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COMPARING TIME SERIES FORECASTING METHODS TO ESTIMATE WIND SPEED IN KIRIKKALE REGION

ABSTRACT

Due to the non-storable nature of electric energy, short-term and long-term electricity generation and consumption forecast are critical to keeping electricity market in balance. In addition, the production estimate of wind energy is parallel to the estimate of wind speed. Since wind speed forecasts includes seasonal and time-dependent trends, time series forecasting methods produce successful results in wind energy forecasting. However, choosing the most appropriate time series forecasting method for short-term and long-term production forecasts is of special importance. In this study, short-term and long-term wind speed estimations were made for the wind turbine at Kırıkkale University by using Exponential Smoothing (ES) and ARMA (Auto Regressive Moving Average) methods. The most suitable methods for forecasting short-term and long-term wind speed have been determined with the obtained results.

Keywords: Wind Energy, Time Series, Forecasting, ARMA, ES

1. INTRODUCTION

With increasing human population and evolving technology, electronic devices, which are increasingly entering our lives, continue to increase electricity demand. Since fossil fuels used in electricity generation are limited and the impact on the environment is detrimental, developed countries plan their own energy production policies on the use of renewable energy sources [1]. One of the most common uses of renewable energy resources is wind energy. However, the stochastic and intermittent characteristic of the wind makes the energy obtained from this form constantly vary. Because of the high cost and complexity of solving this problem in wind energy, producers often prefer to transmit the generated energy directly to the electricity grid. This causes problems of instability and imbalance on the electricity grid [2]. In order prevent this imbalance in the grid, estimating the production of renewable energy resources at high precision is one of the most appropriate solutions. When the amount of energy produced by renewable energy sources is estimated, it is possible to plan the operation of the electricity grid with other energy resources and the grid uncertainty can be minimized. Various methods have been investigated in the literature to estimate wind speed and wind energy production. Okumus and Dinler have developed a hybrid method by combining ANFIS and ANN methods for the hourly estimation of wind energy in their work. Thanks to the algorithm they developed, they obtained successful results in the results ranging from 2.25% to 3.85% with MAPE metric for the data in different location [3]. A hybrid ANN-ANFIS system has been proposed for online prediction of effective wind speed. Predictors performance have been investigated for the National Renewable Energy Laboratory (NREL), a 5 MW offshore wind turbine, and the simulation results obtained from the proposed system shows the satisfactory results [4]. Nikolic et al. presented a new model based on the extreme learning machine (ELM) for sensorless estimation of wind speed based on wind turbine parameters. In the study where the wind turbine power coefficient, blade angle and rotation speed are taken as inputs and wind speed is estimated, in order to confirm the ELM model, the results were compared with predictions with genetic programming (GP), artificial neural network (ANN) and Radial Basis Function kernel SVM (SVM-RBF). The results clearly demonstrate that the improved algorithm can be used effectively in estimating sensorless wind speed [5]. Cheng et al. suggests that estimating of wind power production up to 3 hours may be improved by integrating wind speed data from anemometers that wind turbines have in an air prediction system. With the developed technique, it is revealed that the mean absolute error can be reduced up to 30%-40% on the basis of the six-day case study [6]. Kantar et al., used the Extended Generalized Lindley distribution (EGLD) for the first time to find the potential for wind energy in a particular region. The EGLD is flexible enough to accommodate different wind speed data and includes other forms of Lindley's distribution for special cases. In addition, tests were conducted on actual wind speed data measured in various regions of Turkey to test the performance of the EGLD.

The results of the analyzes show that EGLD is more appropriate than the Wiebull Distribution compared to the cases of wind speed data examined. For this reason, EGLD can be used as an alternative distribution for assessing the wind energy potential [7]. Wang et al. examined and compared forecasting methods using popular parametric and nonparametric models for wind speed probability distribution in four different regions of China [8]. In this study, combined wind speed estimation approaches are used to estimate wind speed. To examine the methods in detail, a combination model of negative constraint theory (NNCT) and artificial intelligence algorithm is proposed [9]. Neural network-based controls have been used to estimate the wind speed and hence the wind-generated energy without using wind speed sensors [10,11]. ANN-based techniques for wind energy estimation and MPPT power monitoring are also proposed [12].

2. RESEARCH SIGNIFICANCE

Energy forecasting has vital importance for electricity market operation. Because of the uncertain nature of the renewable energy resources especially wind energy cause several problems in electricity balance market, some power quality problems for distribution companies. Wind speed based energy forecasting also various benefits for wind turbine itself since estimating wind speed provides control system to take precaution protect wind turbine components. In this study, the wind speed is tried to be estimated by selecting three important algorithms working based on time series. Algoritms are compared in the basis of produced energy from wind turbine. Obtained results shows the successfulness of the algorithms.

3. MATERIALS AND METHODS

3.1. Autoregressive Moving Average Method

The Autoregressive Moving Average Method (ARMA) is also known as Box and Jenkins Method, a time series method that is used to estimate the future time interval with the same time interval looking at the data distribution at equal time intervals. This method gives estimated data as linear data polynomial from actual data and old estimation error [13]. ARMA method can be represented with following equation;

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (1)$$

ARMA model consist of AR and MA process. Given equation represents basic combination of both AR and MA process. The AR(p) model shows that there is a linear combination of a noise term on a situation that occurs at a time t and a previous state. AR process can be represented with following equation;

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \quad (2)$$

where; p represents order of model, c represents constant, φ represents parameters of model and ε_t represents noise error. MA (q) identifies the correlated noise structure on our set of data and takes forward the traditional assumption that errors are occurring. MA process can be represented with following equation;

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (3)$$

where; r represents order of model, μ represents expectation of model, θ represents parameters of model and ε_t represents noise error. ARMA method has extensive usage on many areas and it gives satisfactory results.

3.2. Exponential Smoothing

Exponential smoothing, a popular method that is used to forecast Time Series. Considering the moving average based methods deal with equal time intervals, exponential smoothing method deals with exponential time intervals. This situation provides recent data has more impact according the previous data on observations [14]. Exponential smoothing method can be represented with following equation [15];

$$ES_t = \alpha y_{t-1} + (1-\alpha) ES_{t-1} \quad (4)$$

In this equation ES_t represents smoothed value with time period t and α smoothing constant. Using of moving averages, the data weights assigned to equal for estimating future data, but using exponential smoothing, smoothing parameters determine the weights assigned to observation for estimating future data. In this study, we have used Triple Exponential Smoothing method cause of our data contains trend and seasonality. If data contains trend and seasonality basic smoothing approach does not work and we must care of seasonality and trend on overall process. Triple Exponential Smoothing method can be represented with following equations, these equations are also known as "Holt-Winters" (HW) method to respect the inventors.

$$ES_t = \alpha \frac{y_t}{I_{t-L}} + (1-\alpha)(ES_t + b_{t-1}) \qquad \text{Overall Smoothing}$$

$$b_t = \gamma(ES_t - ES_{t-1}) + (1-\gamma) b_{t-1} \qquad \text{Trend Smoothing}$$

$$I_t = \beta \frac{y_t}{S_t} + (1-\beta) I_{t-L} \qquad \text{Seasonal Smoothing}$$

$$F_{t+m} = (ES_t + m b_t) I_{t-L+m} \qquad \text{Forecast}$$

y: Represents Observation
ES: Represents Smoothed Observation
b: Represents Trend Factor
I: Represents Seasonal Index
F: Represents Forecast at m Period
t: Represents Index Denoting a Time Period

Exponential smoothing method is very useful method to forecasting, it has been used for many applications and successful results have been obtained in many applications with this method.

3.3. Extreme Value Theorem

Extreme value distribution has been used on many applications for different areas. There are applications in environment, finance, meteorology, engineering, etc. [16] Extreme value theorem is a statistical distribution based on knowledge of the probability of extreme event occurrence. This knowledge is very useful to plan to event on extreme conditions. There are three types of extreme value distributions that can be called as Gumbel, Frechet and Weibul. The probability density functions of different extreme value theorem types can be represented with following equations.

Gumbell EVT
$$f(x)=\frac{1}{\delta}\exp\left(-\frac{x-\lambda}{\delta}-\exp\left(-\frac{x-\lambda}{\delta}\right)\right) \tag{1}$$

Frechet EVT
$$f(x)=\frac{\alpha}{\delta}\left(\frac{\delta}{x}\right)^{\alpha+1}\exp\left(-\left(\frac{\delta}{x}\right)^{\alpha}\right) \tag{2}$$

Weibull EVT
$$f(x)=\frac{\alpha}{\delta}\left(\frac{x-\lambda}{\delta}\right)^{\alpha+1}\exp\left(-\left(\frac{x-\lambda}{\delta}\right)^{\alpha}\right) \tag{3}$$

λ: Represents Location Parameter
δ: Represents Scale Parameter
α: Represents Shape Parameter

This study, we have used Gumbel type extreme value distribution. Gumbel Extreme Value Distribution contains 2 parameters that represent location and scale parameters. We have used maximum likelihood method to estimate scale and location parameters, yet we have used methods of the moments for the first estimation. Representation of scale and location parameters according to methods of moments can be represented as following equations.

$$\lambda_{mom}=\bar{L}-0{,}5772.\delta_{mom} \tag{4}$$

$$\delta_{mom}=\frac{S_{dev}\sqrt{6}}{\pi} \tag{5}$$

Maximum likelihood method based maximization process can be done with the following equation.

$$LL=\sum_{i=1}^{n}\ln(f(x_i,\lambda,\delta)) \tag{6}$$

The maximization process can be best performed with iteration of function with numerical analysis methods.

4. RESULTS AND DISCUSSION

In this study, the wind speed was estimated by using the wind speed data obtained from the wind turbine located on the campus of Kırıkkale University. ARMA and Exponential Smoothing methods of time series methods were used to estimate the wind speed and to determine the power that the turbine would produce for the next day. The data predicted by both methods was compared with the mean absolute percentage error (MAPE) metric within 30 minutes and the performance was checked. Also, the total power to be produced for the next day was compared and the day-end prediction was checked.

4.1. ARMA and ES

As mentioned above, some preliminary work is needed to determine what type of model is (AR, MA, ARMA) in this method. General Overview of System with ARMA is shown Figure 1.

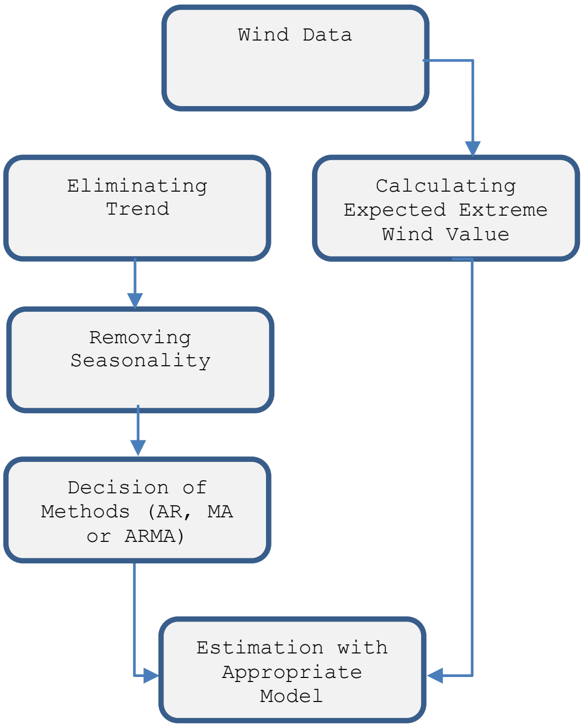


Figure 1. General overview of system with ARMA

The wind speed data loaded into the system is shown in Figure 2.

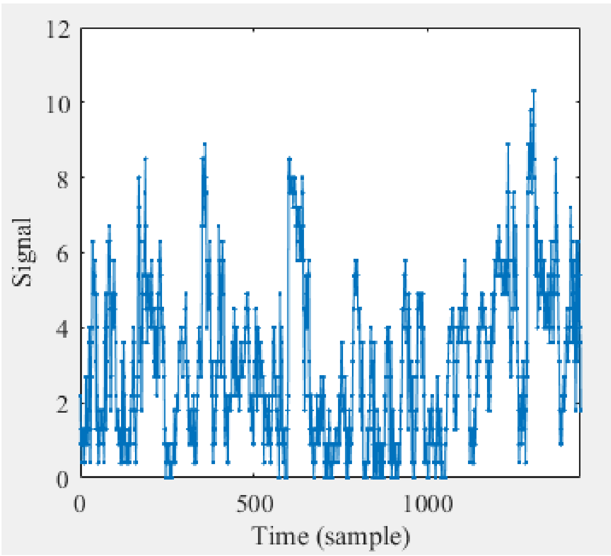


Figure 2. General distribution of wind data

First, the average removal process is applied to the data and the filter is applied to eliminate the observed trend. The resulting graphics of these operations are shown in Figure 3 and Figure 4.

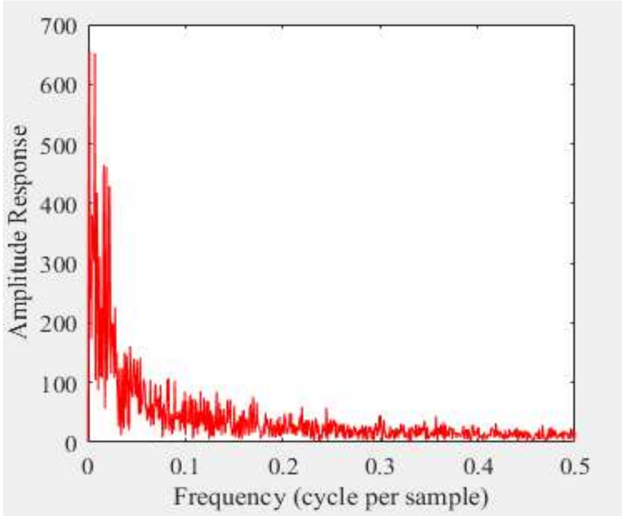


Figure 3. Resulting graphics of eliminated trend

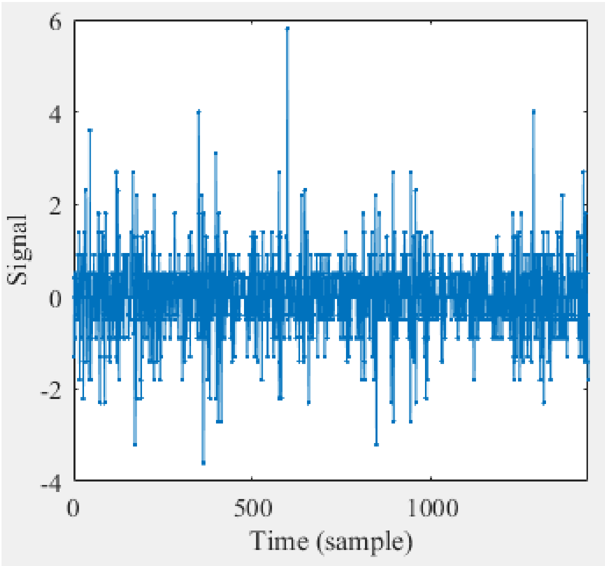


Figure 4. Resulting graphics of eliminated trend

After this process, the highest three harmonics were found to remove the seasonality, and the least common multiples of these harmonics were used to remove the seasonality effect. After this process, we need to decide which model we will construct from our graphics. To understand this, when we analyze the autocorrelation and partially autocorrelation graphs of the data, it is determined that both charts cut off after two lags. The corresponding graphs are shown in Figure 5 and Figure 6.

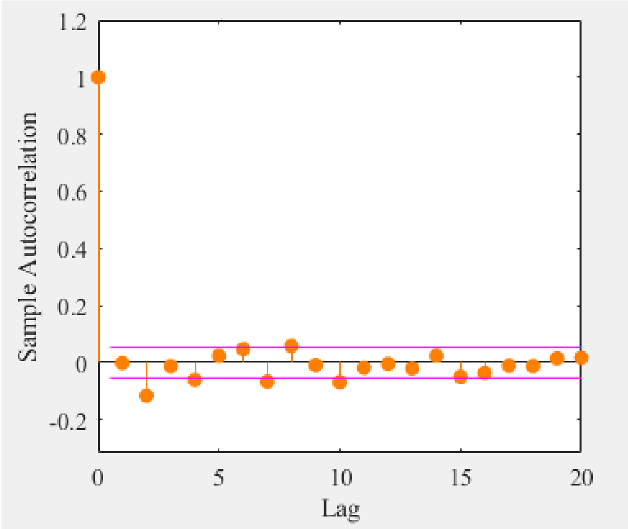
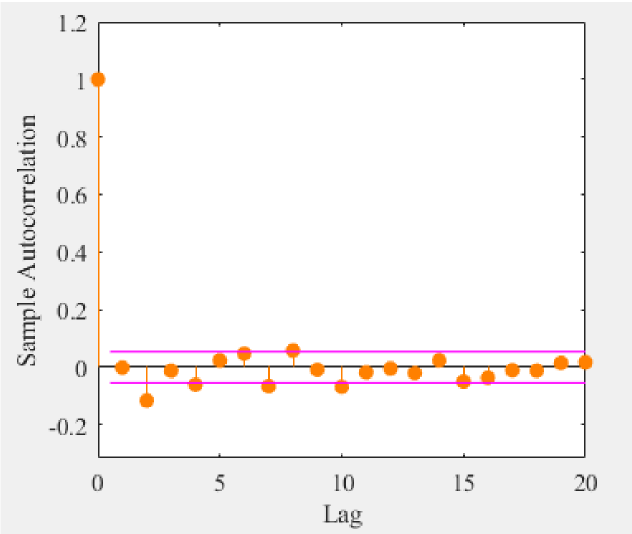


Figure 5. Resulting Graphics of Eliminated Trend



(b)

Figure 6. Resulting graphics of eliminated trend

After all these operations a model will be built for the data determined as the ARMA model. It is estimated 48 data for the next day for the selected model. 24 different forecasting data will be used for next day forecasts. When these estimates are made, the Extreme Value Theorem (EVT) is used to limit the data. By analyzing the data for one year and limiting the maximum wind speed, 24 different forecasts have been obtained. The maximum and minimum values of the data obtained by this method are omitted and the average wind speed estimates are determined. As described in above, Exponential Smoothing (ES) method is also used to predict future data in time series. With this simple and easy-to-use method, 48 data for the next day are estimated. General Overview of System with Exponential Smoothing is shown in Figure 7 below.

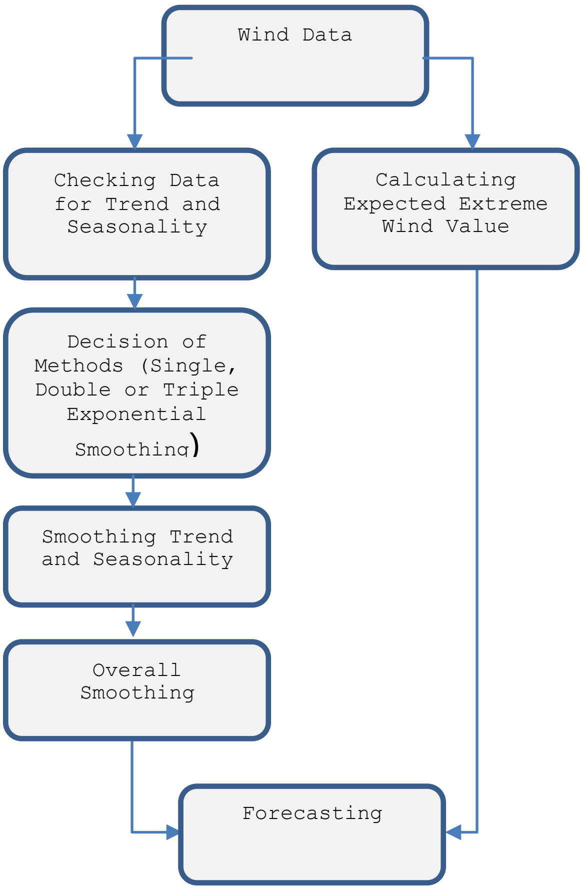


Figure 7. General Overview of System with Exponential Smoothing

Various methods are used in the literature such as MSE, RMSE, MAE, MAPE for evaluating time series predictions [17]. The MAPE evaluation metric [18] is more preferred because it appears to make a more accurate assessment for the time series in the literature. Therefore, the results obtained by both methods are compared with the Mean Absolute Percentage Error (MAPE) metric for the instantaneous values and the total wind power to be produced for the next day. The results obtained with the MAPE metric were 11.74% and 14.12% for ARMA and ES respectively. When the data were compared for the total power estimation the next day, the ARMA method was estimated with an error of 3,857% while the ES method was estimated with an error of 5,06%. ARMA eliminates seasonal effects, detects and reduces trends, and so on. Because of its advantages, this method is expected to give better results. It has been understood that the obtained data give better results due to the above-mentioned advantages of ARMA.

5. CONCLUSION AND FUTURE WORKS

The study results showed that the results obtained with the ARMA model are more successful than those obtained with the ES method. It is also shown that this is related to the removing of seasonality and trend effects in ARMA model. Moreover, with the increase of the data pool, it is predicted that the mentioned effects will be further reduced and that the results obtained will be more successful if the relationship between the data is considered to be further increased. In future studies, it is thought that the data pool can be increased and a combination of several methods can be tested together to achieve more successful results.

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NOTICE

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