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Research Article

Prediction of Wind Speed by Using Chaotic Approach: A Case Study in Istanbul

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Abstract

Renewable energy sources have gained great popularity due to the increasing importance given to a sustainable environment and economic development. Because of the environmental friendliness of renewable energy compared to fossil fuels, the tendency and investments in this field have increased. Wind energy comes into prominence among renewable energy sources because of its potential power that is used in various areas currently. Wind energy having stochastic nature is more sensitive to the extreme values of wind speed. Therefore, in order to create wind energy effectively, an accurate wind speed forecast is needed. In this study, nonlinear dynamical system approaches have been implemented by using reconstructing of phase space based on specifying minimum embedded dimension and delay time. In order to find out performance, different error metrics (MSE, RMSE, MAE, and MAPE) have been implemented. According to results, RMSE has been found 0.47 and 0.85 in hourly and daily dataset, respectively. Also, the correlation coefficient between the measurement and the obtained data set was as high as 0.92 in the hourly wind variable. In addition, a lesser correlation coefficient of 0.62 was found in the daily wind speed.

Keywords: Energy, Chaos Theory, Wind Speed, Turkey

Introduction

Since the industrial revolution in the 18th century, an intense energy requirement that has played a major role in the development of technology and industry has been increased. To meet that requirement, usually fossil fuels have been used. However, as the effects of global warming increase, renewable energy has gained importance and countries aim to reduce their greenhouse gas emissions and carbon footprint by increasing their investments in this sector. Wind energy, having a large place in the energy market due to its rapid growth, is the most important renewable energy throughout the world (Cassola and Burlando, 2012; Ülker et al., 2018; Kodak, 2022). It can be clearly seen from Figure 1 that after the 2000s, dramatic increases in wind energy capacity were recorded and this amount reached 18039 MW to 650758 MW in the 2000-2019 period.

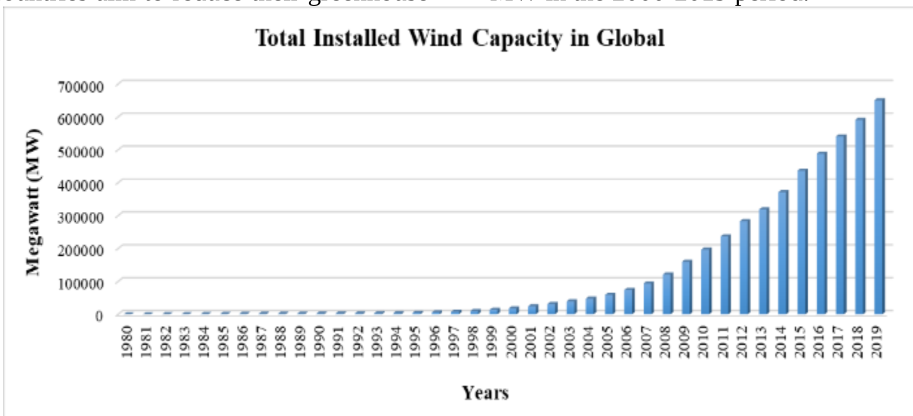


Fig. 1. Total installed wind capacity in global (WWEA, 2020).

Wind speed varies depending on synoptic systems and atmospheric conditions. For obtaining electrical energy from wind energy, it is important to have an appropriate wind forecast first. Making the correct estimation of the wind and estimating the energy to be produced increases the reliability and efficiency of all electricity grid systems. For this reason, lower costs for the electricity market means a more balanced market and at the same time less CO_2 emissions. By making the wind forecast correctly, reducing the costs integrated into the electricity grid provides the reduction of mandatory climate change and air pollution. (Wilczak et al., 2015; Mersin et al., 2021; Otter et al., 2021). Also, the forecasting of generated output power may be challenging because of not only the highly non-linear relationship between wind speed and output energy but being the stochastic time-varying due to local air properties and atmospheric composition (Sánchez, 2006). Methods including Lyapunov exponents, autocorrelation function, mutual information that is based on dynamical systems, and chaotic approaches must be implied in order to analyze the behavior of such systems (Karakasidis and Charakopoulos, 2009; Uzun and Ustaoğlu, 2022).

In literature, there are several studies have been conducted in various fields of study using chaotic approaches. For example, Brzozowska and Borowska (2016) have reconstructed phase space by using the Mutual Information Function method, False Nearest Neighbours method, and Cao’s method for EHG signals of Uterus. In addition, B. Kliková and A. Raidl (2011) have given information about some of the dynamical system approach for non-linear time series and tested their variants by using the TIme SEries ANalysis (TISEAN) program for both Lorenz and Henon systems. Jamil and Zeeshan (2018) have discussed the performance of NAR and NARX nonlinear autoregressive models and Mackey–Glass equation-based time series prediction on monthly wind speed variable measured in Gujarat, India. In Turkey, Yildirim and Altinsoy (2018) have found that monthly temperature dataset between 1960 and 2006 in the Marmara region shows possible chaotic underlying behavior according to positive Lyapunov exponent. In another study, Yilmaz et al. (2017) have investigated chaotic characteristics of sunshine duration and global solar irradiation data gathered from Diyarbakır, Gaziantep, Batman, and Mardin provinces by using Lyapunov Exponents and phase spaces. Also, Miraji (2015) have examined chaotic characteristics of wind speed data gathered from Atatürk Airport by inspecting Poincaré Section and Lyapunov exponents in order to detect the behavior in phase space and conducted an example of forecast study by using the TISEAN program. In another study, Vaheddoost and Koçak (2019) investigated the temporal dynamics of evaporation values for Lake Urmia in Iran with the help of chaos theory.

In this study, various methods are used in the chaotic approach to estimate hourly and daily wind speed characteristics: reconstruction of phase space, finding time delay by using Mutual Information Function (MIF) and determining minimum embedding size by using False Nearest Neighbours (FNN) method. Also, various error indicators (MSE, RMSE, MAE, MAPE) have been used to find out the performance of chaotic methods applied on daily and hourly windspeed datasets.

Material and Methods

Data and Study Area

Istanbul is a city acting as a bridge between the European and Asian continents (Governorship of Istanbul). The strait locating Istanbul connects the Aegean Sea to the south and the Mediterranean to the north (Figure 2). In this context, the direction of the Bosphorus and the hills in Istanbul shape the dominant wind direction as NE and SW.

Fig. 2. Map of Istanbul and location of the station

In the study, hourly and daily wind speed data are taken from the Turkish State Meteorological Service (MGM) were used. The observation period was taken for the hourly dataset as July to August 2015 to be for Florya station (40.9758 N,28.7843 E). In addition, the daily wind speed dataset period covering 5 years is taken as 2011-2015.

Methodology

In this study, TISEAN program containing nonlinear time series analysis methods based chaotic approach is used (Hegger et al., 1999). Time delays (τ) are determined with the help of MIF. Then, embedding sizes (m) are obtained by applying the FNN method. In addition, Mean Squared Error (MSE), Relative Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) have been used to test the performance of prediction.

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \qquad \text{(Eq. 1)}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \qquad \text{(Eq. 2)}$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |e_t| \qquad \text{(Eq.3)}$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \left|\frac{e_t}{y_t}\right| \qquad \text{(Eq.4)}$$

Reconstruction of Phase Space

The first step of the chaos theory method is the reconstruction phase space of the dynamics generating time series of a variable (Özgür and Koçak, 2011). Phase space is the space that contains all possible states of a system (Fig. 3). Therefore, any dynamic system can be expressed as a moving point in phase space. In addition, embedding variables such as embedding dimension and delay time must be found to create phase space (Koçak et al., 2004).

$$X(t_i) = [x(t_i), x(t_i+\tau), x(t_i+2\tau), \ldots, x((t_i+(m-1)\tau) \qquad \text{(Eq. 5)}$$

where the t_i represents time in phase space, i represents number of scalar variables, τ is time delay and m is the embedding dimension.

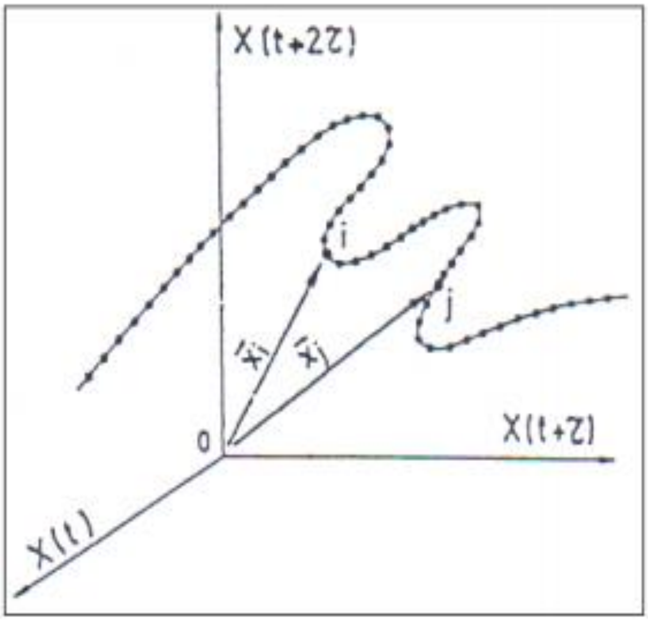


Fig. 3. Constructing the phase space from a state variable (Bergé et al., 1984).

There are two important reasons for the reconstruction of the phase space: understanding the complexity of the attractor and determining the behavior of the dynamic system (Baydaroğlu and Koçak, 2014).

Time Delay

Time delay (τ) must be chosen precisely when applying Takens (1981) the attractor reconstruction method. If a small value of tau (τ) is chosen, the values of e x [n] and x [n + τ] are almost equal. In this case, the system dynamics does not have enough time to change and makes gathering valuable information impossible. If a high value of tau is chosen the vectors will be located randomly in the phase space (Özgür, 2010). To find the time delay value, the Mutual Information Function (MIF) was chosen instead of the autocorrelation function. Since autocorrelation function is used where the data conform to the normal distribution and it measures linear dependence (Özgür and Koçak, 2011). Fraser and Swinney (1986) states that, the first minimum gives best result for choosing time delay in their recursive method of calculating mutual information and they also have suggested using MIF because it gives better results compared to auto-correlation function.

Determining the Minimum Embedding Size

Kennel et al. (1992) have proposed a method called False Nearest Neighbour (FNN) to determine sufficient embedding dimension. The main idea behind the method is if a variable in phase space is embedded in a lower-dimensional space, the variable is expected to appear as a neighbor with points that are not actually neighbor with variable. However, as the size gradually increased step by step, the percentage of these false neighborhoods will gradually decrease. In addition, if it is plotted the percentage of false closest neighborhoods by embedding size, the value corresponding to the minimum percentage value will indicate the requested embedding size (Kennel et al., 1992; Özgür and Koçak, 2016).

Application and Results

According to the Table 1 and Figure 4, hourly and daily wind speeds ranging 0.6 to 7.1 m/s have been taken as an input to the TISEAN program consist of 1825 and 1488 data points accordingly.

Table 1. Descriptive statistics of hourly and daily wind speed data

	Hourly wind speed	Daily wind speed
Count	1488	1825
Max	6.9	7.1
Min	0.6	0.6
Mean	2.97	2.53
Median	2.8	2.3
Std. Dev.	1.32	1.01

The time delay was calculated as 11 and 4 by using the MIF method for hourly and daily wind speed data, respectively (Figure 5). Embedding dimensions (m) are calculated by using the FNN method that using the time delay of the observed variables. Embedding dimensions were found as 4 and 3 for hourly and daily wind speed data, respectively (Figure 6).

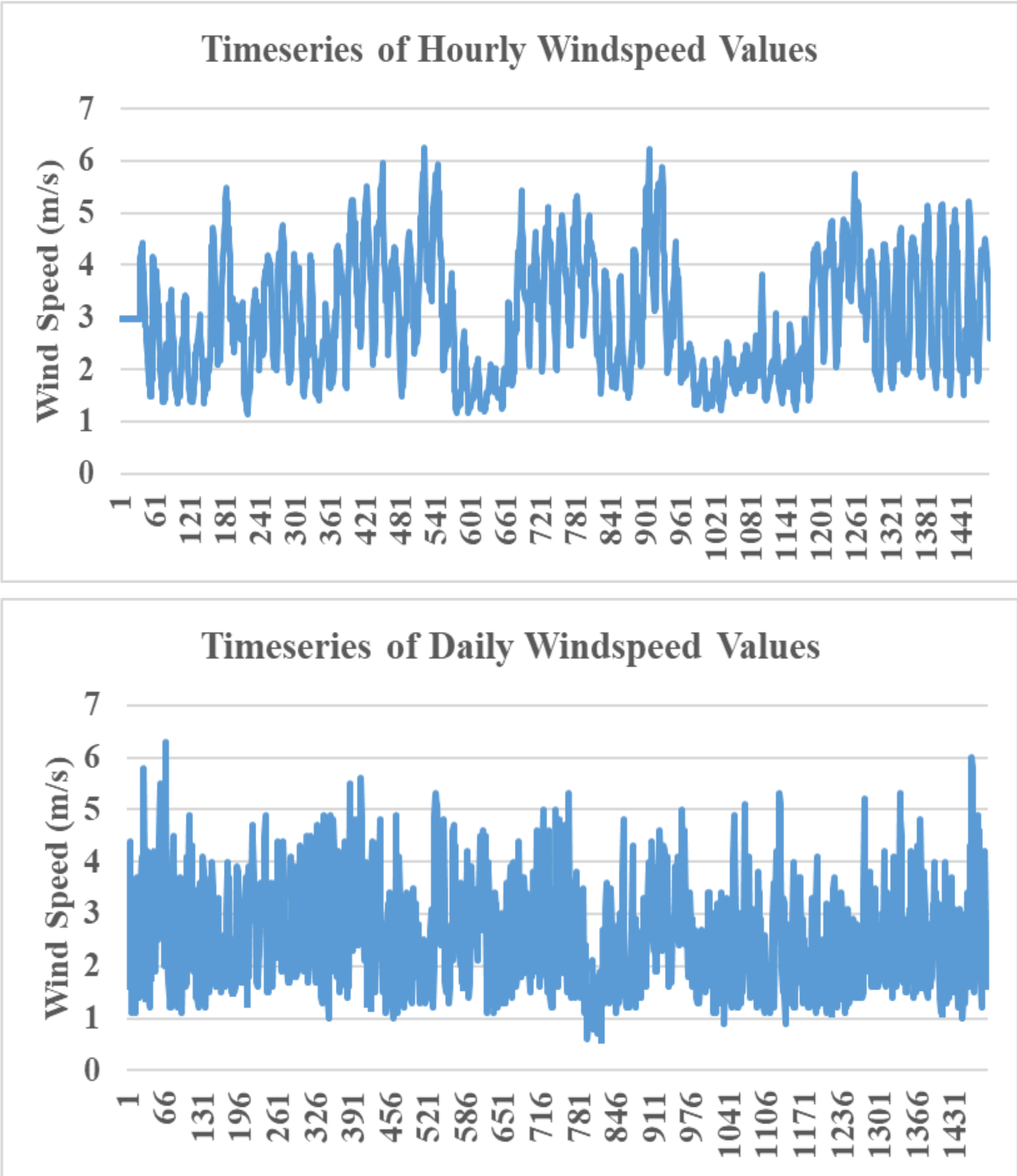
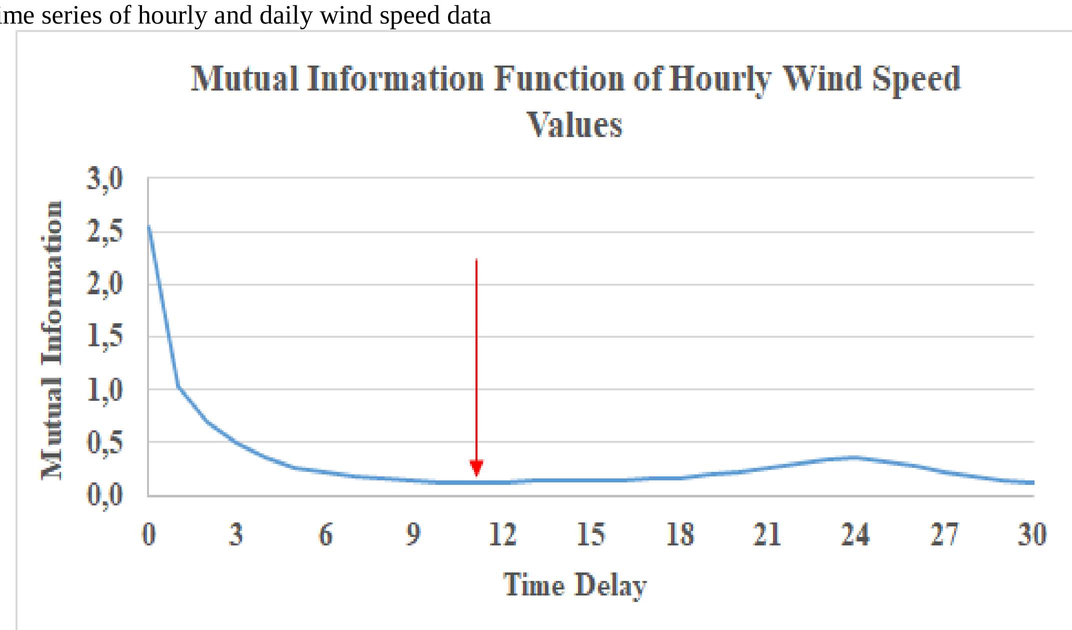


Fig. 4. Time series of hourly and daily wind speed data



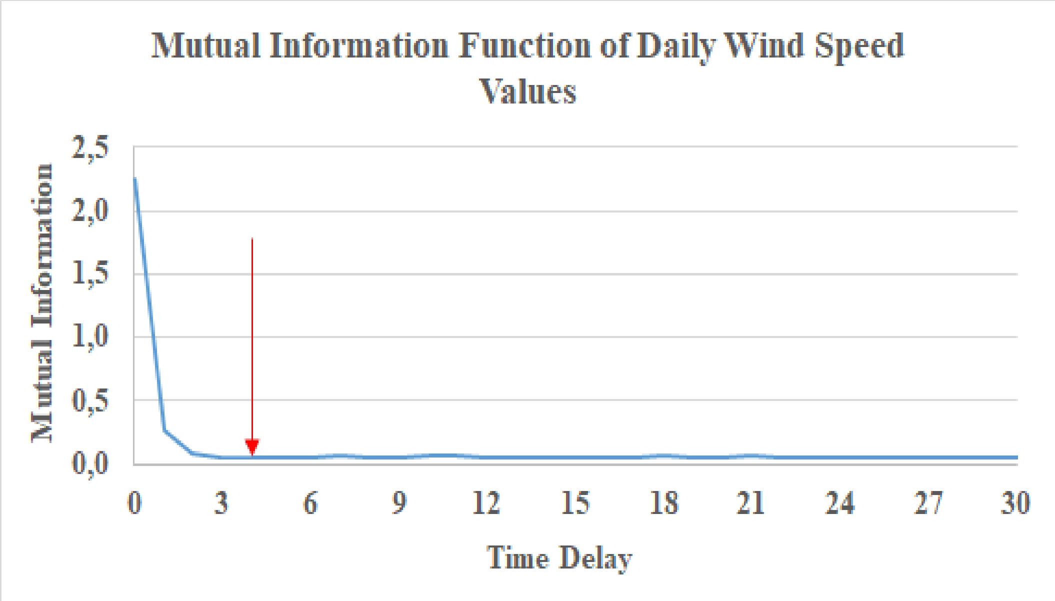


Figure 5. MIF of hourly and daily wind speed data.

Figure 6. FNN of hourly and daily wind speed data

By using predetermined time delay and embedding dimension information, predictions have been carried out. Predicted hourly and daily wind speed values ranging from 1.14 to 6.3 m/s have an average of 2.9 m/s and 2.5 m/s, respectively (Table 2). According to Figure 7, it is seen that the last 100 predicted values have been generally following the trend. However, the prediction did not give a particularly good result, especially where there are sharp peaks in the daily average wind variable.
In addition, it can be clearly seen that in Figure 8, the Pearson correlation coefficient was found as 0.92 in hourly wind speed data. In this context, this value shows a high relationship between the observed and the predicted data. In addition, the correlation coefficient was found as 0.59 in the daily mean wind data. It can be considered a lesser relationship compared to hourly wind speed data.

Table 2. Descriptive statistics of predicted hourly and daily wind speed data

	Hourly wind speed	Daily wind speed
Count	1488	1825
Max	6.25	6.30
Min	1.14	1.14
Mean	2.97	2.52
Median	2.79	2.43
Std. Dev.	1.15	0.60

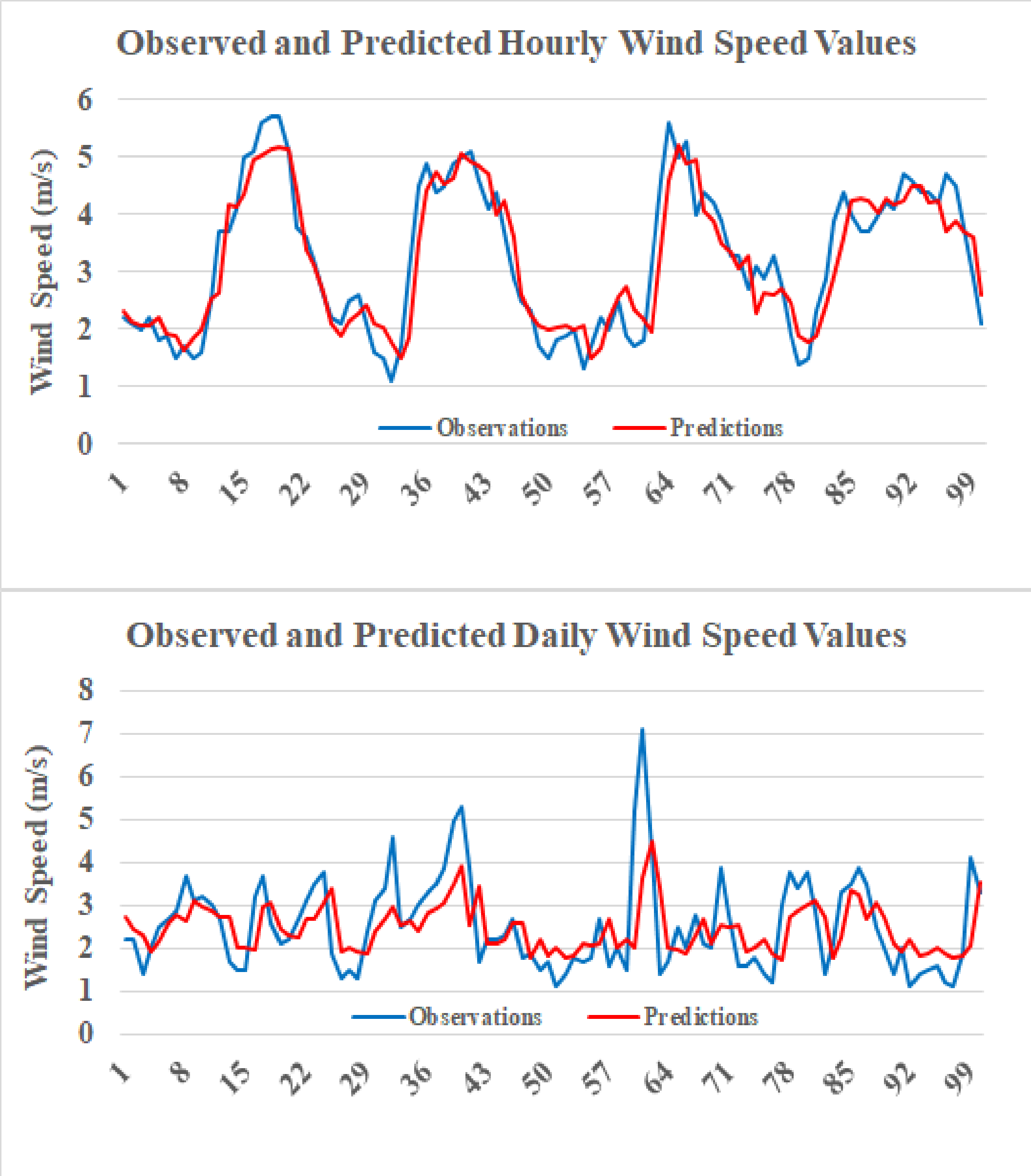
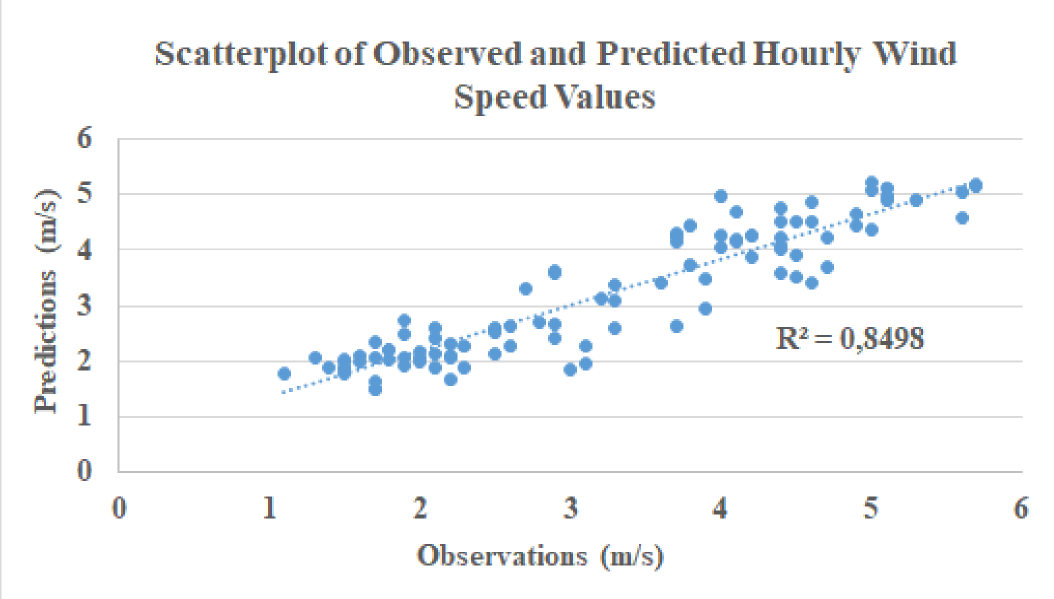


Fig. 7. Observed and predicted hourly and daily wind speed



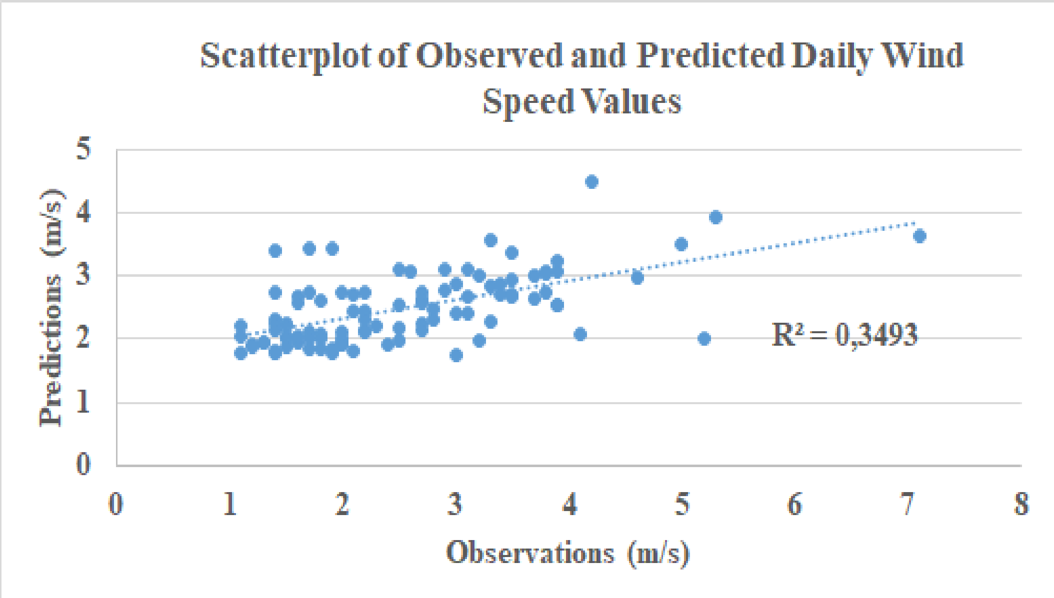


Fig.8. Scatterplot of observed vs predicted hourly and daily wind speed.

In order to test the performance of the chaotic approach, error metrics have been used. Root Mean Square Error (RMSE) indicating data points are how far from the regression line is commonly used in testing predictions. According to Table 3, RMSE has been found 0.47 and 0.85 in hourly and daily dataset, respectively. In addition, Mean Absolute Error (MAE) measuring the difference between two data is found to be 0.36 and 0.67 in the same datasets.

Table 3. Error metrics of predicted variables

	Hourly wind speed	Daily wind speed
MSE	0.22	0.73
RMSE	0.47	0.85
MAE	0.36	0.67
MAPE	16.14	29.78

Conclusions and Recommendations

The prediction of wind speed, which is a particularly important variable in energy production, is more challenging than other temporal and spatially changing meteorological variables. Different methodologies including chaotic approach must be used for improving prediction of wind speed. In this study, the prediction of daily and hourly average wind speed data of meteorology station located in Istanbul, Florya was made using the chaotic approach. In order to do this, phase space has been re-constructed. Also, time delay was determined by using Mutual Information Function in TISEAN program. Then, for this time delay, the embedding dimension was found by using False Nearest Neighbor approach and finally, the phase spaces were reconstructed. Daily wind speeds of two stations were estimated using the local prediction method.

Given the character of the wind data, the results are very promising. Predictability is restricted because wind data are inherently more complex and show sudden changes compared to other meteorological variables. As a result of the application of the method, a correlation of 0.92 has been observed between the measured and predicted values of the hourly average wind speeds of the station. In addition, a lesser correlation with 0.59 has been found in daily average wind dataset. Also, estimates made using chaotic methods generally followed the trend of observation. However, deviations were observed in the sharp peaks and therefore the Pearson correlation coefficient was found to be low in the daily wind average. Error metrics and correlation values obtained because of the study show the applicability of chaotic methods for the forecasting wind speed. In the future, to obtain a comprehensive view of chaotic method applicability, it is recommended that comparing with Numerical Weather Prediction (NWP) model or Machine Learning (ML) algorithms outputs.

The results attained from this study will help decision-makers for planning and managing wind-based sectors such as energy and weather forecast. In the future, it is planned to apply the method for more stations and more meteorological variables in order to obtain regional results all over the country.

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