Prediction of Wind Speed by Using Machine Learning

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Abstract. Due to the depletion of fossil fuel resources and environmental concerns caused by traditional fuel systems in recent years, the share of renewable energy sources in current energy production has been increasing. Among these energy sources, wind and solar energy stand out compared to other sources. Wind energy is a clean, sustainable and low-cost energy source. Wind and solar energies vary considerably according to the stochastic environment of meteorological conditions. Solar and wind energy variability and uncontrollability lead to power quality, generation-consumption balance and reliability problems of solar and wind energy systems. For this reason, it is important to know and predict the wind speed and solar radiation characteristics of the regions where the systems are installed. In this study, meteorological data of Antalya Serik Region were analyzed using statistical methods and wavelet transform. Thus, the potentials of wind and solar energies in the study area and large and small-scale events affecting these potentials were determined. In addition, a short-term estimation study was made for wind intensity and solar radiation using the time series of meteorological data. Besides SARMA, SARMAX and NAR models, Wavelet-NARX, SARMAX-NAR and NAR-SARMAX hybrid models are employed. Hybrid models are successfully produced better results than component forecasts.

Keywords: ANN · Wind speed forecasting · Hybrid forecasting · NAR · NARX · SARMA · SARMAX · Wavelet

1 Introduction

Wind energy and other renewables are emerging energy sources since European Green Deal and other similar decrees force nations to decrease their carbon emission levels. Wind energy forecasts have economic value for both short and long term considerations. Wind speed of Serik, Antalya region is forecasted in this paper which is the first one in the region. Results may contribute also Mediterranean wind speed predictions in general.

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Depending on the advancing technology all over the world, the needs of people for electrical energy are also increasing. Since the existing fossil resources used in electrical energy production are limited, they are decreasing day by day and they will be exhausted one day, on the one hand, electrical energy saving studies are carried out, on the other hand, studies on generating electrical energy using renewable resources continue at a great pace. The importance of the studies for the use of renewable resources in the production of electricity is obvious for the future of the countries, since they reduce the dependence on foreign sources. One of the studies carried out in this context is the generation of electrical energy by using the wind potentials, which have shown great development in the world, especially in Europe and Turkey in recent years.

Considering the cost of the wind turbine, it includes the decision of the region where the wind turbine will be installed and the measurement of the wind. Long-term wind measurements are made in the region where the wind turbine is planned to be installed, and as a result, it is decided whether it is suitable for installing a turbine, that is, the selection of the wind turbine becomes important. In our study, determining the place where the wind turbine will be installed and knowing how the wind values will be in the future will be a great gain for the investment to be made by the establishment to be established and the calculation of its return. In this study, it is planned that the changes in the future wind situation, which has not been done until now, that is, the wind modeling, and the determination of the situation, so that the operator will have the opportunity to make comfortable investments. In the study area, which is a tourism region, it is planned to meet the energy need with clean energy.

Both statistical and machine learning forecasting approaches are used to predict wind speed. Seasonal auto-regressive moving average (SARMA), SARMA with explanatory variable (SARMAX), nonlinear auto-regressive neural network (NAR), NAR with explanatory variable (NARX) and Wavelet transform are used as component forecasts and also their hybrid models are employed to reduce forecast error. ARIMA method uses differencing when trend exists in the data which can be detected by correlogram and unit root tests. When the forecast completed first term and differenced series are summed or integrated to reach the final forecast. Forecasting process combines auto regressive components with a finite moving average process. Auto regressive component consists of lagged response variables, while residual series obtained from a regression equation and also lagged series constitute the latter component. Auto regressive neural networks (NAR) is a specialized ANN model for time series forecasting. The input nodes consist of actual response variable and its lagged versions while output node presents the forecast series. In general, one hidden layer with multiple nodes is used between input and output layers. When explanatory variables are included to NAR model, it is called NARX model.

Combination and hybrid forecasting procedures use more than one forecasting technique in order to improve forecast accuracy measures. The forces generating series and underlying process behind the data are generally not visible to the forecaster to combining forecast models is can produce better results than the component forecasts. The idea behind combining is that disadvantages of component forecasts can be eliminated by supporting it with another model. For instance, ARIMA model is a very strong and

versatile tool for short term time forecasting but forecast function of it is the linear combination of lagged variables and residuals. However, NAR models have the ability to model nonlinear patterns. ARIMA-NAR and NAR-ARIMA hybrid models combine the advantages of both models and so improve forecast accuracy [1, 2]. Combination procedures started with simple average of component forecasts. Then, weighted averaging with different approaches is employed. Correlation coefficients did not work well, but regression coefficients are strong estimates for weights. When heterocedasticity exists in the component forecast series, it is better to use WLS. Constraining coefficients to be nonnegative and sum to one also improves forecast accuracy. Multi-layer perceptron of ANN model can be used also as a nonlinear combination procedure [3].

Zhang [1] combined ARIMA and ANN models in his hybrid models where instead of ARIMA, SARMAX model is used because of the fact that data contain seasonality but not trend. Zhang forecasted the response variable with the first model. Then, residual series obtained from first model is forecasted with second model. After that, residual forecasts are summed to first models forecast results to reach final forecast. He used both ARIMA and ANN as first and second models.

One approach to support nonlinear autoregressive time series forecasting model is to support it with explanatory variables obtained from Wavelet transform. By doing so, the impact of wavelet transforms and data preprocessing on the performance of estimation using NARX was demonstrated. The comparison of the relationship between model outputs and observations, as well as the reliability and precision of the models, were thoroughly discussed.

2 Study Area and Methodology

Selected region represents Mediterranean region of Turkey. Therefore, this paper is a pilot study for the general impacts of climate change on wind speed and wind energy potential on the Mediterranean region. Selected region is available below. Then, literature review and methodology is presented in this section.

2.1 Study Area

Serik is a district of Antalya, located in the Mediterranean Region of Turkey. The district, situated in the central part of Antalya province, is located between 36–37° latitude and 31–32° longitude. It is an important tourist center of our country, with an increasing population during the summer season due to tourism, but decreasing in the winter season when students leave the district. The district center, which is approximately 38 km east of Antalya city center, is located 7 km inland from the coast and at an altitude of 26 m above sea level.

The district center of Serik is 30 km east of Antalya. The district has a 22 km coastline on the Mediterranean Sea and its center is located 8 km inland at an altitude of 26 m above sea level on a partly undulating plain terrain. The district's area is 1,550 km^2, of which 45,360 hectares are agricultural land and 65,764 hectares are forest land. Serik constitutes an eastern extension of the Antalya Plain. The district is bordered by Aksu

district of Antalya in the west, Manavgat district in the east, Bucak district of Burdur and Sütçüler district of Isparta in the north, and the Mediterranean Sea in the south.

Livestock farming and forestry are carried out in the mountainous areas, while agriculture, especially early vegetable cultivation, is common in the plain areas. The district's commercial life is connected to the Antalya city center. The western Taurus Mountains begin to rise in the north of the district.

The district has a Mediterranean climate. Summers are dry and hot, and winters are mild and rainy (although this can sometimes vary). As a result of this climate, the natural vegetation is maquis. The region's most important rivers are Köprüçay and Aksu Stream (Fig. 1).

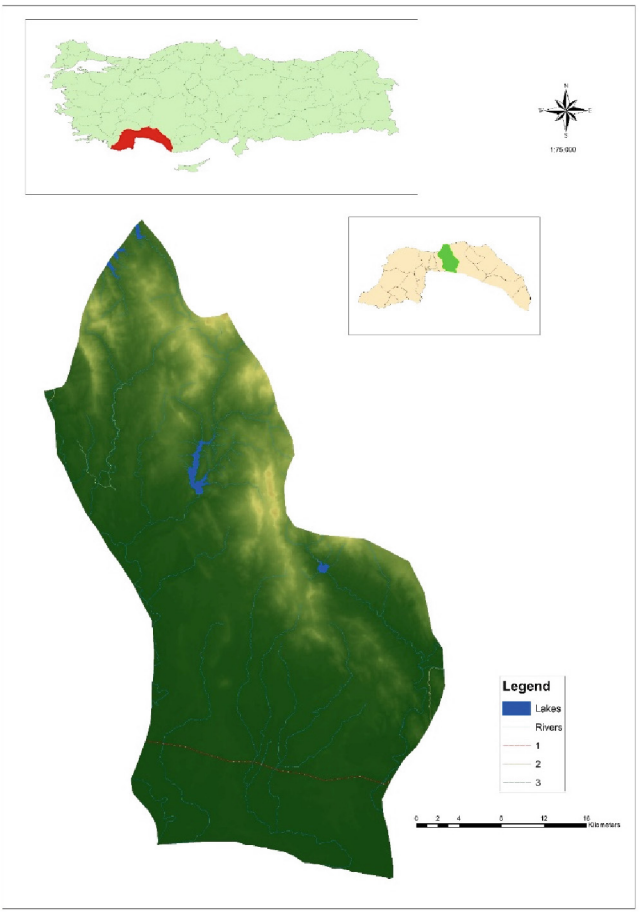

Fig. 1. Serik map

2.2 Nonlinear Autoregressive Neural Network (NAR, NARX)

The term "artificial intelligence," which is used frequently nowadays, is quite difficult to define. This is because artificial intelligence is a notion that gets into numerous academic fields, including computer science, psychology, physics, medicine, and philosophy. The simplest definition of artificial intelligence is the effort to simulate the behaviors that we refer to as human intelligence in machines—reasoning, making sense, generalizing, learning from past mistakes, etc. This method, which was created for a variety of goals, is becoming more and more common, which increases the dependency of individuals on technology. The idea of artificial intelligence, which was introduced by John McCarthy in 1956 at the Dartmouth Conference, has evolved over time with the theory that creating tailored answers to the issues encountered can improve the success of the models. ANN technique was one of the several models developed for this study. As is usually observed in the literature, artificial neural networks have demonstrated effectiveness in a wide range of domains, including prediction, modeling, and classification applications [4–6]. ANN model is constructed with connected nodes of weights which is used also for multivariate forecasting purposes. Multi-layer Perceptron (MLP) is the most often used network structure for forecasting. MLP generally contains three layers in which first layer is used for explanatory variables, second layer is the hidden one and third layer is for predicted variables [7, 8].

ANN has specialized networks for time series forecasting which are nonlinear autoregressive neural network (NAR) and nonlinear autoregressive neural networks with exogenous inputs (NARX). The NARX neural network approach has frequently been discovered in the literature for providing successful results in modeling studies of chaotic data [9, 10]. A kind of feedback ANN model known as NARX networks is renowned for its ability to forecast time series data accurately. It is noted that it delivers more effective learning and converges faster than conventional feedback network architectures [11, 12]. NARX model can be expressed mathematically with the following function [13];

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-ny), x(t-1), x(t-2), \ldots, x(t-nx)) \quad (2.1)$$

The equation's terms $y(t-1)$, $y(t-2)$, …, $y(t-ny)$ represent in for net outputs, and $x(t-1)$, $x(t-2)$, …, $x(t-nx)$ stand for network inputs. The number of inputs is represented by the nx parameter. The ny parameter displays how many previous outputs will be used as feedback. By returning the signal of the prior output value and the prior independent input signal, the y(t) depending on the output parameter is determined.

The literature review showed that merging an additional analysis technique with an ANN model improved prediction accuracy [14, 15]. In Wavelet transform (WT), it is well recognized that choosing the right main wavelet and deciding on the decomposition level effectively capture the properties of the data and improve performance. In order to improve the accuracy of wind forecasting, a hybrid Wavelet-NARX method has been created in this study. We compared performances of component forecasts with hybrid ones including Wavelet-NARX, SARIMAX-NAR and NAR-SARIMAX.

2.3 Wavelet

Alfred Haar introduced the term "wavelet" for the first time in 1909. Many significant researchers have worked on the wavelet transform, one of the preprocessing approaches for signal processing, including Daubechies, Coifman, and Wickherhouser.

Any signal is split into smaller signals by the wavelet transform, which analyzes the changes in chaotic data over time. This is done through multiple stages of processing in the time frequency domain. It establishes which sub components of this time series' major modes of variability are and how these modes evolve over time. In other words, it enables the transformation of the original dataset into a different format that offers a clearer justification. The discrete wavelet transform produces two complimentary signals, the approximation (A) and detail (D) components, from the original signal, which is represented by the symbol S. The generated coefficients can be examined at various frequency and resolution ranges. The A data exhibits the general properties of the original signal in its abridged form during the decomposition process. On the other hand, detail components assist us in identifying time series with high-frequency rapid changes.

Mathematically, the discrete wavelet transform (ADD) is defined as follows [16];

$$\mathrm{cD1} = \sum\nolimits_{-\infty}^{+\infty} (\mathrm{f[n].g[2n - k]}) \tag{2.2}$$

$$\mathrm{cA1} = \sum_{-\infty}^{+\infty} (\mathrm{f[n].h[2n - k]}) \tag{2.3}$$

The original signal is represented by f[n], which is given in the equation. The filter level is represented here by n. In the formula, the value of k indicates the level of dissociation. Decomposition can be accomplished by processing both g(k) and h(k) through high-low pass filters, respectively. Discrete wavelet transform detail data was used in the study's analysis to access the wind data's specific characteristics and catch unexpected changes.

2.4 ARIMA

Auto regressive (AR) models use lagged predicted variables as explanatory variables, because they are correlated with predicted variables when the time series data have serial correlation. In this case, serial correlation problem is used for the benefit of the model. ACF/PACF figures reveal whether serial correlation exists which can be observed in almost all of the time series data sets. Auto regressive moving average (ARMA) models combine AR component with a finite moving average process (MA). MA component of the model relies on the interdependency between error series and predicted series so lagged residual series obtained from the regression is included to model similar to AR component. If differencing is employed to the predicted series of ARMA model, it is called auto regressive integrated moving average (ARIMA) model. When there is trend pattern in the series, ARIMA model employs differencing for removing trend before combining AR and MA variables. After forecast series calculated, it is integrated (summed) to reach final forecast.

ARIMA is actually univariate forecasting technique but explanatory variables can be included to the model with transfer function [17].

2.5 Forecast Accuracy

Regression based models fit the forecasting function with respect to minimization of sum of squares error $SSE = \sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2$ so conventional regression models are called ordinary least squares (OLS), where t is the period number, n is the quantity of periods, $\hat{Y}_t$ is the forecast at period t and Y_t is the actual data at period t [18]. When we divide SSE to the quantity of periods in the models we will reach mean square error $MSE = \frac{\sum_{t=1}^{n}(Y_t-\hat{Y}_t)^2}{n}$. Square root of MSE is called $RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t-\hat{Y}_t)^2}{n}}$ which is a popular forecast accuracy measure. SSE and MSE are in square level compared with actual data but after taking square root, RMSE is converted back to the level of actual figures, so this fact makes it comparable with Y_t. All forecast accuracy measures explained here which are based on SSE have the range of [0,∞) and lower values indicate better forecasts [19, 20].

Many researchers prefer using forecast accuracy measures based on percentages of error term e_t in actual data Y_t. This scaling error term with respect to actual data makes forecast accuracy measure more comparable between the forecasting techniques even for different data sets. Mean percentage error MPE is used to determine whether model underestimates or overestimates the actual figures which is calculated by $\text{MPE} = \sum_{t=1}^{n}\frac{Y_t-\hat{Y}_t}{Y_t}$. Negative MPE indicates that forecast figures are greater than actual data so model overestimates the real situation. Conversely, positive MPE means underestimation. Mean absolute percentage error is the most popular forecast accuracy measure and calculated with the formula $\text{MAPE} = \sum_{t=1}^{n}\frac{|Y_t-\hat{Y}_t|}{|Y_t|}$ [18]. Percentage error based forecast accuracy measures explained here have the range of [0,1] and forecast accuracy is better when it is close to zero. Symmetric mean absolute percentage error $\text{SMAPE} = \sum_{t=1}^{n}\frac{|Y_t-\hat{Y}_t|}{\left(|Y_t|+\left|\hat{Y}_t\right|\right)/2}$ is percentage of the error term in the absolute averages of actual d predicted data [11]. Absolute operator is not the part of original formula but added to make statistic a positive percentage. Theil's U is another measure we would like to present in this paper which is calculate by Theil's $U = \frac{\sum_{t=1}^{n-1}\left(\frac{Y_{t+1}-\hat{Y}_{t+1}}{Y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{Y_{t+1}-Y_t}{Y_t}\right)^2}$ [21].

3 Results

Missing values in the hourly data set from 2015 to 2022 were estimated using linear interpolation. Out of 69.503 data points, only 200 were missing, indicating that the data set is reliable. The data for 2022 was separated as out-of-sample periods. The data from 2015 to 2021 was used to fit the Wavelet-NARX model, while the data from 2022 to 2021 was used for other models.

The SARMA model is fitted with 52 weeks periodicity, including MA, AR, SAR (seasonal autoregressive) and SMA (seasonal moving average) components. 2020–2021 in sample data set is used for model fitting and stationary R square is for selecting best model. Data does not contain trend, so differencing is not required theoretically. Seasonal ARMA(1,0,2)(2,0,1) model bested other ARIMA procedures in all error measures. Selected model is used to forecast 2022 out of sample periods.

For SARMAX model, seasonal exponential smoothing forecast of wind speed with 24 h periodicity is included to the model as explanatory variable with transfer function in order to represent a daily average wind speed to SARMA model. SARMAX-NAR model is applied to normalized data set. Z-score normalization is used because it produced lower error measures compared with the min-max method. Mean of in sample periods is subtracted from data point and result is divided to the standard deviation of the in sample periods. 2020–2021 in sample data is used for training model. In sample data is divided as 60% for training, 20% for validation and 20% for test. 77 autoregressive components are included to the model and 129 hidden nodes are used between input and output layer. MSE is minimized for training. Optimized net is used to forecast out of sample periods.

NAR-SARMAX and SARMAX-NAR hybrid models are formulated such that forecast started with forecasting wind speed with the former method which is NAR in NAR-SARMAX. Residual series obtained from NAR is forecasted with latter SARMAX model. SARMAX residual forecast results is summed with NAR forecast of wind speed to have final forecast. SARMAX-NAR model is formulated with reverse order.

Wavelet-NARX hybrid were employed to evaluate a dataset of 69.503 hourly wind speed data for the years 2015–2022. Both approaches utilized the hourly data set from 2015 to 2021 as the input for the network, and the out-of-sample period of 2022 was projected using a selected model. The 2022 out-of-sample dataset was used for model fitting, and the stationary R square was employed to select the best model. 60% percent of the data were used for training, while the remaining 40% were used for validation and testing. The number of hidden layer neurons varied based on the performance of the network. All error measures demonstrated that the Wavelet-NARX model outperformed all other alternatives. The section on results presents the accuracy of the predictions made for both past periods and also first future year.

In the study, multiple methods were used to predict wind speed, and NAR was one of them. The success of the network was evaluated by comparing the R test results. The study found that the best R performances were 0.79 for training, 0.79 for validation, and 0.78 for test values. The analysis results were presented in Fig. 2, which showed the graphic and prediction outcomes.

For Wavelet-NARX hybrid methodology started with wavelet analysis and wind speed series are divided into wavelets. The d4 wavelet, which is known to produce effective results in the literature, was used to divide the data into three levels. The study found that large and medium-sized events had an impact on the change in wind speed for the Serik region. As a result, data related to these events were introduced to the network as input along with the NARX data, while actual wind data were used as output.

The hybrid model, which was developed by using wavelet transform analysis, showed more successful results than the model that was developed using only NAR. The hybrid study resulted in R values of 0.92 for training, 0.92 for validation, and 0.91 for test data. The study found that the average wind speed in 2022 was 2.97 m/s. Based on the hybrid model, the wind prediction for 2023 was determined to be 2.98 m/s. The results suggest that there will be a slight increase in the average wind speed in 2023 compared to 2022. Figure 3 presents the graphic and prediction outcomes generated based on the analysis results.

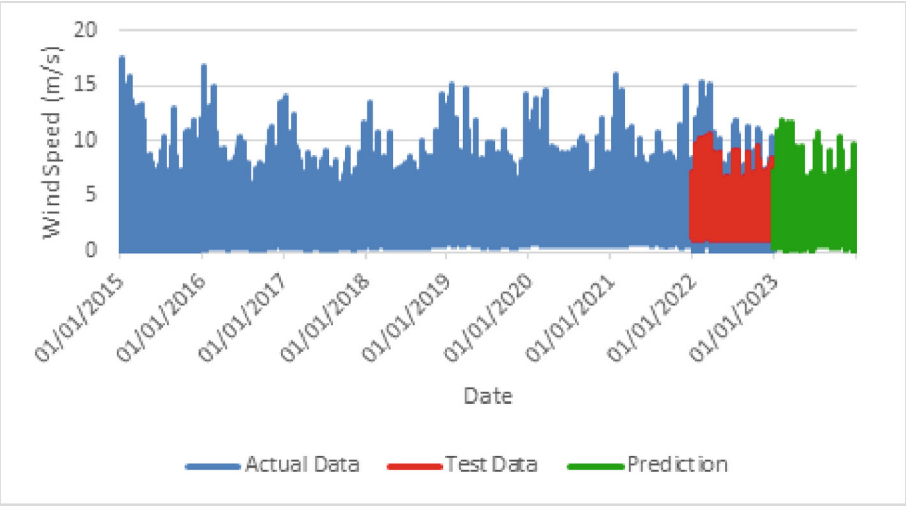

Fig. 2. Temporal wind speed variation of ANN model between 2015–2023 in Serik

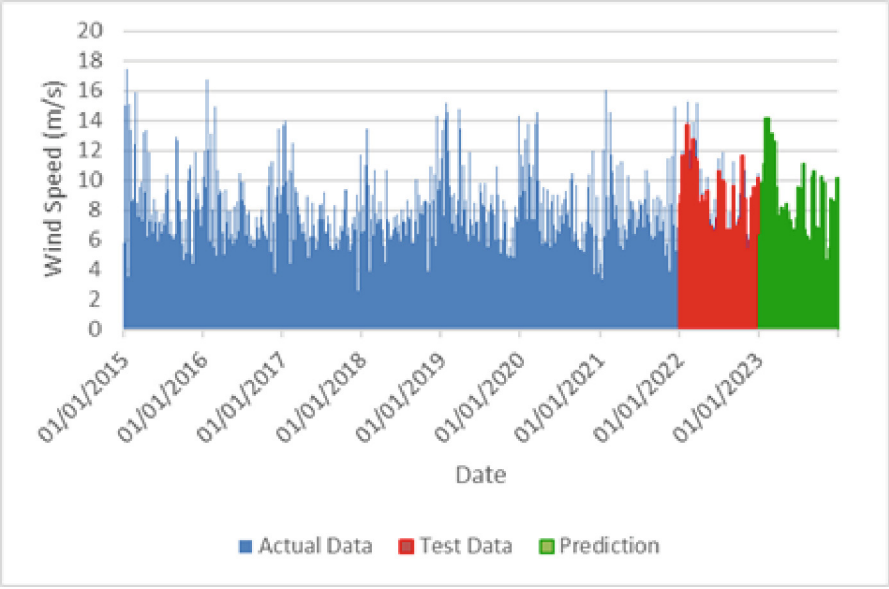

Fig. 3. Temporal wind speed variation of WAVELET-NARX model between 2015–2023 in Serik

According to in sample periods, NAR-SARIMA model produced better error measures compared with other models in general. In percentage error measures of MPE and MAPE, NAR model is slightly better. Among component forecasts NAR model is better than SARIMA and SARIMAX models. SARIMA-NAR hybrid model did not improved results than component forecasts (Tables 1, 2 and 3, Figs. 4 and 5).

Table 1. Forecast accuracy measures for training data (2020–2021)

2020–2021 Training	SARMA	SARMAX	NAR	SARMAX NAR Hybrid	NAR SARMAX Hybrid
MSE	0.97	1.01	0.57	1.07	0.58
RMSE (m/s)	0.98	1.00	0.76	1.03	0.76
MAE	0.63	0.63	0.54	0.62	0.54
MPE (%)	−10.2%	−10.1%	−10.9%	−10.0%	−6.7%
MAPE (%)	24.2%	24.3%	22.4%	24.6%	21.4%
SMAPE (%)	21.5%	21.5%	19.9%	22.0%	19.7%
U1	0.14	0.14	0.11	0.14	0.11
U2	1.07	1.09	0.90	1.21	0.89

Table 2. Forecast accuracy measures for test period of next month

Test with next month (01/2022)	SARMA	SARMAX	NAR	SARMAX-NAR Hybrid	NAR SARMAX Hybrid	Wavelet-NARX Hybrid
MSE	1.87	1.83	2.49	6.60	2.37	1.01
RMSE (m/s)	1.37	1.35	1.58	2.57	1.54	1.00
MAE	1.00	0.97	1.16	1.92	1.12	0.73
MPE (%)	N/A	N/A	N/A	N/A	N/A	N/A
MAPE (%)	N/A	N/A	N/A	N/A	N/A	N/A
SMAPE (%)	33.7%	31.9%	39.0%	62.5%	38.1%	25.2%
U1	0.18	0.18	0.20	0.30	0.20	0.13
U2	0.86	0.12	0.29	1.36	0.39	0.37

2022 data set of 8060 data points contain 84 h as zero so MPE and MAPE cannot be calculated for out of sample periods. For short-term forecasting of first consecutive month; Wavelet-NARX model bested others.

Table 3. Forecast accuracy measures for test period of next year

Test with next year (2022)	SARMA	SARMAX	NAR	SARMAX-NAR Hybrid	NAR SARMAX Hybrid	Wavelet-NARX Hybrid
MSE	1.49	1.47	1.92	4.99	1.76	0.86
RMSE	1.22	1.21	1.39	2.23	1.33	0.93
MAE	0.88	0.85	1.01	1.56	0.96	0.68
MPE	N/A	N/A	N/A	N/A	N/A	N/A
MAPE	N/A	N/A	N/A	N/A	N/A	N/A
SMAPE	33.3%	31.5%	37.7%	55.6%	36.5%	26.9%
U1	0.18	0.17	0.19	0.29	0.19	0.13
U2	0.90	0.52	0.77	0.92	0.72	0.37

For long-term forecasting Wavelet-NARX model bested others in almost all statistics.

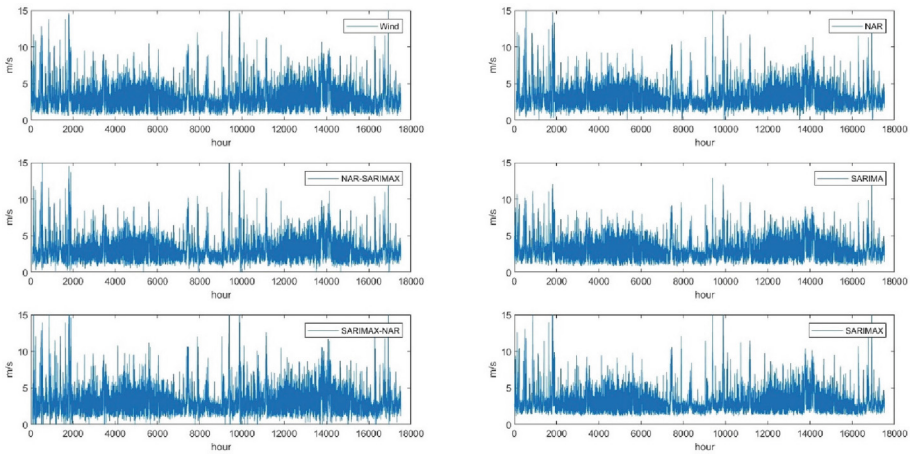

Fig. 4. Training period estimations

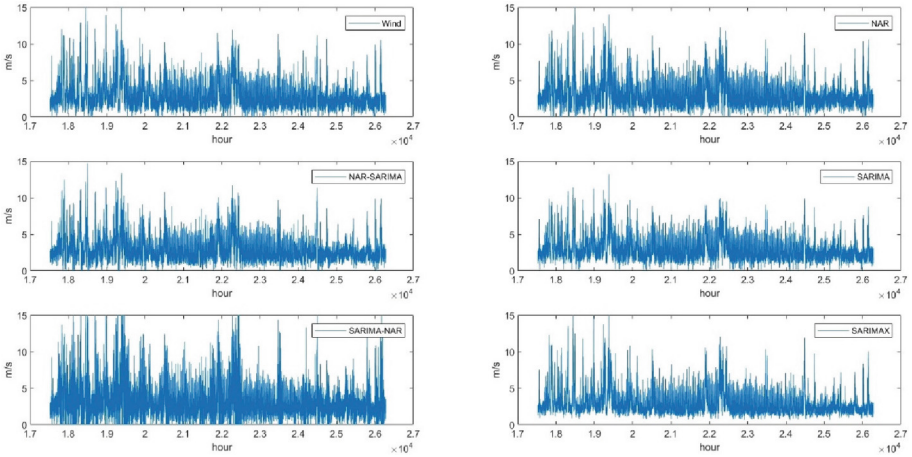

Fig. 5. Test period estimations

4 Discussion

Objective of the paper is presenting wind speed forecast and also testing hybrid forecasting models with hourly wind data in order to see whether they improve forecast accuracy measures or not. SARMA, SARMAX, NAR and Wavelet transform are used as component forecasts in SARMAX-NAR, NAR-SARMAX and NARX-Wavelet hybrid models in which NARX-Wavelet performed best. While the prediction accuracy of the ARIMA and NAR methods are high for time series forecasting, it is well-established that utilizing hybrid models can further improve performance [22, 23]. Results showed that the NARX-Wavelet outperformed the NAR model, while achieving an R value of 0.91 on the test data, compared to 0.78 for the ANN model. This resulted in a 16% increase in prediction accuracy when using the hybrid model.

Considering the vast alternatives of hybrid models to be employed in the future; Wavelet transform can be included to SARMA with transfer function model as explanatory variable or with the methodology presented by Zhang (2003). Combination forecasting approaches can be used to combine given component forecasts. Decomposition models can be applied to formulate seasonality indices.

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References

1. Kim, S., Choi, C.Y., Shahandashti, M., Ryu, K.R.: Improving accuracy in predicting city-level construction cost indices by combining linear ARIMA and nonlinear ANNs. J. Manage. Eng. **38**(2), (2022). https://doi.org/10.1061/(asce)me.1943-5479.0001008
2. Zhang, G. P.: Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing **50**, 159–175 (2003). www.elsevier.com/locate/neucom

3. Terregrossa, S.J., Sener, U.: Employing a generalized reduced gradient algorithm method to form combinations of steel price forecasts generated separately by ARIMA-TF and ANN models. Cogent Econ. Finance **11**(1), (2023). https://doi.org/10.1080/23322039.2023.2169997
4. Kurani, A., Doshi, P., Vakharia, A., Shah, M.: A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. Ann. Data Sci. **10**(1), 183–208 (2023)
5. Coelho, L.B., Zhang, D., Van Ingelgem, Yves, Steckelmacher, Denis, Nowé, Ann, Terryn, Herman: Reviewing machine learning of corrosion prediction in a data-oriented perspective. npj Materials Degradation **6**(1), 8 (2022). https://doi.org/10.1038/s41529-022-00218-4
6. Kechagias, J.D., Tsiolikas, A., Petousis, M., Ninikas, K., Vidakis, N., Tzounis, L.: A robust methodology for optimizing the topology and the learning parameters of an ANN for accurate predictions of laser-cut edges surface roughness. Simul. Model. Pract. Theory **114**, 102414 (2022)
7. Zhang, G.P., Qi, M.: Neural network forecasting for seasonal and trend time series. Eur. J. Oper. Res. **160**(2), 501–514 (2005). https://doi.org/10.1016/j.ejor.2003.08.037
8. Zhang, G.P.: Neural Networks in Business Forecasting (2011). https://doi.org/10.4018/978-1-59140-176-6
9. Sunny, J., Schmitz, J., Zhang, L.: Artificial neural network modelling of Rossler's and Chua's chaotic systems. In: 2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE), pp. 1–4. IEEE (2018)
10. Koschwitz, D., Frisch, J., Van Treeck, C.: Data-driven heating and cooling load predictions for non-residential buildings based on support vector machine regression and NARX Recurrent Neural Network: a comparative study on district scale. Energy **165**, 134–142 (2018)
11. Shin, Y., Smith, R., Hwang, S.: Development of model predictive control system using an artificial neural network: a case study with a distillation column. J. Clean. Prod. **277**, 124124 (2020)
12. Wunsch, A., Liesch, T., Broda, S.: Groundwater level forecasting with artificial neural networks: a comparison of long short-term memory (LSTM), convolutional neural networks (CNNs), and non-linear autoregressive networks with exogenous input (NARX). Hydrol. Earth Syst. Sci. **25**(3), 1671–1687 (2021)
13. Sum, J.P.F., Kan, W.-K., Young, G.H.: A note on the equivalence of NARX and RNN. Neural Comput. Appl. **8**(1), 33–39 (1999)
14. Reşat, H.G.: Design and development of hybrid forecasting model using artificial neural networks and ARIMA methods for sustainable energy management systems: a case study in tobacco industry. J. Fac. Eng. Archit. Gazi Univ. **35**(3), 1130–1140 (2020)
15. İşler, B., Aslan, Z.: Modeling of vegetation cover and spatio-temporal variations. J. Fac. Eng. Archit. Gazi Univ. **36**(4), 1863–1874 (2021)
16. Küçük, M., Agiralioglu, N.: Wavelet regression technique for streamflow prediction. J. Appl. Stat. **33**(9), 943–960 (2006)
17. Box, G.E.P., Jenkins, G.M.R.G.C., Ljung, G.M.: Time Series Analysis Forecasting and Control, 5th edn. Wiley, New Jersey (2016)
18. Makridakis, S., Wheelwright, S.C.: Forecasting Methods and Applications, 3rd edn. John Wiley & Sons (1997)
19. Adli, K.A., Sener, U.: Forecasting of the US steel prices with LVAR and VEC models. Bus. Econ. Res. J. **12**(3), 509–522 (2021). https://doi.org/10.20409/berj.2021.335
20. Şener, U.: Türkiye'de Binek Otomobili Endüstrisinin Talebine Kantitatif Bir Yaklaşım, Istanbul Aydin University (2015)
21. Bliemel, F.: Theil's forecast accuracy coefficient: a clarification. J. Market. Res. **10**(4), 444 (1973). https://doi.org/10.2307/3149394

22. Kreinovich, V., Nguyen, H.T., Ouncharoen, R.: How to Estimate Forecasting Quality: A System-Motivated How to Estimate Forecasting Quality: A System-Motivated Derivation of Symmetric Mean Absolute Percentage Error Derivation of Symmetric Mean Absolute Percentage Error (SMAPE) and Other Similar Characteristics (SMAPE) and Other Similar Characteristics (2014). https://scholarworks.utep.edu/cs_techrep
23. Jadhav, V., Reddy, B.V., Gaddi, G.M.: Application of ARIMA Model for Forecasting Agricultural Prices (2017). www.SID.ir