

Wind Speed Forecasting using Time Series Analysis Methods

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Abstract

As a natural, non-consumable, clean and sustainable energy resource, wind energy is becoming crucial throughout the world. Forecasting wind speed is noteworthy to design and install wind power stations. In this study, several time series analysis methods for wind energy were compared considering long-term-monthly-average wind speed data between the years of 1960 and 2014 at nine meteorological stations throughout five geographical areas in Turkey. The low performance measure values seen in results indicate that the methods used in this study can be forecast for wind speed.

Keywords: Wind energy, Wind speed forecasting, Time series analysis methods, Statistical performance measures

Zaman Serisi Analiz Metotları Kullanılarak Rüzgâr Hızının Tahmin Edilmesi

Öz

Doğal, tükenmeyen, temiz ve sürdürülebilir bir enerji kaynağı olduğundan rüzgâr enerjisi dünyada önem kazanmaktadır. Rüzgâr enerjisi istasyonlarının tasarlanması ve kurulması için rüzgâr hızı tahmini önemlidir. Bu çalışmada, Türkiye'deki beş farklı coğrafi bölge ve dokuz meteorolojik istasyondan 1960 ve 2014 yılları arasındaki uzun dönemli aylık ortalama rüzgâr hızı verileri dikkate alınarak rüzgâr enerjisi için farklı zaman serisi analizi metotları karşılaştırılmıştır. Çalışmanın sonucunda elde edilen düşük performans ölçüm değerleri, rüzgâr hızı tahminleri için bu çalışmada ele alınan metotların kullanılabilirliğini göstermektedir.

Anahtar Kelimeler: Rüzgâr enerjisi, Rüzgâr hızı tahmini, Zaman serisi analizi metotları, İstatistiksel performans ölçümleri

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1. INTRODUCTION

With developing technology, the energy need of countries is increased. A great majority of this need is currently met from fossil fuel. Owing to the decrease of fossil fuel reserves and increase in environmental pollution, the studies interested in renewable energy sources are becoming crucial. Among renewable energy sources, wind energy is, commercially, one of the most optimum renewable energy sources [1]. Therefore, the use of wind energy is predicted to increase throughout the world.

There are many of methods to analyze wind speed in literature. Lun and Lam [2] examined three locations and 30 years of long-term wind records using Weibull distribution parameter. Ewing et al. [3] studied time series analysis of wind speed using vector autoregression. In this study, wind speed data was measured in the same location at four different heights. A statistical analysis on the wind energy of Turkey's was presented by Togrul and Ertekin [4]. Su et al. [5] presented correlation analysis for wind speed and failure rate using time series analysis. Assareh et al. [6] used artificial neural networks for wind speed prediction. Shu et al. [7] presented statistical analysis of wind characteristics and wind energy potential in Hong Kong using Weibull distribution model. They examined six-years of wind data at five meteorological stations in Hong Kong; they found the highest Weibull scale parameter on a hilltop, and the lowest at an urban site. Zhang et al. [8] presented prediction study and application of wind power development based on filtering error threshold. Saberivahidaval and Hajjam [9] studied a comparison between performances of different neural networks for wind speed forecasting. Zuluaga et al. [10] presented short-term wind speed prediction based on robust Kalman filtering. Based on support vector regression, a hybrid methodology for wind speed forecasting was presented by Santamaria- Bonfil et al. [11]. They used wind speed data from the Mexican Wind Energy Technology Center to evaluate their method. Support vector machine method was used to predict wind speed at hub-height by Mohandes

et al. [12]. Ambach and Croonenbroeck [13] investigated three years of data from seven weather stations in order to forecast short to medium term wind speed. A periodic vector autoregressive model with seasonal lags was used in their model. Doucoure et al. [14] developed a prediction method for renewable energy sources. They presented an application for wind speed data using time series prediction with artificial wavelet neural network and multi-resolution analysis. Liu et al. [15] are used correction methods based on multiple linear regression, radial basis function neural network and Elman neural network to estimate wind speed and analyze the effect on the wind power forecasting. Jiang et al. [16] developed a hybrid forecasting model based on simulation annealing algorithm and they presented a case study of wind speed forecasting. Cadenas et al. [17] compared a univariate ARIMA model and a multivariate NARX model for prediction wind speed. Huang et al. [18] developed a hybrid model to forecast short term wind speed.

To use wind energy, wind power stations should be installed in countries. And, to install wind power stations, the geographical position of wind speed in countries should be investigated. So; in this paper, it is proposed to determine wind speed forecasting throughout five geographical areas in Turkey using time series analysis. Moving average method, exponential smoothing method, exponential smoothing with trend method, and exponential smoothing with trend and seasonality method was used for forecasting. To evaluate the models' performance, mean error (ME), mean absolute error (MAE) [11, 19-20], mean square error (MSE), mean absolute percentage error (MAPE) [8, 17] and root mean square error (RMSE) [8, 11, 19-20] statistics were calculated. The low performance measure values seen in results indicate that the methods used in this study can be forecast for wind speed.

The paper unfolds as follows: Section 2 presents the study area and using methodology. In section 3, results are given for each of the meteorological stations and finally, the conclusion is presented in section 4.

2. STUDY AREA AND METHODOLOGY

2.1. Study Area

Wind energy is a clean, renewable, natural, and eco-friendly energy sourced from the sun. Solar heat is not homogenous in the earth nor its atmosphere. Because of this, temperature and pressure differences occur. As a result of temperature and pressure differences, air flow occurs. In consequence of the air flow, air masses change place resulting in wind. Turkey can be considered as a successful production point as it has a rich geographical position in respect to wind energy. The distribution of average wind speed by region in Turkey seen in Table 1.

Table 1. Distribution by regions of average wind speed in Turkey (10 meters in height) [21]

Geographical region	Average wind speed (m/s)
Marmara	3.3
Southeastern Anatolia	2.7
Aegean	2.7
Mediterranean	2.5
Black Sea	2.4
Central Anatolia	2.5
Eastern Anatolia	2.1

Table 2. Observation network

Geographical region	Station	Latitude	Longitude
Mediterranean	Osmaniye	37.1021	36.2539
Black Sea	Corum	40.5461	34.9362
Mediterranean	Adana	37.0041	35.3443
Black Sea	Tokat	40.3312	36.5577
Mediterranean	Mersin	36.7808	34.6031
Marmara	Canakkale	40.1410	26.3993
C. Anatolia	Cankiri	40.6082	33.6102
S. Anatolia	Adiyaman	37.7553	38.2775
C. Anatolia	Kirsehir	39.1639	34.1561

In this study, nine meteorological stations with five geographical areas in Turkey (the data for Aegean and Eastern Anatolia geographical areas are not obtained) are investigated seen in Table 2.

2.2. Methodology

2.2.1. Time Series Analysis Methods

Time series analysis methods are the methods which used previously observed data to predict future data by means of statistical models. The most commonly used time series methods are moving average method (eq. 1), exponential smoothing method (eq. 2), exponential smoothing with trend method (eq. 3-4) and exponential smoothing with trend and seasonality method (eq. 4-7) [22].

Moving average method (MA) calculated as;

$$MA_n = \frac{1}{n} \sum_{i=1}^n A_i \quad (1)$$

where, n= number of observation, A_t = actual value at observation t.

Exponential smoothing method calculated as;

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t \quad (2)$$

where α =smoothing constant, F_t = forecast value for observation t.

Exponential smoothing with trend method calculated as;

$$F_t = \alpha A_t + (1-\alpha)(F_{t-1} + T_{t-1}) \quad (3)$$

$$T_t = \beta(F_t - F_{t-1}) + (1-\beta)T_{t-1} \quad (4)$$

where β =smoothing constant for trend,

T_t = smoothed trend for observation t.

Exponential smoothing with trend and seasonality method (Holt-Winters seasonal method) calculated as;

$$T_t = \beta(F_t - F_{t-1}) + (1-\beta)T_{t-1} \quad (4)$$

$$F_t = \alpha \frac{A_t}{I_{t-m}} + (1-\alpha)(F_{t-1} + T_{t-1}) \quad (5)$$

$$I_t = \gamma \frac{A_t}{F_t} + (1-\gamma)I_{t-m} \quad (6)$$

$$F_{t+1} = F_t * I_{t+1-m} \quad (7)$$

where γ =smoothing constant for seasonality,

I_t = seasonal factor for observation t, m =the period of the seasonality.

2.2.1. Statistical Performance Measures

To examine the adequacy of proposed models, it should be investigated in terms of the errors in the proposed models. For this purpose, mean error (ME) (eq.9), mean absolute error (MAE) (eq.10), mean square error (MSE) (eq.11), mean absolute percentage error (MAPE) (eq.12) and root mean square error (RMSE) (eq.13) are used as statistical performance measures.

$$e_t = A_t - F_t \quad (8)$$

$$ME = \frac{1}{n} \sum_{t=1}^n e_t \quad (9)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |e_t| \quad (10)$$

$$MSE = \frac{1}{n} \sum_{t=1}^n e_t^2 \quad (11)$$

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left(\frac{e_t}{A_t} \right) \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2} \quad (13)$$

where, n = number of observation, A_t = actual value at observation t, F_t = forecast value for observation t and e_t = error value at observation t.

3. RESULTS AND DISCUSSIONS

The long-term-monthly-average-wind-speed data between the years of 1960 and 2014 for each

station are shown in Table 3 and the descriptive statistics for each station are shown in table4.

The forecast models for each meteorological station are seen in Figure1. The performance measure values (ME, MAE, MSE, MAPE and RMSE) can be seen in Table 5. For a good forecasting model, performance measure values should be low [11]. ME near-zero shows there is not a bias in forecast [22]. MAE shows the proximity between the forecast and actual value at observation [23]. MAPE shows percentage error in forecast [22]. RMSE says there is not a bias in errors and fit a normal distribution [11, 23].

Based upon the data in Table 5, it can be said that exponential smoothing with trend and seasonality model is the best fit for all stations.

4. CONCLUSION

Wind energy is a natural, non-consumable, native, sustainable resource for countries. It does not cause acid rains, atmospheric heating and carbon-dioxide emission. In addition to these advantages, it is not a negative effect to natural vegetation and human health. Also, wind power stations can be put into use in a short time and can be removed in a short time, too. Therefore, this provides ease of investment for countries. On the other hand, wind power stations have some disadvantages as noise, visual pollution, cause of bird death (if the stations are installed on the migration route) and cause interference on radio and television receiver within 2-3 km² area.

A lot of wind speed forecasting models have been studied in literature to develop long-term wind speed forecasting correctness. In this study, to forecast wind speed, moving average method, exponential smoothing method, exponential smoothing with trend method, and exponential smoothing with trend and seasonality method were used at nine meteorological stations in five geographical areas in Turkey. Considering the values of ME, MAE, MSE, MAPE and RMSE, it is seen that the lowest values of error were obtained by exponential smoothing with trend and

seasonality model. Therefore, it can be said that forecast values of data are affected by seasonal fluctuations. Furthermore, seen in forecast values obtained from the forecast models in this study, it can be said that Turkey with a rich geographical position can be considered as a successful production point in respect to wind energy.

4. ACKNOWLEDGEMENTS

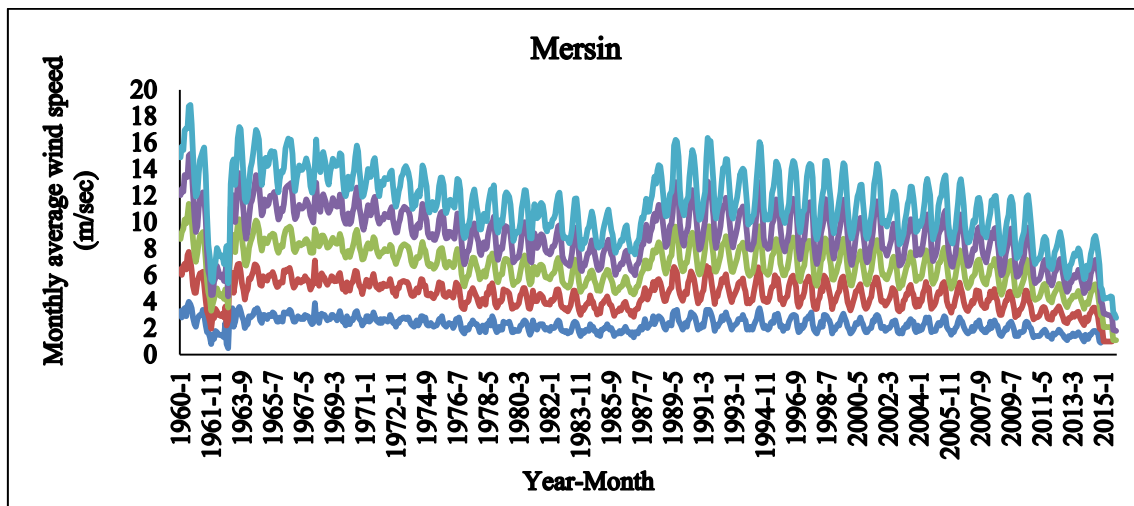
The author would like to thank Turkish State Meteorological Service for sharing information, and the reviewers for their contributions to the paper.

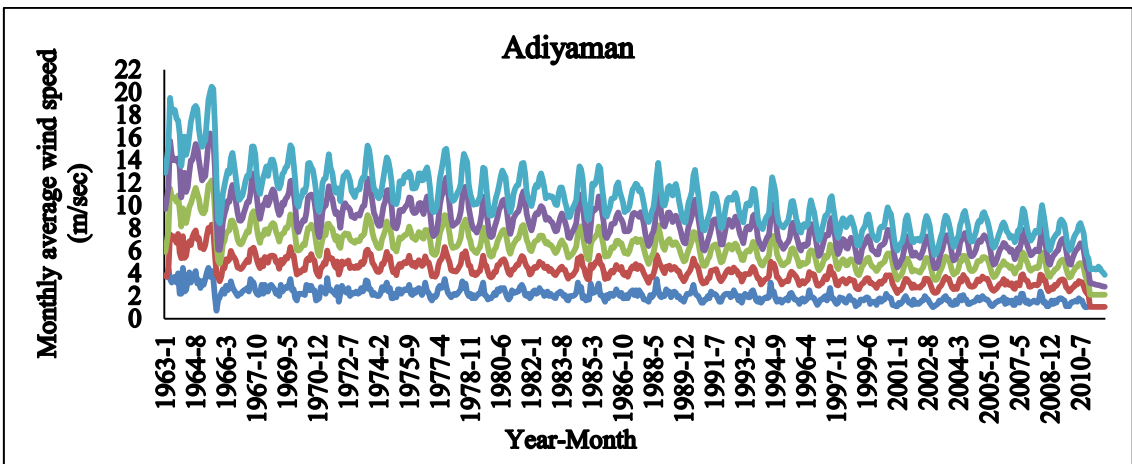
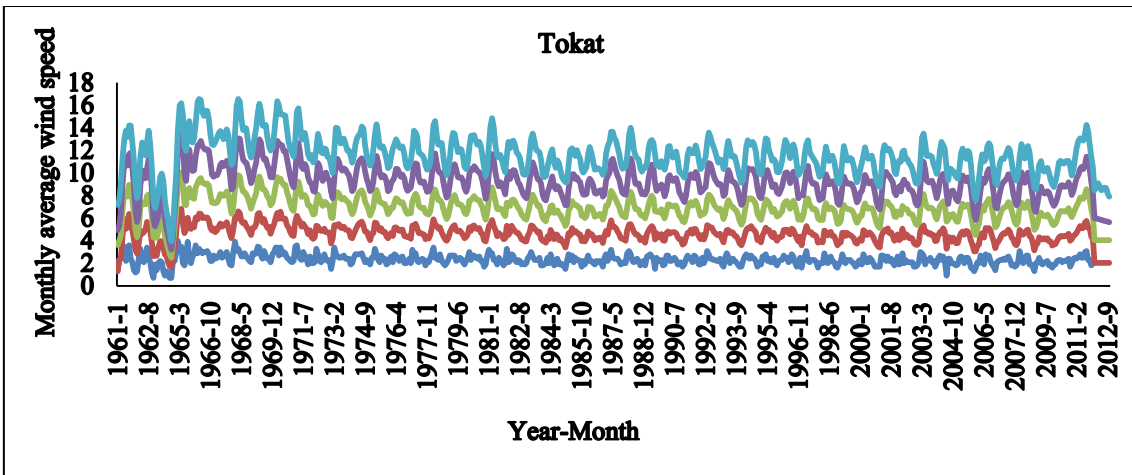
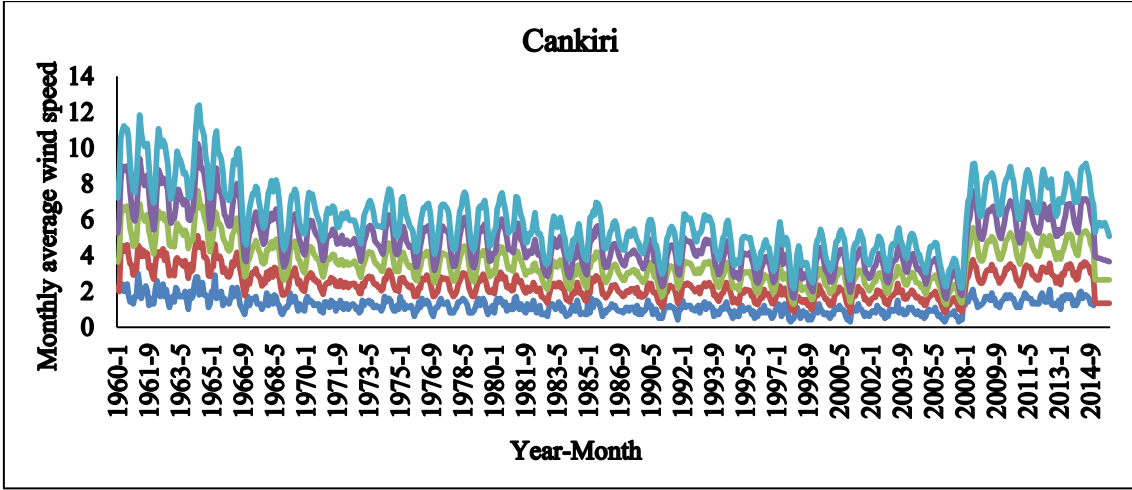
Table 3. Long-term-monthly-average-wind-speed for each station (m/sec)

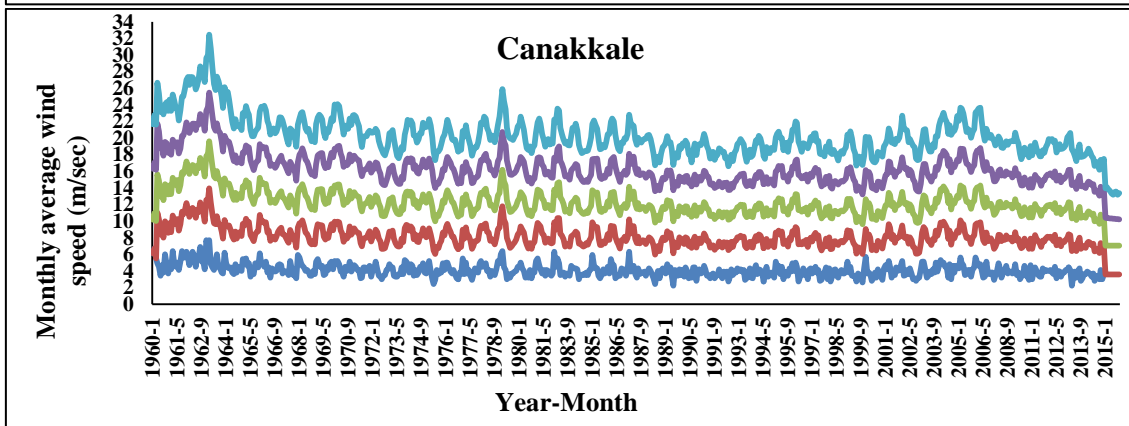
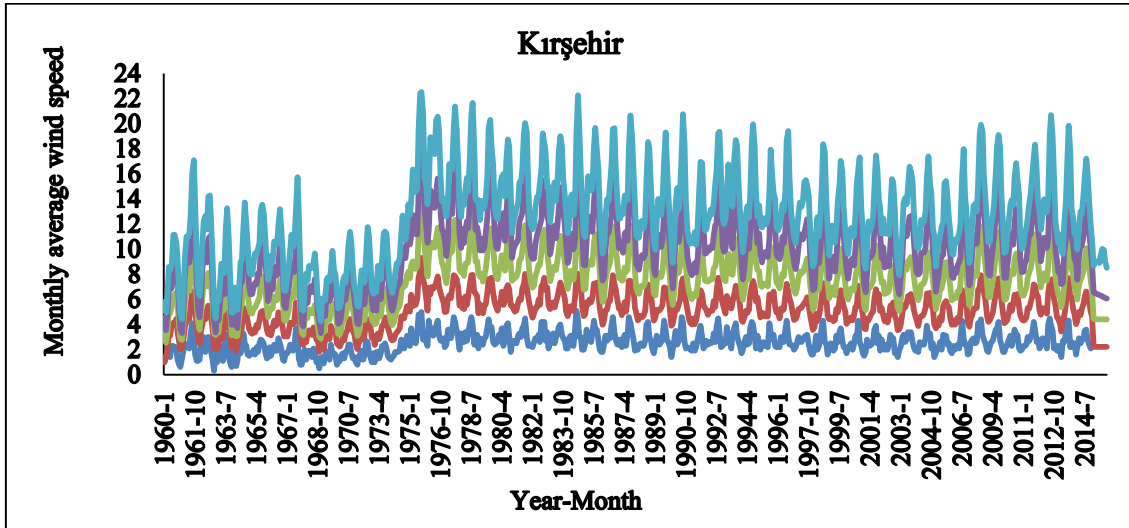
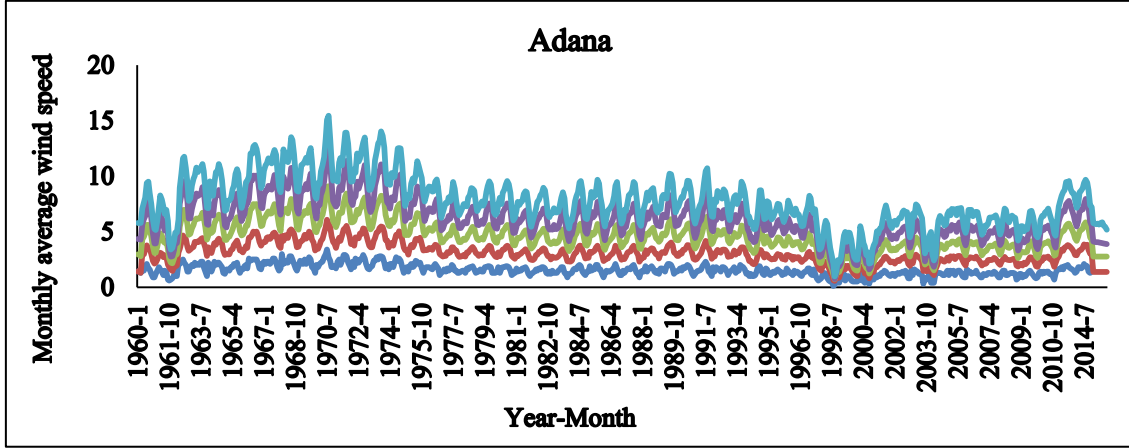
	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec
Mersin	2.1	2.1	2.2	2.3	2.4	2.7	2.7	2.6	2.3	2.0	1.8	2.0
Cankiri	1.0	1.2	1.4	1.5	1.3	1.4	1.4	1.3	1.1	1.0	0.9	0.9
Tokat	2.3	2.5	2.8	2.6	2.3	2.3	2.5	2.5	2.1	1.9	1.9	2.1
Adiyaman	1.9	2.0	2.1	2.1	2.1	2.5	2.4	2.2	2.0	1.7	1.7	1.8
Adana	1.5	1.5	1.6	1.6	1.7	1.8	1.9	1.7	1.5	1.2	1.2	1.4
Kirsehir	2.0	2.3	2.5	2.5	2.4	2.9	3.7	3.5	2.7	2.2	1.9	1.9
Canakkale	4.5	4.7	4.3	3.9	3.6	3.4	3.9	4.0	3.8	4.0	4.1	4.6
Osmaniye	1.4	1.6	1.7	1.8	1.8	2.0	2.1	1.9	1.6	1.2	1.0	1.2
Corum	1.3	1.6	1.9	2.0	1.9	2.1	2.6	2.6	2.0	1.5	1.2	1.3

Table 4. Descriptive statistics for each station

	Mersin	Cankiri	Tokat	Adiyaman	Adana	Kirsehir	Canakkale	Osmaniye	Corum
Mean	2.3	1.2	2.3	2.1	1.6	2.5	4.1	1.6	1.8
Max	4.0	3.0	4.0	4.5	3.4	5.1	7.7	3.4	5.2
Min	0.5	0.3	0.7	0.7	0.1	0.3	2.2	0.1	0.2
Std. Dev.	0.55	0.44	0.47	0.62	0.51	0.84	0.79	0.51	0.76







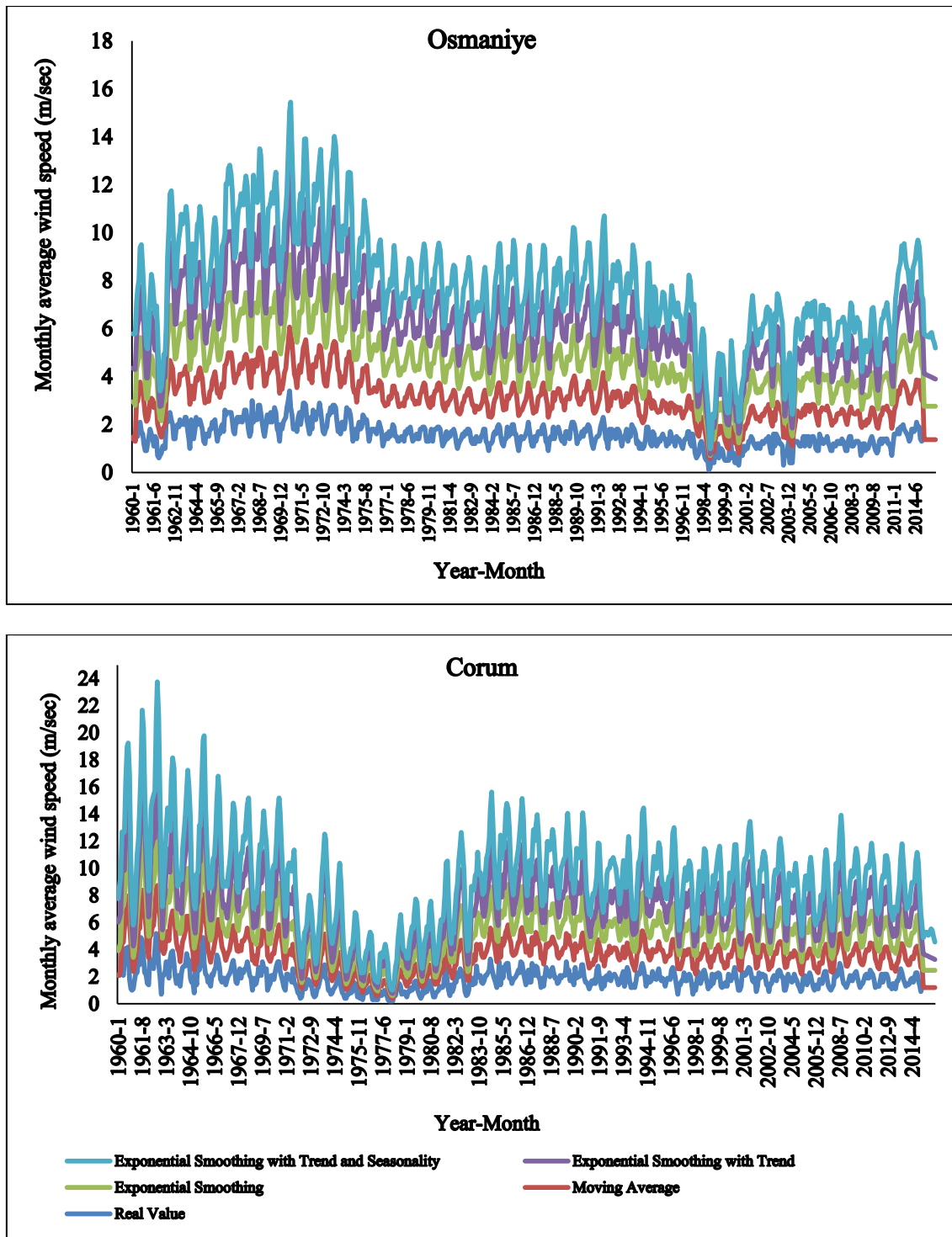


Figure 1. Forecast models for stations

Table 5. Statistical performance measure values

Mersin Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.9$)	Exponential Smoothing with Trend ($\alpha=0.9; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.4; \beta=0.1; \gamma=0.1$)
ME	-0.0066	-0.0020	-0.0006	-0.0000
MAE	0.3087	0.2504	0.2594	0.1902
MSE	0.1571	0.1110	0.1196	0.0732
MAPE	14.5356	11.6189	11.9825	8.7390
RMSE	0.3964	0.3332	0.3458	0.2705
Çankırı Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.6$)	Exponential Smoothing with Trend ($\alpha=0.6; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.2; \beta=0.1; \gamma=0.1$)
ME	-0.0022	0.0003	-0.0008	-0.0027
MAE	0.2390	0.2253	0.2340	0.1869
MSE	0.0977	0.0872	0.0950	0.0586
MAPE	22.2986	20.6840	21.3859	17.0070
RMSE	0.3126	0.2953	0.3082	0.2421
Tokat Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.6$)	Exponential Smoothing with Trend ($\alpha=0.6; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.2; \beta=0.1; \gamma=0.1$)
ME	-0.0007	-0.0009	-0.0012	-0.0003
MAE	0.3672	0.3386	0.3527	0.2578
MSE	0.2269	0.1921	0.2106	0.1299
MAPE	16.6566	15.3031	15.794	11.8490
RMSE	0.4763	0.4383	0.4589	0.3604
Adıyaman Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.6$)	Exponential Smoothing with Trend ($\alpha=0.7; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.1; \beta=0.1; \gamma=0.1$)
ME	-0.0105	-0.0030	-0.0008	-0.0031
MAE	0.3228	0.3037	0.3163	0.2384
MSE	0.1856	0.1684	0.1784	0.1131
MAPE	16.2832	14.8524	15.4053	11.7487
RMSE	0.4308	0.4104	0.4224	0.3363

Adana Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.9$)	Exponential Smoothing with Trend ($\alpha=0.9; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.4; \beta=0.1; \gamma=0.1$)
ME	-0.0001	-0.0003	-0.0004	-0.0014
MAE	0.2710	0.2304	0.2405	0.1814
MSE	0.1173	0.0872	0.0954	0.0584
MAPE	20.9066	17.3591	17.9874	14.6885
RMSE	0.3425	0.2953	0.3089	0.2417
Kirsehir Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.9$)	Exponential Smoothing with Trend ($\alpha=0.9; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.2; \beta=0.1; \gamma=0.1$)
ME	0.0019	-0.0006	-0.0010	-0.0074
MAE	0.6115	0.5331	0.5558	0.3575
MSE	0.5791	0.4421	0.4811	0.2077
MAPE	27.3638	23.2086	23.9201	16.0407
RMSE	0.7610	0.6649	0.6936	0.4557
Canakkale Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.1$)	Exponential Smoothing with Trend ($\alpha=0.1; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.1; \beta=0.1; \gamma=0.1$)
ME	-0.0081	-0.0095	-0.0024	-0.0073
MAE	0.5895	0.5557	0.5749	0.4825
MSE	0.5890	0.5018	0.5397	0.3858
MAPE	14.7832	13.9642	14.4076	12.1024
RMSE	0.7674	0.7084	0.7346	0.6211
Osmaniye Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.9$)	Exponential Smoothing with Trend ($\alpha=0.9; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.4; \beta=0.1; \gamma=0.1$)
ME	-0.0001	-0.0003	-0.0004	-0.0014
MAE	0.2710	0.2304	0.2405	0.1814
MSE	0.1173	0.0872	0.0954	0.0584
MAPE	20.9066	17.3591	17.9874	14.6885
RMSE	0.3425	0.2953	0.3089	0.2416
Corum Station				
Performance measure	Moving Average	Exponential Smoothing ($\alpha=0.9$)	Exponential Smoothing with Trend ($\alpha=0.9; \beta=0.1$)	Exponential Smoothing with Trend and Seasonality ($\alpha=0.2; \beta=0.1; \gamma=0.1$)
ME	-0.0035	-0.0010	-0.0008	-0.0158
MAE	0.4886	0.4064	0.4242	0.3048
MSE	0.3945	0.2805	0.3072	0.1620
MAPE	32.3636	25.2254	26.1184	19.1555
RMSE	0.6281	0.5296	0.5543	0.4025

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