outcomes are compared to in situ measurements. The details of this technique are given in the methodology section.

3. Methodology

The suggested wind speed/power prediction method is based on weather data and wind speed at 40 m. The data that we analyze in this paper came from Project OMÜ-BAP REK.1906.09.003 [19], which took place on Dedebuğazı Hill in Samsun, Turkey. The wind monitoring tower is 60 m in height and has GSM-based wireless access. Wind speed measurements were done at heights of 40 m, 50 m, and 60 m, while wind directions were obtained from 48 m and 58 m. Weather data such as temperature, relative humidity, and air pressure were collected from 20 m. The monitoring tower is located at an altitude of 588 m above sea level. All measurements were obtained at 10-min intervals for a period of 1 year, beginning 24 August 2009.

The overall wind speed/power prediction scheme is shown in Figure 1.

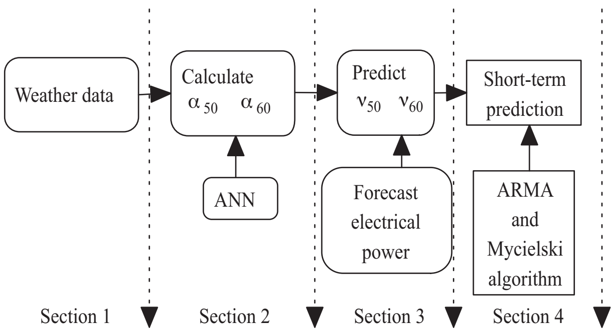


Figure 1. The overall wind speed/power forecasting scheme.

In Figure 1, section 1 describes the weather data (temperature (°C), relative humidity (%), and air pressure (mmHg)) collected at 20 m at the measurement site. Section 2 describes the calculation method of the Hellman coefficient at 50 m and 60 m based on an ANN. Section 3 is the prediction of wind speeds and related electric power at 50 m and 60 m. Finally, section 4 is the short-term wind speed/electric power prediction of the next month based on the ARMA and Mycielski algorithms.

In this work, exponent coefficient α of the Hellman equation, in Eq. (1), is estimated using a feed-forward backpropagation neural network. The Hellman exponent equation is defined as:

$$v_{est} = v_{known}\left(\frac{h_{est}}{h_{known}}\right)^{\alpha}, \tag{1}$$

where v_{known} and v_{est} are the known and estimated wind speeds over level terrain at elevations h_{known} and h_{est}, respectively. The magnitude of α depends on the nature of the location, wind levels, and time of day. The average and standard deviation of the weather data, i.e. temperature, relative humidity, and air pressure (also known as local conditions), are calculated and formed as input for the neural network. The local conditions may influence the wind profile, which is the speed and direction of the wind as a function of time. Wind velocity, as a vector field, is determined by air pressure differences (high-low) and boundary conditions, i.e. terrain. Air pressure differences can also exist locally due to heat transfer between the earth's surface and the air. For the training of the neural network, the targets are the exponential part of Eq. (1), calculated by using Eqs. (2) and (3).

$$\alpha_{50} = \log\left(\frac{v_{50}}{v_{40}}\right) / \log\left(\frac{50}{40}\right) \tag{2}$$

$$\alpha_{60} = \log\left(\frac{v_{60}}{v_{40}}\right) / \log\left(\frac{60}{40}\right) \tag{3}$$

Here, v_{60}, v_{50}, and v_{40} are the wind speeds at heights of 60 m, 50 m, and 40 m, respectively. The average values of α_{50} and α_{60} are calculated and used as target values in the neural network. Table 1 shows the input and target values of the neural network, where α_{50} and α_{60} are the average values calculated by Eqs. (2) and (3).

Table 1. Input and target values of neural network.

Inputs				Targets	
Temperature (°C)		Relative humidity (%)	Air pressure (mmHg)	α_{50}	α_{60}
1	19.0360	76.5816	948.3071	0.1717	0.3146
2	1.7289	12.7016	1.9998		
3	17.1732	81.0667	947.5896	0.1822	0.1404
4	2.7309	12.5054	3.4168		
5	17.6767	69.9641	948.5412	0.2654	0.1941
6	5.2335	27.2933	3.0212		
7	12.0006	66.0561	948.6276	0.1915	0.2255
8	4.6258	22.1166	5.1229		
9	12.2891	64.4419	944.0123	0.2027	0.2187
10	4.0100	22.8935	6.2125		
11	8.5934	70.3910	942.1257	0.4791	0.3773
12	5.1676	21.9730	4.9457		
13	6.9249	73.6092	948.1270	0.4711	0.3068
14	4.9261	24.8393	7.1589		
15	10.2044	75.5208	948.4203	0.4219	0.3462
16	3.9564	20.1344	4.9733		
17	15.9942	67.6641	945.2175	0.5636	0.4221
18	4.4049	19.9251	2.9002		
19	19.7039	79.3634	943.2856	0.4011	0.3439
20	2.8683	16.5366	3.2278		
21	20.6090	89.4452	946.1424	0.5167	0.4254
22	1.2279	7.2187	1.6195		

In Table 1, the odd indexes represent the average values, while the even indexes represent standard deviations in the input section. The weather data cover the period from August 2009 to July 2010.

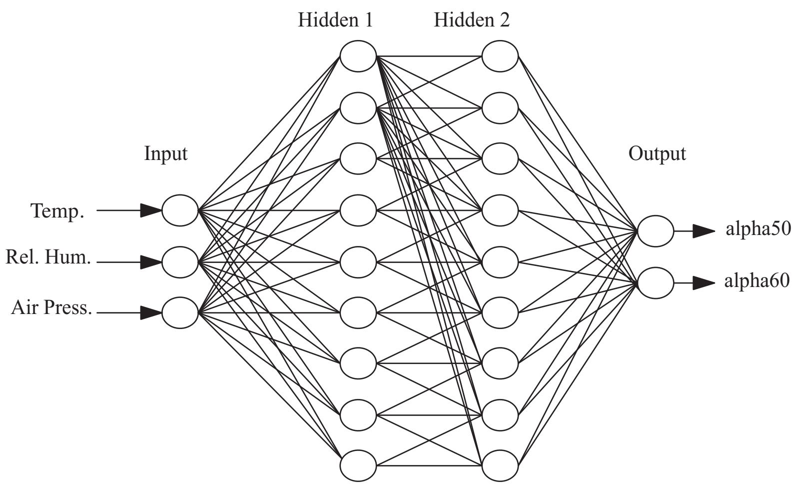


Figure 2. Proposed feed-forward backpropagation network type.

The neural network used in this study consists of 4 layers: 1 input layer with 3 neurons, 2 hidden layers with 10 neurons, and 1 output layer with 2 neurons. The proposed network structure was found to be quite adequate after trying several feed-forward backpropagation structures. Table 2 shows the neural network parameters. Figure 2 shows the proposed network structure.

For simplicity, not all connections between hidden layers 1 and 2 are shown.

Table 2. Neural network parameters.

Number of iterations	20,000
Learn rate	0.07575
Minimum learn rate	0.001
Maximum learn rate	0.07575
Momentum	0.8
Tolerance	0.000001

The prediction of v_{50} and v_{60} is calculated from Eq. (1). As a quality index/indicator, the root mean square error (RMSE) and coefficient of determination (R^2) are used as defined in Eq. (4).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(v_{est} - v)^2} \tag{4}$$

Here, N is the number of wind samples and v_{est} is the estimated wind speed at a particular height. Table 3 demonstrates RMSEs for predicting wind speeds at 50 m and 60 m.

Table 3. RMSEs for predicting wind speeds from August 2009 to July 2010.

RMSEs		
August 2009	0.2778	0.9053
September 2009	0.2713	0.4457
October 2009	0.3677	0.5208
November 2009	0.3025	0.5965
December 2009	0.8360	1.7121
January 2010	0.7050	1.6052
February 2010	0.9147	1.3879
March 2010	0.7880	1.0082
April 2010	0.6095	0.9666
May 2010	0.7140	1.1248
June 2010	0.6592	1.0729
July 2010	0.8104	1.2692

In Table 3, the values in the first column and the second column belong to elevations of 50 m and 60 m, respectively. As seen in Table 3, maximum RMSEs belong to December 2009 and January 2010, in which severe wind turbulence was experienced.

The power output of a wind turbine depends on the wind speed, which varies with time and depends on regional weather patterns and the type of landscape. The related electric power from predicted wind speeds (monthly) is calculated from Eq. (5), assuming an ideal generator without maximum or minimum speed cutout.

$$P = \frac{1}{2}\rho v^3 S C_p \tag{5}$$

Here, ρ is the air density of the measurement site (calculated as 1.1557), v is the wind speed, S is the area that the wind passes through in the wind turbine vane, and C_p is the coefficient of wind energy use, known as Betz's limit, which can be selected as 0.35 for a good design. Generally, C_p is calculated as in Eq. (6).

$$C_p = \frac{\text{electricity produced by wind turbine}}{\text{total energy available in the wind}} \tag{6}$$

From Eq. (5), it can be seen that the relationship between wind speed and power is nonlinear, basically cubic. Any error in wind speed forecasting will actually give a large (cubic) error in wind power. Moreover, for the entire wind farm, this relation is more complex as different turbines in the farm use multiple wind directions and speeds to achieve the optimal power output of the wind farm. Hence, a small error in wind speed estimation can generate a larger error in the wind power forecast.

4. Short-term prediction

In this paper, short-term prediction is achieved using the ARMA algorithm, and its performance is compared to in situ measurements. R^2 is used as a performance criterion (goodness-of-fit value).

4.1. Definition of ARMA algorithm

As a statistical approach, ARMA models are the most popular type of time-series-based approaches for predicting future values of wind speed or power. Several variations of ARMA models can be found in the literature.

One of the most complicated tasks in wind speed forecasting is the wind speed model identification step. An ARMA model was used to build the wind speed model in this work. ARMA models are reasonably simple and inexpensive forecasting tools. They do not require a huge amount of historical data and, most importantly, they have a greatly improved performance as compared to the simplistic persistence model that is usually taken as the reference model [20,21].

The ARMA model of order (p, q) can be characterized by:

$$X_t = \sum_{j=1}^{p} \phi_j X_{t-j} + \sum_{k=1}^{q} \phi_k \varepsilon_{t-k} + C + \varepsilon_t, \tag{7}$$

where $\{X_t, t \geq 0\}$ is the time series (with X_t being the value at time t), ϕ_j is the AR parameters for lag j, ϕ_k is the MA parameter for lag k, C is a constant, p is the AR order (number of AR parameters), q is the MA order (number of MA parameters), and $\{\varepsilon_t, t \geq 0\}$ is the white-noise sequence (with ε_t being the value of the noise at time t). Usually, it is assumed that the sequence of error terms, $\{\varepsilon_t, t \geq 0\}$, is a sequence of independent and identically distributed random variables assumed to have a normal distribution, and then the white noise is usually known as Gaussian noise. As a result, the AR operation retains the information about the historic dependence/influence between future and past values; the MA operation retains the information about successive errors.

5. Simulation results

As explained in the methodology section, Hellman exponents for 50 m and 60 m were estimated by using an ANN for the current month. Local conditions and wind speed at 40 m were required for the required ANN computations. As a first stage, wind speeds/powers at 50 m and 60 m were estimated using the Hellman exponents for that month.

Figure 3a shows the measured and estimated wind speeds at 50 m and 60 m, and Figures 3b and 3c show the related probability (frequency analysis) and energy density (W/m^2) at 50 m for September 2009. For simplicity, diurnal values are shown in the Figures.

In Figure 3a, the horizontal label represents time in hours and the vertical label represents wind speed in meters per second for September 2009.

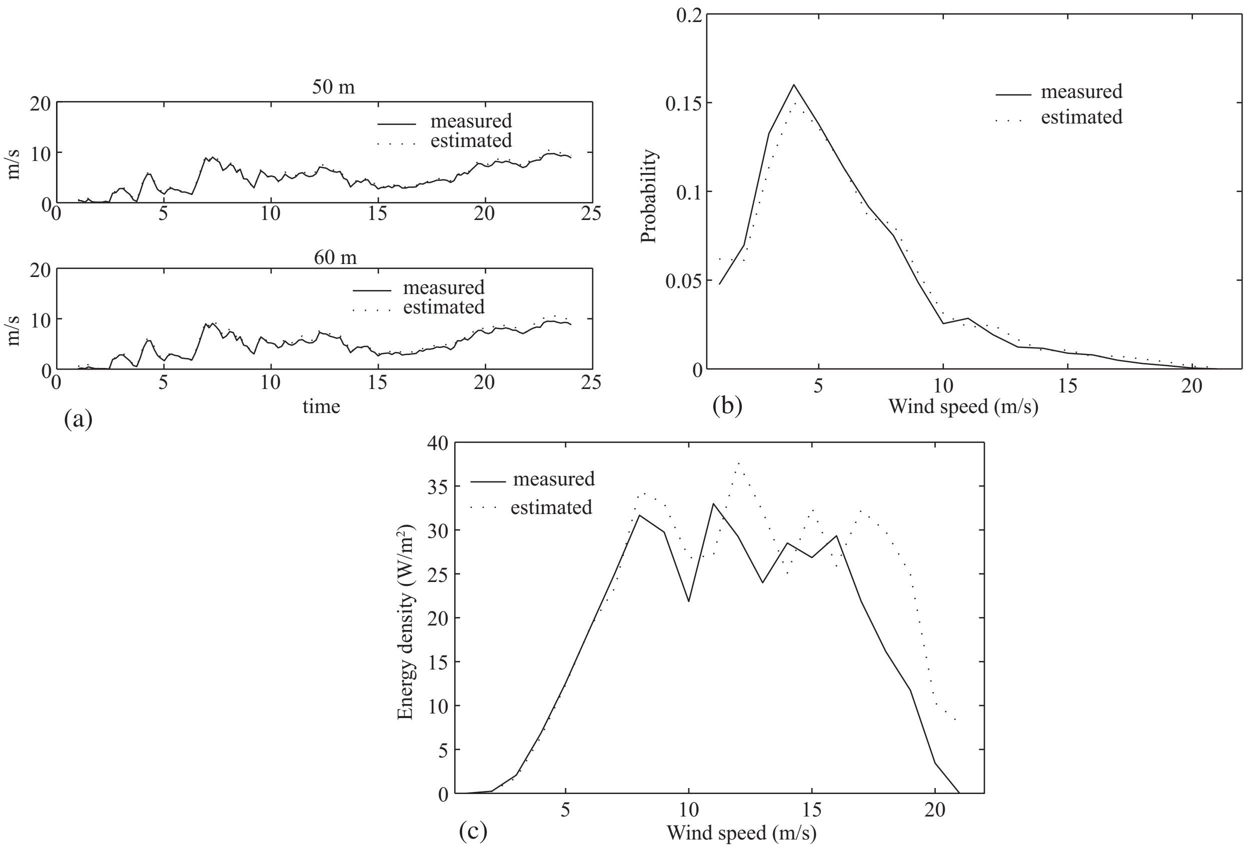


Figure 3. a. Measured and estimated wind speeds at 50 m and 60 m for September 2009. RMSE for 50 m is 0.9937; RMSE for 60 m is 0.9822. b. Measured and estimated probability curve at 50 m for September 2009. RMSE is 0.0058, measured average speed is 5.3317 m/s, estimated average speed is 5.4829 m/s, and $R^2 = 0.9865$. c. Measured and estimated energy density at 50 m for September 2009. RMSE is 4.2539, measured energy density is 223.1508 W/m^2, estimated energy density is 246.1882 W/m^2, and $R^2 = 0.8522$.

Figures 4a and 4b show the related probability (frequency analysis) and energy density (W/m^2) at 60 m for September 2009.

After predicting wind speeds for 1 month at 50 m and 60 m, the next month's wind speeds were forecasted with the Mycielski and ARMA algorithms at 50 m and 60 m. The results are shown in Figures 5a and 5b. The Mycielski algorithm is a powerful and relatively new approach for forecasting wind speed; it uses quantized data. Unlike in other papers [16,17], different quantization levels (2 to 8) were used here. The optimum quantization level representing the lowest RMSE was then selected. Eq. (11) was used for quantizing the wind speed data.

$$v_{quantized} = round(2 * v)/2 \tag{8}$$

Although only diurnal data are shown in the Figures, the RMSE and R^2 values are for monthly data.

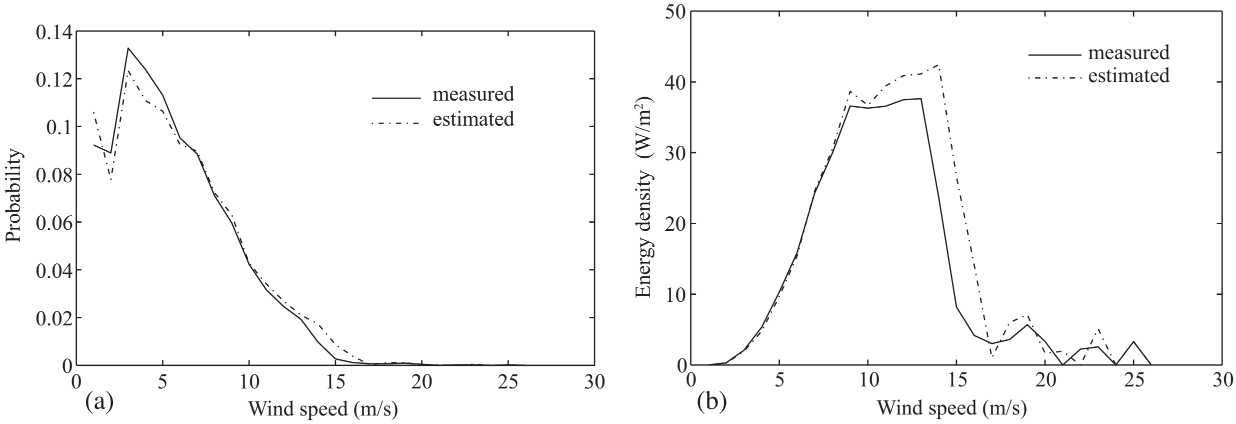


Figure 4. a. Measured and estimated probability curve at 60 m for September 2009. RMSE is 0.0068, measured average speed is 5.3313 m/s, estimated average speed is 5.5660 m/s, and $R^2 = 0.9815$. b. Measured and estimated energy density at 60 m for September 2009. RMSE is 6.3798, measured energy density is 215.5931 W/m^2, estimated energy density is 257.4224 W/m^2, and $R^2 = 0.6874$.

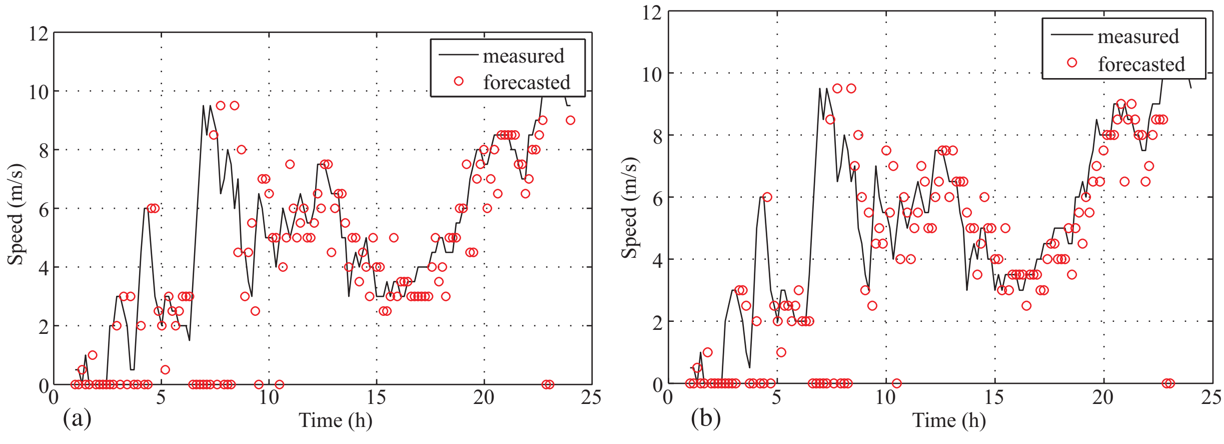
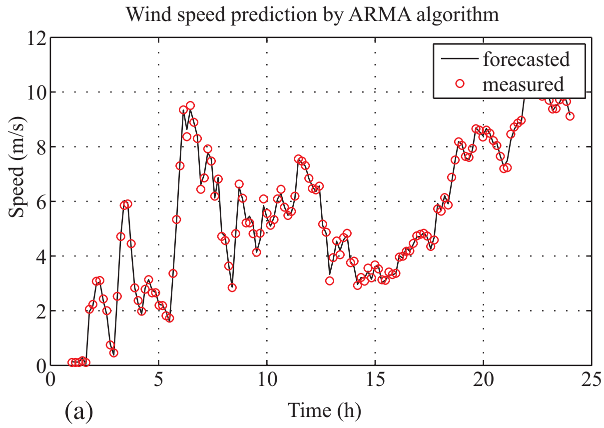


Figure 5. a. Measured and estimated wind speeds for the next month at 50 m. RMSE is 0.75, R^2 is 0.93, average value of measured wind speed is 5.331 m/s, and average value of forecasted wind speed is 5.448 m/s. b. Measured and estimated wind speeds for the next month at 60 m. RMSE is 0.803, R^2 is 0.9309, average value of measured wind speed is 5.340 m/s, and average value of estimated wind speed is 5.5374 m/s.

In Figures 4a and 4b, the measured wind speed data are estimated wind speed data belonging to the previous month, and the forecasted wind speed data are the next month's predicted wind speed data. Figures 6a and 6b show the next month's wind speed data as forecasted by the ARMA algorithm.



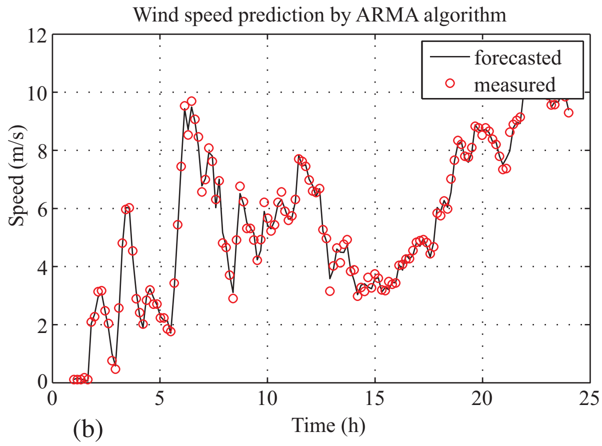


Figure 6. a. Measured and estimated wind speeds for the next month at 50 m. RMSE is 0.65, R^2 is 0.975, average value of measured wind speed is 5.331 m/s, and average value of estimated wind speed is 5.3049 m/s. b. Measured and estimated wind speeds for the next month at 60 m. RMSE is 0.73, R^2 is 0.9707, average value of measured wind speed is 5.340 m/s, and average value of estimated wind speed is 5.2453 m/s.

In Figures 6a and 6b, the measured wind speed data are the estimated wind speed data belonging to the previous month, and the forecasted wind speed data are the next month's predicted wind speed data.

Table 4 presents the monthly results of estimated (for the current month) and forecasted (for the next month) wind speeds and related RMSE and R^2 values using the Mycielski and ARMA algorithms.

Table 4. Monthly average wind speeds from August 2009 to July 2010.

Months	MAV50m m/s	MAV60m m/s	AV-A50m m/s	AV-A60m m/s	AV-M50m m/s	AV-M60m m/s
August 2009	5.209	5.695	5.0454	5.5066	5.2140	5.7002
September 2009	5.331	5.340	5.3049	5.2453	5.4480	5.5386
October 2006	5.018	5.100	5.1181	5.2272	5.2210	5.3214
November 2009	5.082	5.146	4.9585	5.2106	5.1609	5.4159
*December 2009	5.823	6.025	6.0748	6.1705	6.4124	6.5154
*January 2010	6.918	7.173	7.2521	7.5567	7.5213	7.8741
+February 2010	–	–	–	–	–	–
March 2010	5.499	5.621	5.8724	5.9727	6.0481	6.1683
April 2010	4.860	4.924	5.2022	5.4483	5.3084	5.5669
May 2010	4.220	4.308	4.6056	4.8741	4.7289	5.0364
June 2010	5.116	5.262	5.4568	5.7236	5.5762	5.8772
July 2010	3.591	3.724	3.9773	4.2861	4.1181	4.4489

*There was data loss at 50 m and 60 m due to an anemometer problem.
+Because of the problems with the anemometers at 50 m and 60 m, these data were not taken into account.

In Table 4, MAV50m and MAV60m are the average values of measured wind data at 50 m and 60 m, respectively. AV-A50m and AV-A60m are the average values of predicted wind data at 50 m and 60 m by the ARMA algorithm, respectively. Finally, AV-M50m and AV-M60m are the average values of predicted wind data at 50 m and 60 m by the Mycielski algorithm, respectively.

Figures 7a and 7b show the graphical representation of the results for 50 m and 60 m, respectively, according to the measured and forecasted results from the Mycielski and ARMA algorithms. The ARMA algorithm represents a better forecasting approach with low RMSE and high R^2 values.

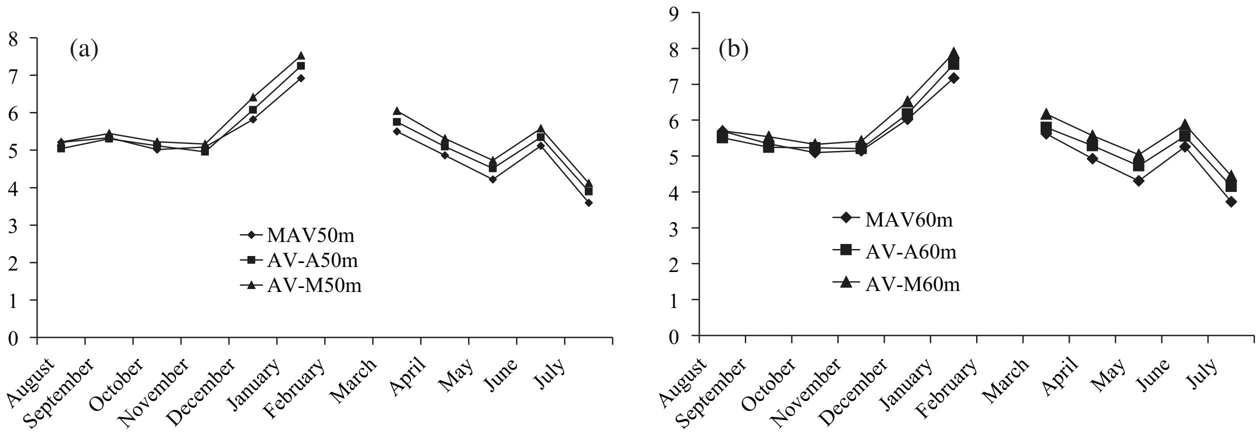


Figure 7. a. Average value of the measured and forecasted wind speed data at 50 m. b. Average value of the measured and forecasted wind speed data at 60 m.

6. Conclusion

The impact of wind power on power systems has drawn great interest in recent years, and reliable prediction models have become crucial tools to help in system security assessment.

This paper presented a novel approach for forecasting wind speed and generated power considering short-term time scales. The main novelty of the paper is the hybridization of the Hellman equation and neural networks based on weather data. Another advantage of the proposed technique is that only a 40-m tower and weather data are needed to forecast wind speeds at 50 m and 60 m. Therefore, the proposed hybrid technique is more economical. Basically, the proposed system provides wind prediction in the current month by using estimated Hellman exponents and short-term forecasting for the next month by using 2 algorithms, Mycielski and ARMA. Their performances are then compared to in situ measured data. According to the goodness-of-fit criterion, RMSE and R^2 approaches are then applied for performance analysis.

Experimental results showed that the ARMA predictor has better goodness-of-fit criteria than the Mycielski algorithm.

Series like wind speed and weather data (4320 $\times$ 3 matrix for 1 month, with 10-min intervals as described above) exhibit long memory, and if the size of the input matrix is reduced by using the technique of so-called principal component analysis, based on singular value decomposition, the performance of the Mycielski algorithm may also be increased.

Notation list

α	Hellmann exponential coefficient
alpha50, α_{50}	Hellmann exponential coefficient at 50 m
alpha60, α_{60}	Hellmann exponential coefficient at 60 m
v_{50}	wind speed (m/s) at 50 m
v_{60}	wind speed (m/s) at 60 m
ANN	artificial neural network
ARMA	autoregressive moving average
h_{known}	known elevation (m)
h_{est}	estimated elevation (m)
v_{known}	known wind speed (m/s)
v_{est}	estimated wind speed (m/s)
Temp.	temperature ($^\circ$C)
Rel. Hum.	relative humidity (%)

Air Press.	air pressure (mmHg)	X_t	time series
RMSE	root mean square error	ϕ_j	AR parameter
R^2	coefficient of determination	ϕ_k	MA parameter
P	electric power (W)	C	constant
Cp	Betz limit	ε_t	error term

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