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A method based on the Van der Hoven spectrum for performance evaluation in prediction of wind speed

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Abstract: Development of techniques for accurate assessment of wind power potential at a site is very important for the planning and establishment of a wind energy system. The most important defining character of the wind and the problems related with it lie in its unpredictable variation. Van der Hoven constructed a wind speed spectrum using short-term and long-term records of wind in Brookhaven, NY, USA, in 1957 and showed the diurnal and turbulent effects. His spectrum suggests that there is a substantial amount of wind energy in 1-min periodic variations. The aim of this paper is to evaluate the results of wind predictions using linear and nonlinear methods following the construction of power spectra (Van der Hoven spectrum) based on airport wind data in İstanbul. In this study, we have constructed power spectra of surface wind speed in order to evaluate the contributions of disturbances at various scales on the total spectrum. For this purpose, data from an automatic weather observation system at Atatürk Airport in İstanbul at a height of 10 m with a sampling rate of 1 min from 2005 to 2009 were used. In the second part of the study, autoregressive (AR) and artificial neural network (ANN) models were applied for prediction of wind speed. The prediction methods were assessed by comparing the characteristic frequency components of the prediction series and the real series. The best results were obtained from the ANN model; however, the AR model was found to moderately show the spectral characteristics.

Key words: Van der Hoven spectrum, autoregressive model, artificial neural networks, time series prediction

1. Introduction

Determining the characteristics of wind resources and developing techniques for accurate assessment of wind power potential at a site are increasingly gaining importance. This information can enhance economic power with advantageous projects in terms of competitiveness. Wind energy is often conveniently integrated into regional electricity supply systems, but its intermittent character creates a significant problem for the energy quality of the grid. Furthermore, this variability continues in both position and time dimensions on a wide range of scales (Burton *et al.* 2007). Winds that develop near the surface are a combination of geostrophic and local winds. These can change depending on the geographic region, climate, height of the terrain, and surrounding obstacles (Bianchi *et al.* 2007).

Because of the variable nature of wind resources, the ability to forecast wind speed is often valuable. Such forecasts fall broadly into 2 categories: predicting short-term turbulent variations over a time scale of seconds to minutes ahead, which may be useful for assisting with the operational control of wind turbines or wind farms, and longer-term forecasts over periods of a few hours or days, which may be useful for planning the deployment of other power stations on the network (Burton *et al.* 2007).

Short-term forecasts necessarily rely on statistical techniques for extrapolating the recent past, whereas the longer-term forecasts can make use of meteorological methods. A combination of meteorological and statistical forecasts can give very useful predictions of wind farm power output (Burton *et al.* 2007).

Generally, prediction methods are classified into 2 groups: linear and nonlinear prediction methods. In this study, both of these methods are used for performing a one-step-ahead prediction. A well-structured predictor should preserve the characteristics of the signal. Thus, we could check the success of the prediction method by comparing the frequency characteristics of the predicted and original signals. In this case, similarities between the frequency characteristics of both signals can be used as an indicator of the success of the prediction method.

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Wind speed distribution has a well-known frequency characteristic, which was first proposed by Van der Hoven (1957). This characteristic can be used as a good criterion for determining the success of a chosen prediction method. The relationship between the real and the prediction series could give us estimations about the future success of the method. Normally, determining the R^2 or χ^2 values of a prediction series or using other similar methods is done to assess a prediction method's success. In this study, a comparison of the frequency characteristics of real and predicted series is proposed as a new and more advanced method for determination of success. This innovation could give us a new and very useful tool to determine the strength of a prediction method that we would like to perform.

Van der Hoven (1957) constructed a wind speed spectrum from short-term and long-term wind records in Brookhaven, NY, USA. This spectrum has significant peaks corresponding to synoptic, diurnal, and turbulent effects. He also presented the contribution of oscillations at various frequencies to the variance of the wind speed, which was found to be proportional to the kinetic energy of the wind speed fluctuations.

Furthermore, in a study by Panofsky and McCormick (1954), the spectral properties of vertical and horizontal turbulence and their cross-spectra were determined at 100 m above ground level. They specified that the frequency at the maximum value of the vertical velocity spectrum decreases with increasing height. Griffith *et al.* (1956) explained the procedure and problems of power spectrum analysis over large frequency ranges. Their method was illustrated by the power spectrum of temperature at University Park, PA, USA, covering periods from 2 to 7300 days. The spectrum was characterized by a major peak at 4 days and several minor peaks. Eggleston and Clark (2000) calculated a power spectrum for Bushland, TX, USA from 13 years of hourly data, 1 year of 5-min data, and 2 particularly gusty days of 1-s average data at 10 m. They found a few peaks similar to the Van der Hoven spectrum for this region. Frye *et al.* (1972) applied the Van der Hoven spectrum for studying the coastal area of Oregon. They showed a diurnal and a microscale peak corresponding to a period of 24 h and about 50 s. Neammanee *et al.* (2007) used the Van der Hoven power spectrum in order to develop a wind simulator based on test generators in wind turbines. In this study, a power–wind speed pattern was generated based on the Van der Hoven spectrum to obtain reference signals to be used as a torque reference for a torque control inverter.

Estimation of these spectral characteristics is very important to plan production of wind energy. The Van der Hoven spectrum indicates that a wind speed signal has specific frequency components, and so if a prediction series contains similar spectral components, this can create an indicator for the adequacy of the prediction method. Thus, the first aim of this paper is to construct power spectra of surface wind speed measured at İstanbul's Atatürk Airport in order to evaluate the contributions from disturbances at various scales on the total spectrum to determine the characteristic frequencies. The second aim is to make predictions using a linear and a nonlinear method, namely the autoregressive (AR) and artificial neural network (ANN) models, respectively, of the wind speed data. The third aim is to construct power spectra of the predicted series to determine the frequency components. As a result, the evaluations of the predicted wind speed series are presented in terms of how well the prediction series represents the characteristic frequency components of the real wind series.

2. Methods and analysis

In this study, the data sets, available for the 5-year period from 1 January 2005 to 31 December 2009 with a sampling rate of 1 min at international aerodrome standards, were taken from an automatic weather observation station (AWOS) installed at a height of 10 m at Atatürk International Airport. The data sets were organized and grouped according to sunrise and sunset times, particularly for local daylight saving time, as shown in the Table.

2.1. Van der Hoven spectrum

The economic return of using short-term forecasting is dependent on its accuracy. As the amount of wind energy requiring integration into the grid increases, short-term forecasting becomes more important for the transmission

Table. Classification of the datasets according to sunrise and sunset times for summer and winter.

Year	Summertime	Summertime sunrise–sunset	Wintertime sunrise–sunset
2005	27.03.2005–30.10.2005	0600–1800 hours	0700–1700 hours
2006	26.03.2006–29.10.2006	0600–1800 hours	0700–1700 hours
2007	25.03.2007–28.10.2007	0600–1800 hours	0700–1700 hours
2008	30.03.2008–26.10.2008	0600–1800 hours	0700–1700 hours
2009	29.03.2009–26.10.2009	0600–1800 hours	0700–1700 hours

and distribution operators. Furthermore, wind power that will join an electricity network is very significant in short-term periods of time, even less than minutes or seconds, due to the effects of turbulence on wind turbine design and performance (Burton *et al.* 2007). Power spectrum analysis is a measure of oscillations with various frequencies that contribute to the variance of a variable. The variance is proportional to the kinetic energy of speed fluctuations where the wind is variable. As shown in Figure 1, the Van der Hoven spectrum shows clear peaks corresponding to the synoptic, diurnal, and turbulence effects that were recorded in Brookhaven, NY, USA (Van der Hoven 1957). The Van der Hoven spectrum suggests that there is a substantial amount of wind energy in 1-min periodic fluctuations of the wind. There also appears to be little energy in a period of once per hour (Straw 2000). In this spectrum there is a spectral gap between the daily and turbulence peaks for a period of approximately 1 h. The presence of a broad and deep gap coincides with oscillation at 0.1-h and 10-h periods. This gap separates the 2 well-formed maxima (at right a micrometeorological maximum and at left a synoptic maximum) (Panchev 1985). There is very little energy in the range between 2 h and 10 min of the spectrum (Burton *et al.* 2007). This spectrum also suggests that high-frequency gusts may not contain large amounts of energy.

A main peak with 0.01 cycles/h coincides with 4-day transit periods of large-scale weather systems and this peak is usually referred to as the macrometeorological peak. The second peak comprises a high-frequency range that coincides with turbulence in the boundary layer in periods of 10 min and less than 3 s. The peak is located in the micrometeorological region. Therefore, the space that is bounded by the 2 peaks and where less fluctuation is seen is called the spectral gap. In this gap, macro- and micrometeorological fluctuations can be analyzed without the effects of other influences (Straw 2000). Van der Hoven's study has 2 main consequences: the first includes doing a wide-range frequency analysis of wind speed to define the important contributions to the total variance, and the second is testing the identification peaks and spectral gap of the spectrum under different terrain and synoptic conditions.

Generally, 2 methods can be applied to obtain spectral estimations in a wide range of frequencies. The first method is to collect wind speed data over a small sampling frequency for a long time span. This gives us the whole spectrum at one time. The second method is to collect data in different weather conditions (thunderstorm, fog, etc.) for short time periods and combine the spectral analysis results of these different data sets. For this study, Van der Hoven's first method was preferred over his second method since it is more practical in terms of keeping the amount of data consistent.

Power-spectrum analysis is a measure of the contribution of oscillations with continuously varying frequencies to the variance of a variable. Where wind speed is the variable, the variance is proportional to the kinetic energy of the wind speed fluctuations (Van der Hoven 1957). The computation of power spectra is based on a theorem by Wiener (1930) and autopower spectral density (APSD) is defined by Eq. (1):

$$APSD_v(\omega) = \left| \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} v(t)\, e^{-j\omega t} dt \right|^2 = V(\omega)\, V^*(\omega) \tag{1}$$

where ω is angular frequency, $v(t)$ is wind speed, and t is time.

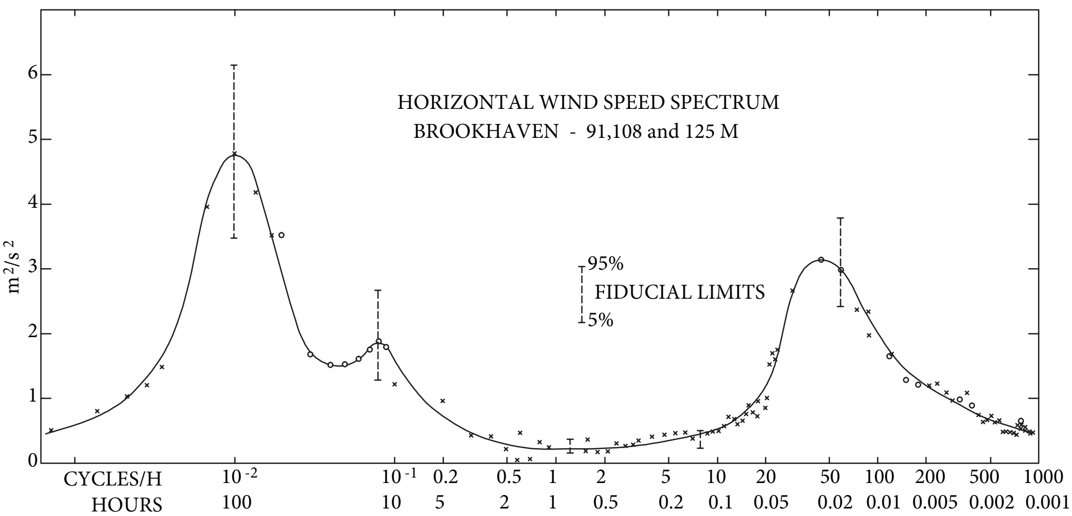

Figure 1. Van der Hoven spectrum (1957).

2.2. Time series analysis

Understanding the time series dynamics of wind speed is an essential element in many types of wind energy applications. For example, the design of wind turbines requires the characterization of several wind processes including wind speed. Models of wind speed are important in the operation of wind farms. For example, the characteristics of wind speed are important factors in the determination of the cut-in and cut-out wind speeds of wind turbines. Wind speed models will likely become an important factor in renewable energy markets having growing popularity. Furthermore, time-domain models account for predicting wind speeds in a region. In addition, studies on system characterization attempt to determine fundamental properties, such as the number of degrees of freedom in a system or the amount of randomness with little or no a priori knowledge (Gershenfeld & Weigend 1994). The aim of forecasting is to accurately predict the short-term evolution of a system, while the goal of modeling is to find a description that accurately captures features of the long-term behavior of the system. The prediction methods mainly fall into 2 groups: linear and nonlinear algorithms. Linear time series models have 2 particularly desirable features: they can be understood in great detail and they are straightforward to implement (Kaya *et al*. 2010).

Broadly speaking, a time series is said to be stationary if there is no systematic change in mean (no trend), if there is no systematic change in variance, and if strictly periodic variations have been removed. Most of the probability theory of time series is concerned with stationary time series, and for this reason time series analysis often requires turning a nonstationary series into a stationary one so as to use this theory. For example, it may be of interest to remove the trend and seasonal variation from a set of data and then try to model the variation in the residuals by means of a stationary stochastic process (Chatfield 1996).

2.3. Time series forecasting

Time series forecasting (prediction) methods can be divided into 2 categories. The first is the physical method, which uses a lot of physical considerations to reach the best prediction precision. The second is the statistical method, like the AR model, which aims at finding relationships in the measured data. However, this classification is not absolute. In recent years, some new methods based on artificial intelligence, like the ANN model, have been developed and are being widely used (Lei *et al*. 2009).

2.3.1. AR model

The AR model is a widely used method because of its simplicity and the presence of efficient algorithms used to determine the model coefficients. The most widely used model selection criteria in AR models are the Akaike information criterion (AIC) and final prediction error (FPE) (Akaike 1969, 1974).

2.3.2. ANNs

The fact that some time series cannot be obtained by linear approximation (such as a logistic equation that can be generated with simple functions) has pointed to the need for a more general theoretical framework for time series analysis and prediction. One of the most interesting developments in this respect is the use of ANNs for time series prediction (Gershenfeld & Weigend 1994). Neural networks have been widely used as time series forecasters. Most often these are feed-forward networks that employ a sliding window over the input sequence (Frank *et al*. 2001). The standard neural network method of performing time series prediction is to induce the function *f* using any feed-forward function approximating neural network architecture, such as a standard multilayer perception model, a radial basis function architecture, or a cascade correlation model (Gershenfeld & Weigend 1994), using a set of N-tuples as inputs and a single output as the target value of the networks. This method is often called the sliding window technique as the N-tuple input slides over the full training set. Figure 2 gives the basic architecture of this method.

As noted by Dorffner (1996), this technique can be seen as an extension of AR time series modeling, in which the function *f* is assumed to be a linear combination of a fixed number of previous series values. Such a restriction does not apply with the nonlinear neural network approach, as such networks are general function approximators (Frank *et al*. 2001).

3. Climate characteristics of İstanbul

Atatürk Airport (40°58′N, 28°48′E) is located to the west of İstanbul. Figure 3 shows the İstanbul region.

Synoptic weather systems with different origins affect the İstanbul region. Low-pressure systems originating in Iceland, Mediterranean nomadic cyclonic systems, and associated frontal systems move in from the west and southwest, and Siberian high-pressure systems move in from the north in fall. The effects of these systems continue until the middle of the spring. In late spring local factors become important, depending on terrestrial warming. In summer, tropical low-pressure systems originating in Africa and Arabia from the south and Azores high-pressure systems from the northwest affect the region. Local-scale systems (sea and land breezes) also have an impact along with the synoptic scale systems in this season.

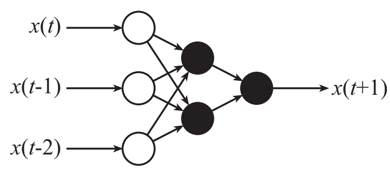

Figure 2. The standard method of performing time series prediction using a sliding window with 3 time steps.

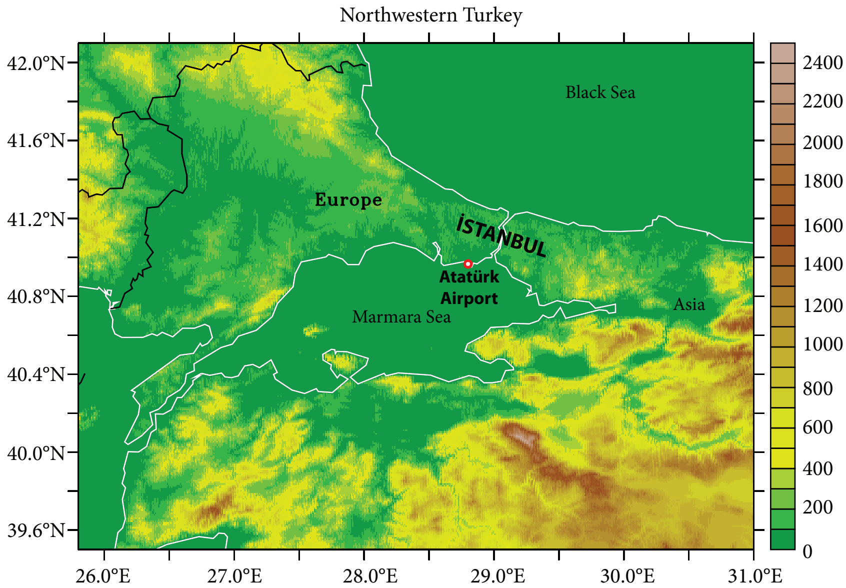

Figure 3. Map of the İstanbul region.

4. Results

In this study, wind data that were obtained from an AWOS at Atatürk Airport between the years of 2005 and 2009 (at 10 m of height and 1-min sampling intervals) were used. Initially, a Van der Hoven spectrum was created using this data, followed by linear and nonlinear prediction spectra. The AR and ANN models were applied to the time signal for wind speed prediction.

The prediction performance was evaluated by comparing the prediction series Van der Hoven spectra obtained from the AR and ANN models with the real signal's Van der Hoven spectrum.

4.1. Spectral power density analysis

Spectral power density is given in Figure 4. To retain the property that the variance contributed with a frequency range that is given by the area under the spectral curve, the original spectral estimates must be multiplied by the frequency (Panofsky 1954; Griffith 1956; Van der Hoven 1957).

As seen in Figure 4, the first and second maximum peak of the Van der Hoven spectrum represent synoptic scale pressure systems that influence the fluctuations in wind speed. In general, the passage of a synoptic scale system over a region lasts 1–3 days. The spectral band contains a third peak that corresponds to semidaily changes in wind speed. Maxima seen at around 2–7 min indicate wind motion close to the surface and always represent turbulence or gusts. In addition, since the measurement site is at an airport, different characteristics of turbulence are seen owing to the airplane activities. Another feature of the spectrum is the spectral gap, which has very low energy between about 10 min and 4 h. This gap is associated with the absence of continuously moving systems within this time interval in the atmosphere.

A 4-day peak and 1-day peak have been seen at Atatürk Airport with a maximum power of 4.00 m^2/s^2 and 10.89 m^2/s^2, respectively. These peaks are related to the effects of synoptic-scale pressure patterns and frontal systems. Particularly starting in fall, these systems are especially influential on this region from the north, northwest, and south. Moreover, these systems lead to significant changes in direction and speed of wind and wind speed increases during their passage. This transition continues until the middle of spring.

The spectral band has a third peak that has the maximum spectral power density (2.50 m^2/s^2). This third peak corresponds to a period of 11.6 h, which corresponds

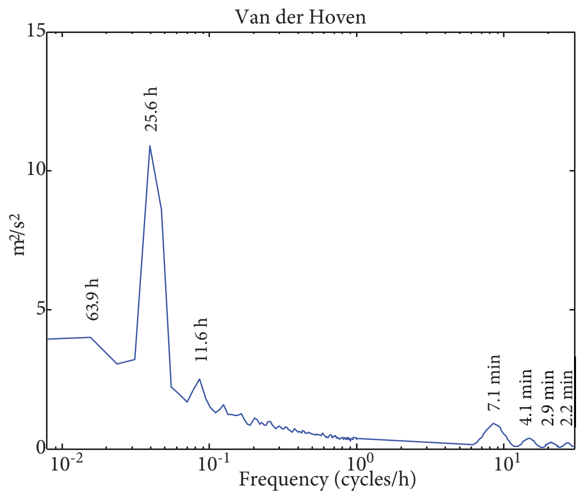

Figure 4. Power density spectrum of the İstanbul region.

to daily variations. İstanbul is surrounded by sea to the north and south and has a hilly topography, so this peak may indicate the impact of the breezes that develop due to the difference between the daytime and nighttime temperatures in the city (Menteş 2007; Ezber 2009). Other peaks show the effects of convective motion in the region during the day. Occasionally, thunderstorms, which are very rare events, have a significant energy contribution on a wider range of time scale. Some thunderstorm activity can occur in the region during the second half of spring and early period of summer and the second half of fall and winter, respectively, because of convectivity and frontal passage systems.

The power density spectrum of the Atatürk Airport-İstanbul region is similar to Van der Hoven's spectrum in that there is a spectral gap with very low energy of 0.30 m^2/s^2 within a time range of a few hours. The peaks with lower energy indicate turbulence, as seen in Figure 4. Additionally, the day and night variations of the wind speed spectral density in winter and summer were evaluated due to the seasonal difference of synoptic-scale systems' and local-scale systems' effects on this region. Figures 5 and 6 show the change of wind speed spectral density in night and day during winter and summer. It can clearly be seen that the total spectral energy is higher in winter than in summer. In the power spectrum, 2-day or 3-day periods have higher energy in winter than summer. This shows that the synoptic-scale pattern is more influential in winter. Moreover, in both figures, semiday peaks are significant for each season. The temperature difference between day and night in summer is greater than in winter; therefore, semiday peaks are more dominant in summer. In the seasonal plot, peaks at a few hours have significant energies according to the Van der Hoven spectrum (Figures 5 and 6).

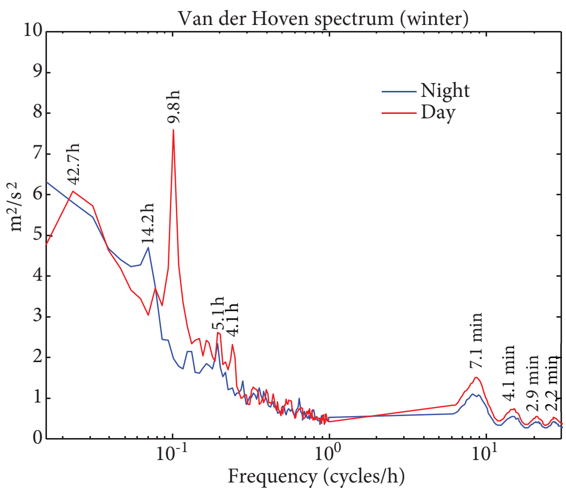

Figure 5. Power density spectrum for the Atatürk Airport-İstanbul region in winter.

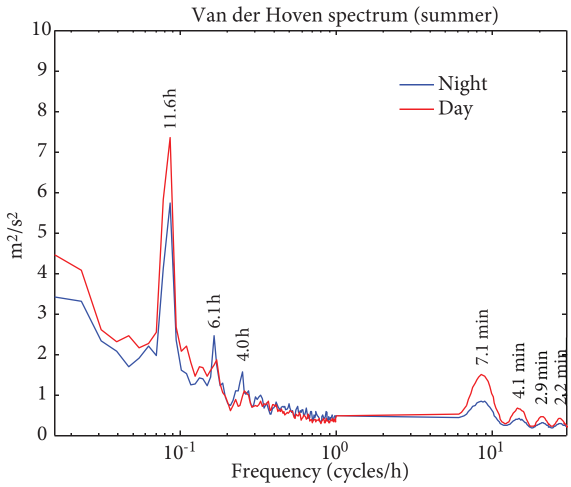

Figure 6. Power density spectrum for the Atatürk Airport-İstanbul region in summer.

4.2. AR model results

In prediction of wind data using the AR model with AIC, the optimal model order was calculated as 11. The coefficients of the model were determined by using the Yule–Walker method (Yule 1927; Walker 1931). Calculated AIC values for all data from 1 to 100 model orders are given in Figure 7. For time series obtained with model order 11, the goodness of fit R^2 was found to be 0.4795. Calculated prediction series with the AR model, original signal, and error series are shown in Figure 8. Results from the Van der Hoven spectrum using an AR model are given in Figure 9.

4.3. ANN results

The ANNs were arranged in the same order as the AR model to allow for direct comparison. In the ANN architecture, there were 11 nodes in the input, 1 hidden layer, and 1 neuron in the output. The preferred ANN architecture is

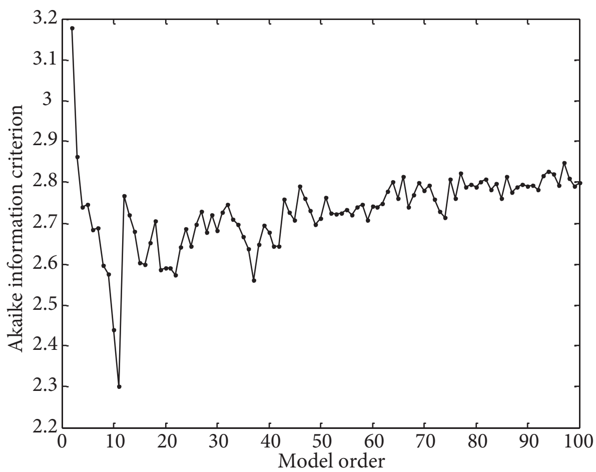

Figure 7. AIC values for model orders from 1 to 100.

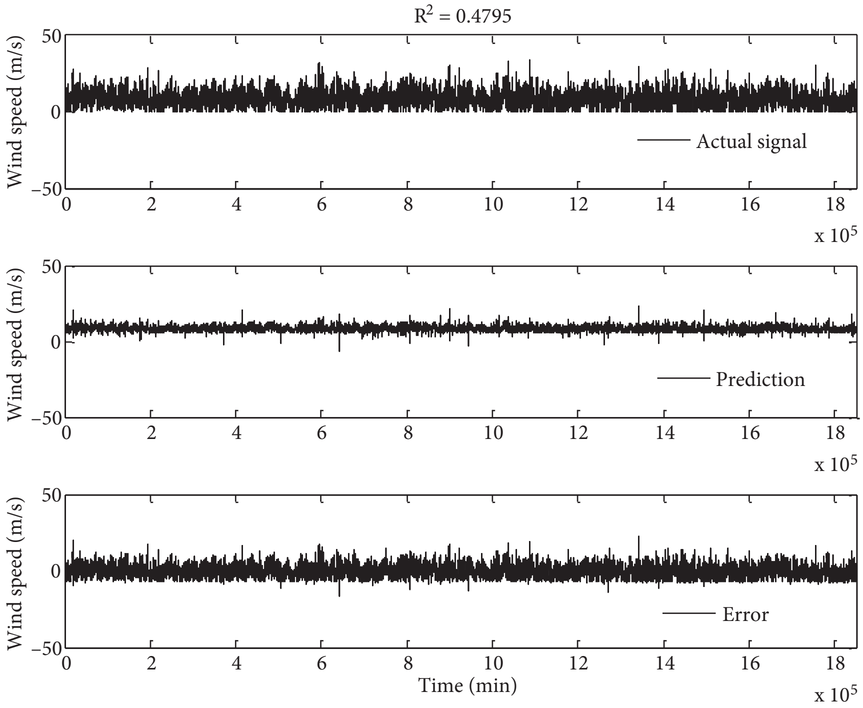

Figure 8. Wind speed prediction obtained using the AR model and error series.

triangle reduction geometry. Therefore, half of the sum of the input nodes and the output neuron (6) was selected as the number of neurons in the hidden layer of the ANN. The ANN was trained using the Levenberg–Marquardt algorithm (Levenberg 1944; Marquardt 1963) in 500 steps. A logarithmic sigmoid activation function was used in both the hidden layer and the output layer of the ANN. For time series obtained with ANN, the goodness of fit R^2 was found to be 0.99965. Calculated prediction series with ANN, original signal, and error series are shown in Figure 10. The Van der Hoven spectrum that was formed from ANN results is given in Figure 11.

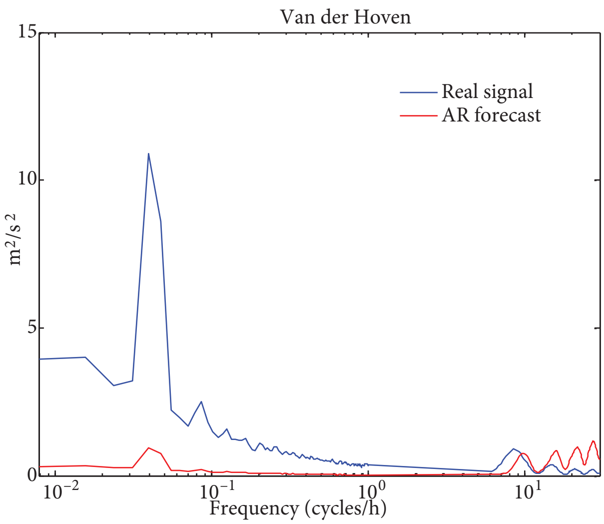

Figure 9. Van der Hoven spectrum obtained using the AR model and real signal.

5. Conclusions

In this study, an evaluation of wind speed predictions was done using linear and nonlinear methods such as AR and ANN models using the İstanbul Atatürk Airport wind data sampled at 1-min intervals. Comparing real and predicted time series' power spectral densities has presented a new approach for defining the success of one-step-forward wind speed prediction.

The general characteristics of temporal wind distribution change due to local factors as well as global-scale flow patterns. The most important success criterion of wind speed energy prediction methods is to see the same power spectral density in both the real and predicted series. In this study, 2 prediction methods (AR model as a paradigm of linear prediction methods and ANN for nonlinear methods) were used at Atatürk Airport in İstanbul. The success of the predictions performed using these 2 methods is defined by comparing the similarity between the Van Der Hoven spectra of the real and predicted series.

First of all, wind speed data were sampled at Atatürk Airport in İstanbul with a 1-min sampling period at a height of 10 m between 2005 and 2009. The autopower spectrum of this signal was calculated using a fast Fourier

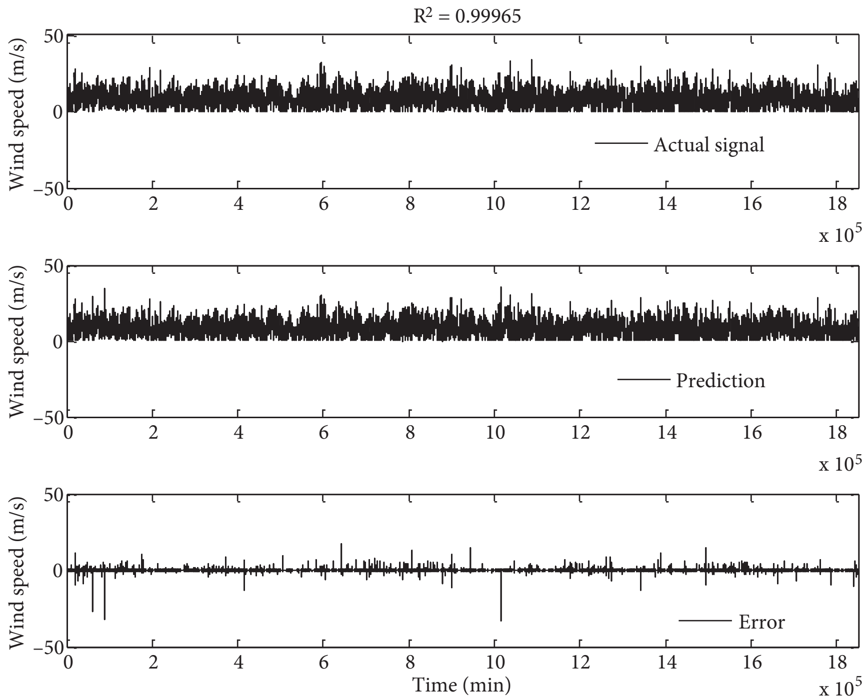

Figure 10. Wind signal prediction obtained using the ANN model and error series.

transform algorithm. This spectrum indicated significant peaks corresponding to synoptic, diurnal, and turbulent effects. The areas under these peaks are proportional to the kinetic energy of the wind speed fluctuations according to Parseval's theorem (Griffith 1956).

The results of power spectral density analysis gave a similar structure to the classic Van der Hoven spectrum. In the total spectrum, the values of the first 2 consecutive peaks cover periods of 1–3 days. This is associated with the passage of active synoptic systems in this region. The third peak of the spectral band corresponds to daily variations. The effects of convectivity and frontal passage systems are seen in the third peak. Moreover, a spectral gap with a very low energy of 0.30 m^2/s^2 for a few hours' width and also turbulence peaks can be seen in the spectrum.

In addition, as shown in Figures 5 and 6, night and day variations of wind speed spectral density in winter and summer were studied. The total spectral energy is higher and the synoptic-scale pattern is more influential in winter than in summer. In both seasons, semiday peaks and a few hour peaks can be distinctly seen.

The success of the prediction methods was determined by looking at the similarity between the spectral densities of the real and predicted time series based on having a similar structure to the classic Van der Hoven spectrum in this region.

For that purpose, the AR and ANN models were applied to predict the wind speed. The results of predictions were evaluated in terms of how well the characteristic frequency components in the predicted time series represented the real series. The best results were obtained by the ANN. The AR model reflects the spectral characteristics only up to a point.

In addition to performance criteria such as R^2, the existence of the basic spectral characteristics of the Van der Hoven spectrum in the prediction series provides a

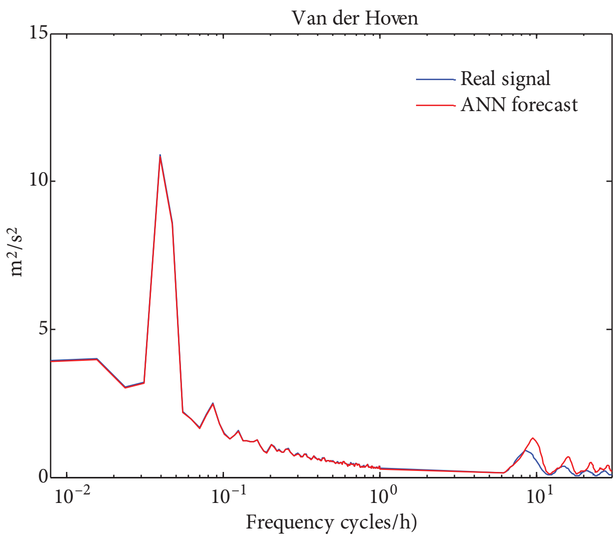

Figure 11. Van der Hoven spectrum obtained using the ANN model and real signal.

further assessment for the success of prediction. For both the linear and nonlinear prediction studies, the basic criterion for the achievement of successful forecasting is how many frequency characteristics exist in the prediction series.

It is found that the spectrum of the prediction series is close to the spectrum of the actual signal for ANN forecasting, but the AR model does not show this characteristic sufficiently. The AR model shows relatively low performance because the wind speed signal does not include enough white noise characters.

For the wind speed prediction, the best results were provided by the ANN model. In addition to having high performance, ANNs do not need the average value of the signals to be removed. Therefore, the ANN model is preferred to linear time series models. The only problem in the ANN-based models is the lack of methods such as AIC or FPE to determine the optimal order.

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