



Artificial NARX Neural Network Model of Wind Speed: Case of Istanbul-Avcilar

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Received: 17 May 2020 / Revised: 25 October 2020 / Accepted: 15 April 2021 / Published online: 23 June 2021
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Abstract

Wind farms have a focus role in environmentally friendly energy production. There are short-term estimates of wind speed in planning energy production in wind power plants. In this article, we analyzed the wind speed in the Istanbul Avcilar region by an artificial neural network method (ANN) and regression method. One of the methods commonly used in estimation processes is Nonlinear Autoregressive Exogenous (NARX). We divide the data into three parts 70%, 15%, and 15%, respectively, for learning, validation, and testing. We used the Levenberg–Marquardt (LM) algorithm for data network training. We compared the predicted wind speed with the measured and tested values. We used MATLAB software in the analysis of the model. We obtained system outputs and regression models of wind speed with artificial neural network simulations. Besides, we calculated the effect sizes.

Keywords Wind speed estimation · Time series prediction · NARX · Neural network · Effect size

1 Introduction

The use of renewable and environmentally friendly wind energy is increasing rapidly. Wind energy is one of the renewable energy sources that minimize the cost of electricity generation.

Variability and uncertainty inherent in wind power have a detrimental effect on the power grid [1]. Estimating wind speed is very important for reducing the risks for the electricity market [2].

The widespread use of renewable resources in energy generation has made the production forecast necessary. In a study, a three-variable model was used to predict wind power generation one day in advance, and we found that the wind speed is highly dependent on the wind direction [3].

The Structural Equation Model (SEM) and the Fuzzy Cognitive Map (FCM) method can be combined to define a reciprocal relationship between factors affecting wind power generation [4].

A hybrid approximation model based on Particle Swarm Optimization (PSO) and Twin Support Vector Regression (TSVR) can also be used to estimate wind speed [5]. A hybrid method has been developed for wind speed estimation and used in the economic distribution problem [6]. Machine learning techniques have become increasingly common in the prediction of energy production performance in recent years [7]. Hybrid wind speed prediction models based on Wavelet Neural Network (WNN) are also used in the literature [8].

Some studies use autoregressive time series and artificial neural network prediction combinations, and the success of the model depends on the determination of combination weights [9]. There is a conditional time series estimation method based on the adaptation of the convolutional WaveNet (WN) architecture for speed estimation, which has been used recently [10]. (ANN) are used

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for anomaly detection and optimum resource allocation. These methods usually consist of a combination of univariate predictive models and machine learning methods [11]. Also, the ARIMA-NARX hybrid model can be used to predict wind speed [12].

Generalized regression neural network (GRNN) coupled with ensemble empirical mode decomposition (EEMD) and assessment of prediction accuracy. The proposed method has high prediction accuracy, quite effectively in forecasting wind energy [13].

(Hoolohan et al. 2018) developed the GPR model for NWP data, getting more accurate predictions. Consideration of atmospheric stability further reduces prediction errors. This method compares the estimated power output with the measured system output [14]. (Zhang, et al. 2018) obtained initial prediction results with the IPSO-BPNN model. Next, they used the Lorenz system to correct the initial predictive value and improve forecast accuracy [15].

Multi-step prediction simulation is applied using real collected short-term wind speed time series. The simulation results here show the higher prediction accuracy of the proposed approach [16].

Effect size helps to understand the magnitude of differences found, whereas statistical significance measures whether the findings are due to chance. There are two types of effect sizes between groups and related measures. Between groups Cohen d^2 , old ratio (OR), and risk ratio (RR); The quantity of the relationship consists of the Pearson correlation (r), the determination coefficient (r^2) [17].

Two methods were used in this study, namely regression and NARX. One dependent and four independent variables in the regression method; In the NARX model, we choose four input variables and one output (Fig. 1).

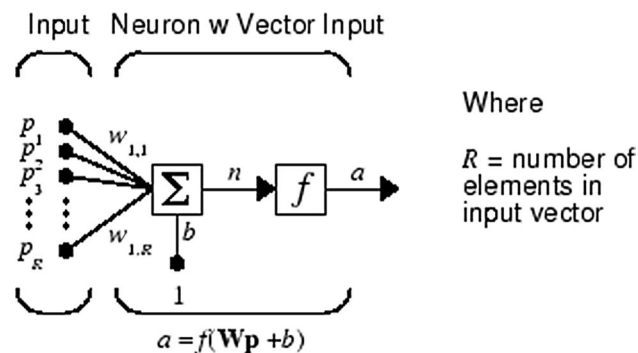


Fig.1 Neural network structure

2 Methods

Used to understand and simulate the nonlinear model behavior of complex systems, Artificial neural networks (ANN) provides a useful alternative approach to both theoretical and real-world problems.

Wind speed modeling includes medical diagnosis, pattern recognition, and many others. These methods are increasingly important in handling noisy or complex data sets [18].

In Eq. (1), ‘ a ’ is the output at the output layer of all the nodes. ‘ w ’ indicates the weight vector and ‘ p ’ is the input. ‘ b ’ is the bias, and ‘ $f(.)$ ’ is the activation function.

$$a = f\left(\sum_{i=1}^n w_i p_i + b\right) \tag{1}$$

Backpropagation algorithms form the basic structure of Neural Networks. In this algorithm, each neuron of the network updates its statistical weight using the delta learning rule.

The sigmoid activation function commonly used in artificial neurons is as follows:

$$\phi(t) = \frac{1}{(1 + e^{-t})} \tag{2}$$

One of the principal training algorithms used in ANN modeling is the Levenberg Marquardt Algorithm (LMANN). This method is a backpropagation curve placement algorithm that uses the least-squares process. Although the LMANN option is a popular choice, it can only achieve a local minimum. It is not always ideal for further generalization.

The solution to this problem is to use the Bayes Smoothing Algorithm (BRANN) method. A neural network trained using BRANN has been shown to produce more robust results compared to ANNs that possess other standard backpropagation networks. Thus, by integrating Bayesian probabilities into the learning algorithm, more accuracy is provided in-network learning and related possibilities. Artificial neuron weights are updated using the new observed data Eq. (3).

$$L(\theta|x) = P(x|\theta); \theta, x : \text{parameters, outcomess} \tag{3}$$

In this application, we will train the network system using the (NARX) method. The correlation coefficient between the estimated output values and the original target values gives the degree of conformity [19]. It used a Mean Square of Average Errors (MSE) error term to measure the accuracy of the prediction.

$$y(t) = f(x(t - 1), \dots, x(t - d), y(t - 1), \dots, y(t - d)) \tag{4}$$

There are two different artificial neural networks that we use for wind speed prediction, namely open and closed loop.

The measured wind data were solved using the NARX network architecture in Fig. 2. Where: x (four variable exogenous entry time series) and y (univariate autoregressive time series),

3 Network Performance

Artificial Neural Networks (ANN) are trained based on the parameters of Mean Square Error (MSE) and Correlation Coefficient (R). Trained ANNs are converted to the closed-loop mode and reformatted to make advanced multi-step estimates output Y(t) is feedback into the inlet of the network. The trained ANN becomes a closed loop by creating a feedback link from the network exit to the network entrance. Thus, the model becomes a Recursive Neural Network (RNN). Learning parameters are selected to minimize estimation errors. The results obtained are evaluated with MSE, Absolute Percent Error (APE), and Mean Absolute Percent Error (MAPE) performance measurements [13].

$$MSE = \sum_{t=1}^N (v_p(t) - v_r(t))^2 \tag{5}$$

$$MAPE = \frac{1}{N} \sum_{t=1}^N \left| \frac{v_p(t) - v_r(t)}{\mu} \right| \times 100 \tag{6}$$

In the formulas, v_p is the predicted wind speed, v_r is the real wind speed, μ is the average value of the predicted samples, and N is the number of sample sizes.

4 Analysis

4.1 Data

The data measurement station is Istanbul University-Cerrahpaşa Avcılar Campus. We recorded the values of the variables (wind speed, wind direction, temperature, relative

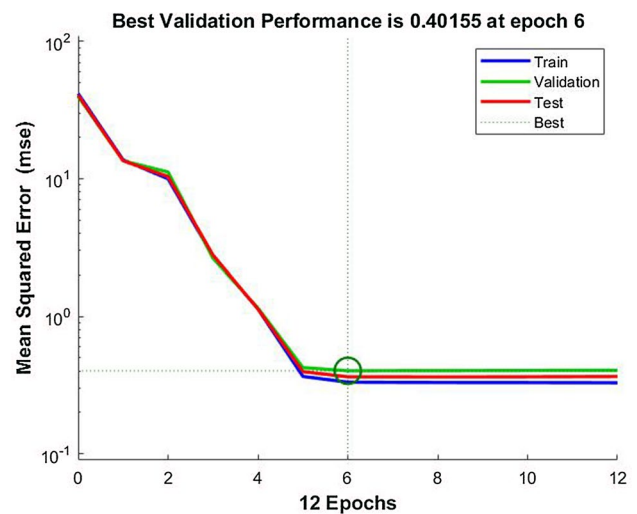


Fig. 3 The Performance Graph of the NARX Training Process

humidity, and pressure) in periods of 10 min. First, we applied a regression analysis to monthly data and obtained estimation equations. Secondly, we reached the network performances, parameters, and explanatory graphs by analyzing the data with the NARX method. We calculated ANN-based wind speed estimates.

4.2 Regression Analysis

We found the coefficient estimates of the regression model by applying the stepwise regression method to monthly data. All of the coefficients of the regression equations of the 12-month wind speed data were found significant at the 0.01 significance level.

4.3 NARX Analysis

4.3.1 Performance Tables and Estimation Equations

Figure 3 performance chart provides the current status of the training process to be known. The X-axis represents

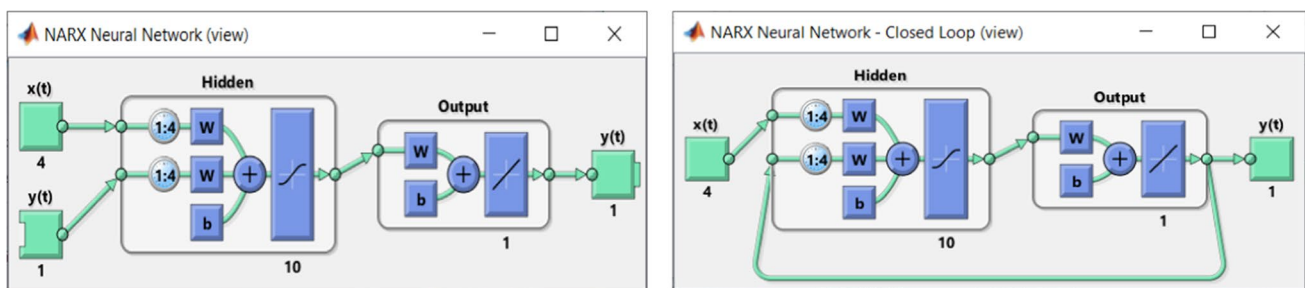


Fig.2 NARX network, open-loop, and closed-loop

the number of iterations (12 stages), the Y-axis represents the MSE that occur for each iteration in the graph (Fig. 2). Training outputs are colored blue, validation results green, and test results red. The best performance is the point where the lines showing training, verification, and test results overlap with each other.

We calculated the best realization score of 6 and the performance value of 0.40155. Training, validation, and test values are almost close to each other for this value (Table 1).

ANNs calculate the gradient of the loss function to explain the error contributions of each of the selected neurons. Figure 4 shows that the gradient value is 0.0062545.

Table 1 Methods and effect sizes

Article reference	Method	Measures of association	Effect Size
[2]	ANN-RBF	0.85	Large
[4]	ECC	0.48	Small
[5]	GA-TSVR (ASU)	0.74	Large
[6]	ARIMA, NARX	0.98	Large
[7]	TEUS	0.99	Large
[8]	BPNN	0.66	Large
[12]	NARX	0.98	Large
[13]	GRNN-EEMD	0.98	Large
[17]	OS-ELM	0.98	Large

This result indicates that the error contributions calculated in neurons are low.

The control parameter of the algorithm used to train the artificial neural network is the training gain (Mu). In Fig. 3, we can see the training gain (Mu) as 0.001. This result shows that the network has a high capacity to estimate wind speed.

We train the network with the LM method and measure its performance with MSE. The performance value of the system is the amount of error minimized during learning. This value is 0.3409 in Table 2.

Figure 3 shows that the training gain of the network is 0.001, variance (gradient) is 0.0062545. The validation process checks if it minimizes the error compared to previous iterations.

The change in the correlation coefficient between input (1) and error (1) is in Fig. 5. Where there is no delay, the correlation coefficient reaches a maximum. This value is around 0.4. If there is a delay, the local maximum for -15 and 15 is about 0.11.

An ANN's Histogram contains valuable information about errors. Error histogram gives values of Error Value (EV) and Error Frequency (EF).

We can classify errors according to their magnitude and variance.

Figure 6 depicts the cumulative instantaneous variation of training, validation, and test errors. In this graph, a vertical line shows the error at the zero points.

Fig. 4 Neural network training

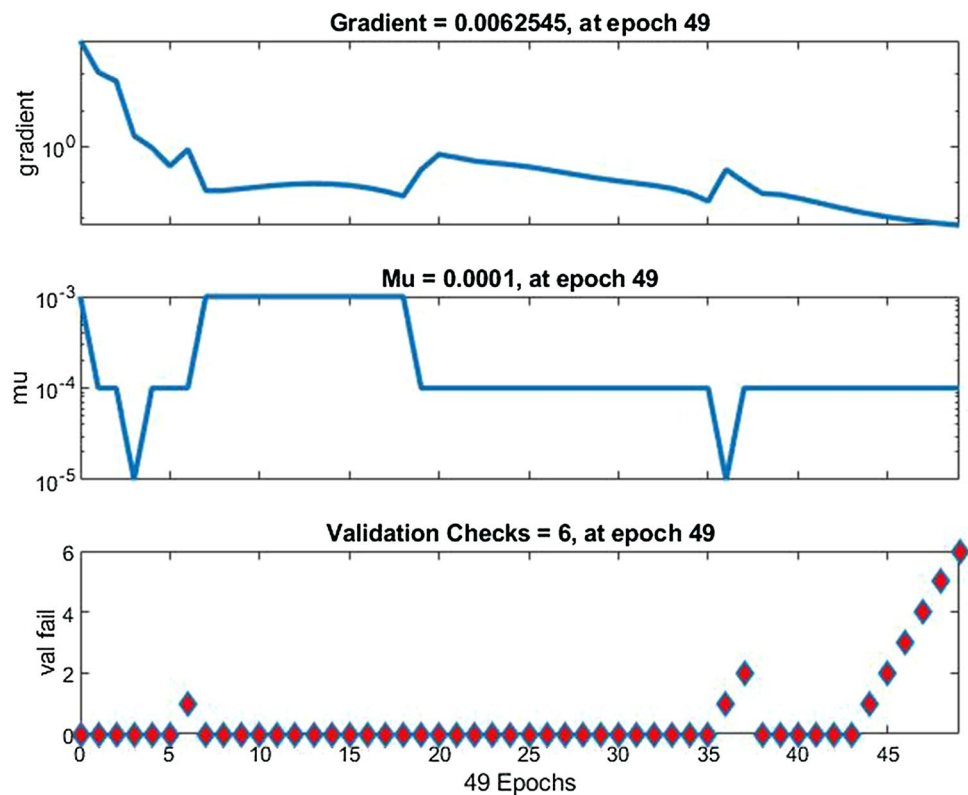


Table 2 The regression equation for 12-month

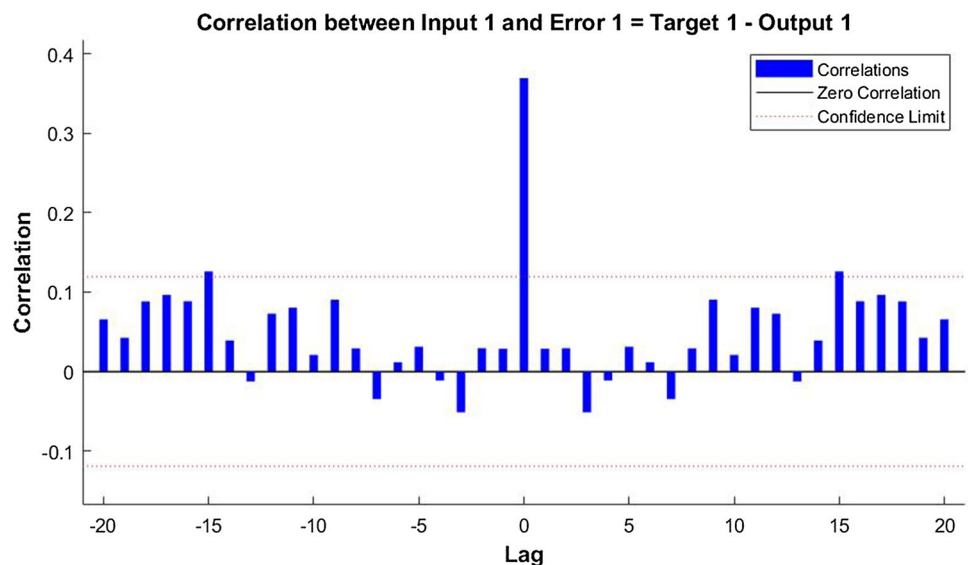
Month	Equation
January	WindS = -0.106 Hum - 0.101 Temp - 0.117 Direc
February	WindS = -0.117 Hum
March	WindS = -0.092 Direc
Nisan	WindS = -0.214 Hum - 0.289 Press + 0.053 Direc
May	WindS = 0.404 Hum + 0.323 Temp + 0.052 Direc
June	WindS = 0.067 Hum + 0.107 Direc
July	WindS = -0.099 Hum + 0.129 Direc
August	WindS = -0.221 Hum + 0.314 Press + 0.072 Direc
September	WindS = 0.315 Hum + 0.293 Press + 0.102 Direc
October	WindS = -0.137 Hum - 0.236 Temp + 0.044 Direc
November	WindS = -0.272 Hum - 0.144 Press - 0.081 Direc
December	WindS = +0.104 Hum + 0.109 Temp - 0.09 Direc

Typically, most of the errors are close to zero, which shows a pretty good fit. Here, most of the error approaches zero (minor errors) in the training datasets that comprise 70% of all samples and test data clusters that correspond to the 15% of the samples.

Autocorrelation explains how estimation errors relate to time. For a perfect training model, autocorrelation should have only one non-zero value at zero delays. Figure 7 describes the autocorrelation function of errors to verify network performance, indicates the presence of this white noise as the estimation errors do not correlate with each other. Here, the autocorrelation of errors is within 95% confidence limits.

The regression graph between the input variables (temperature, pressure, humidity, and direction) and the target variable (wind speed) and the process of training, validation, and testing process is in Fig. 8.

Fig. 5 The input–output cross-correlation function



The regression coefficient, R, shows how strong the relationship between the two variables is. The calculated values for training, validation, test and all data are $R = 0.97837$, $R = 0.97821$, $R = 97,833$, $R = 97,912$, respectively. Regression equations are in Table 3.

Figure 9 is a simulation graph showing the change of input and target values. We see that the error values found as a result of the simulation are very close to zero and that we can use the NARX model to estimate the wind speed.

4.3.2 Network Performance

These performance coefficients and estimates are obtained as below, using the MATLAB code: {

```
MSE = mse(net,targets,outputs, { 1 }, 'regularization', 0.1)
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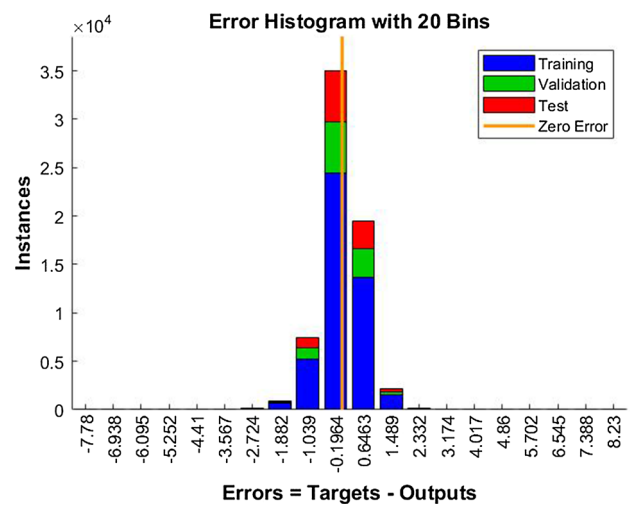


Fig. 6 Error histogram of the NARX prediction model for wind speed

Fig. 7 Autocorrelation plot of prediction error

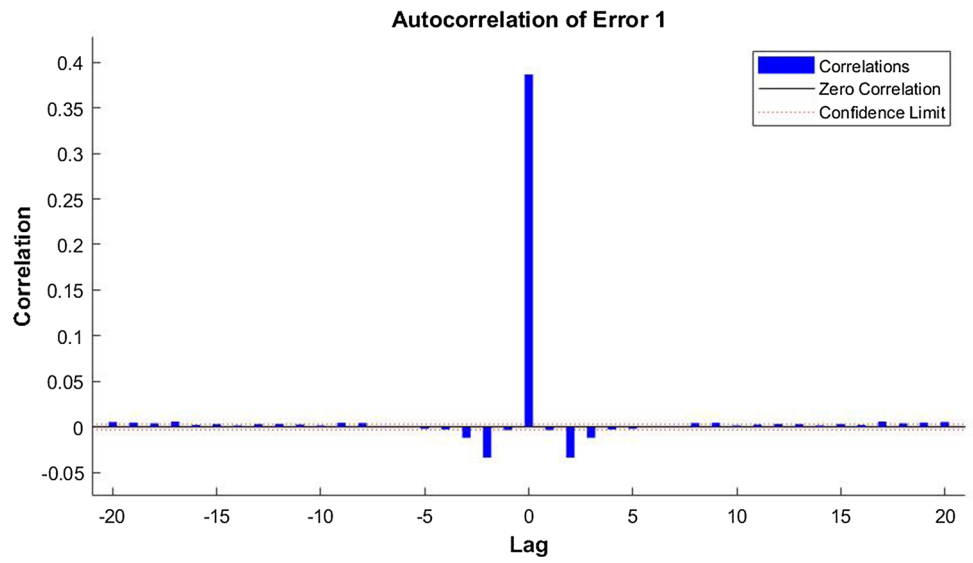


Fig.8 Regression of training, validation, test, and all data

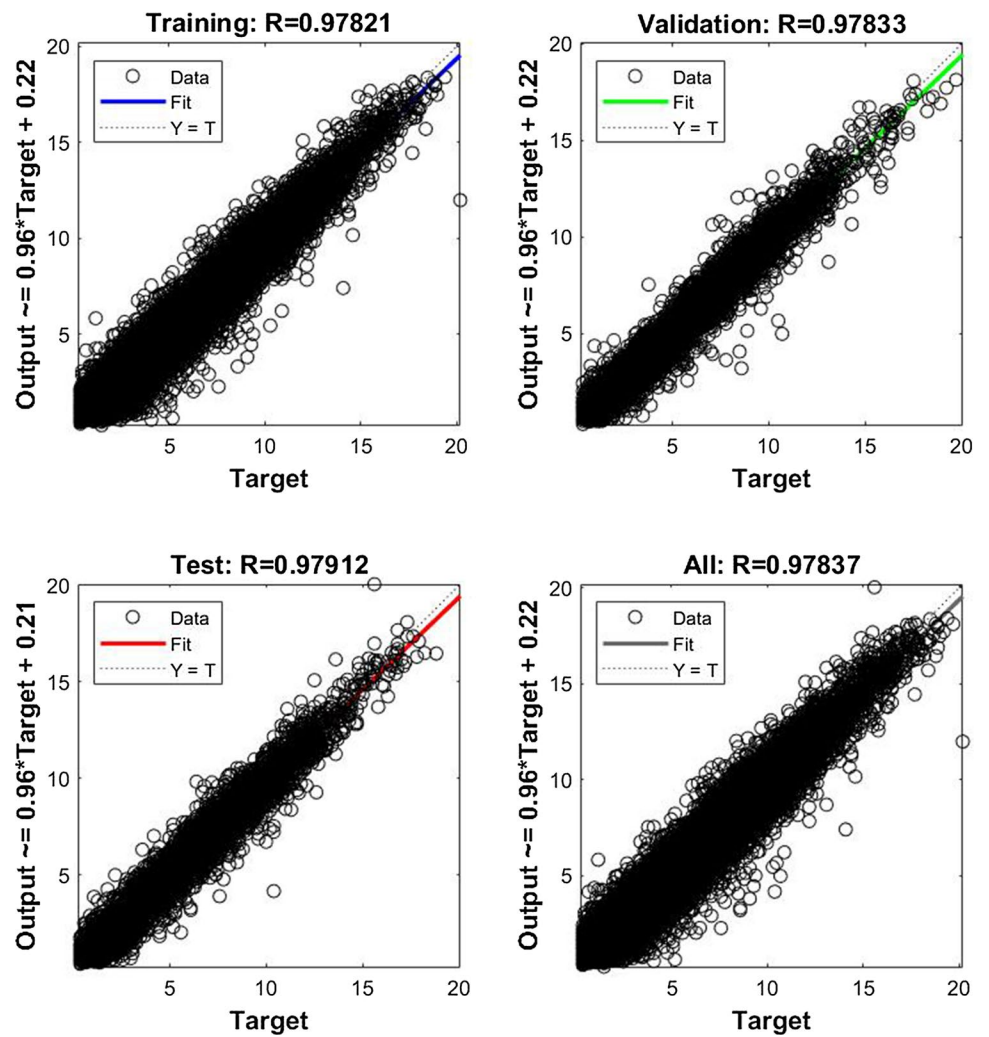


Table 3 Test values of statistical indices for NARX

	Target Values	MSE	R
Training	3124	0.3409	0.9727
Validation	670	0.3388	0.9728
Testing	670	0.3545	0.9726

MAE = mae(net,targets,outputs,{1},'regularization',0.1)
 Performance coefficients: performance = 0.340
 0, MSE = 0.3412, MAE = 0.4343, closedLoopPer-
 formance = 7.9097 earlyPredictPerformance = 0.3400.

4.3.3 }

5 Result

Artificial Neural Networks are superior data-oriented models that we use in the prediction problem. We can explain the relationships between factors affecting wind speed using NARX, correlation, regression methods. Depending on the current data set analysis and geographic location, wind direction affects the wind speed the most. When we train the wind speed model using the learning algorithm (LM), we can see that the NARX model has a good performance in predicting wind speed. The results obtained from the

analysis show that the performance measurements are at the desired accuracy (Table 4).

Average wind speed can be predicted 24 h in advance using ANN estimation methods. A suitable wind database and performance of the NARX model give accurate results in short term wind speed estimation.

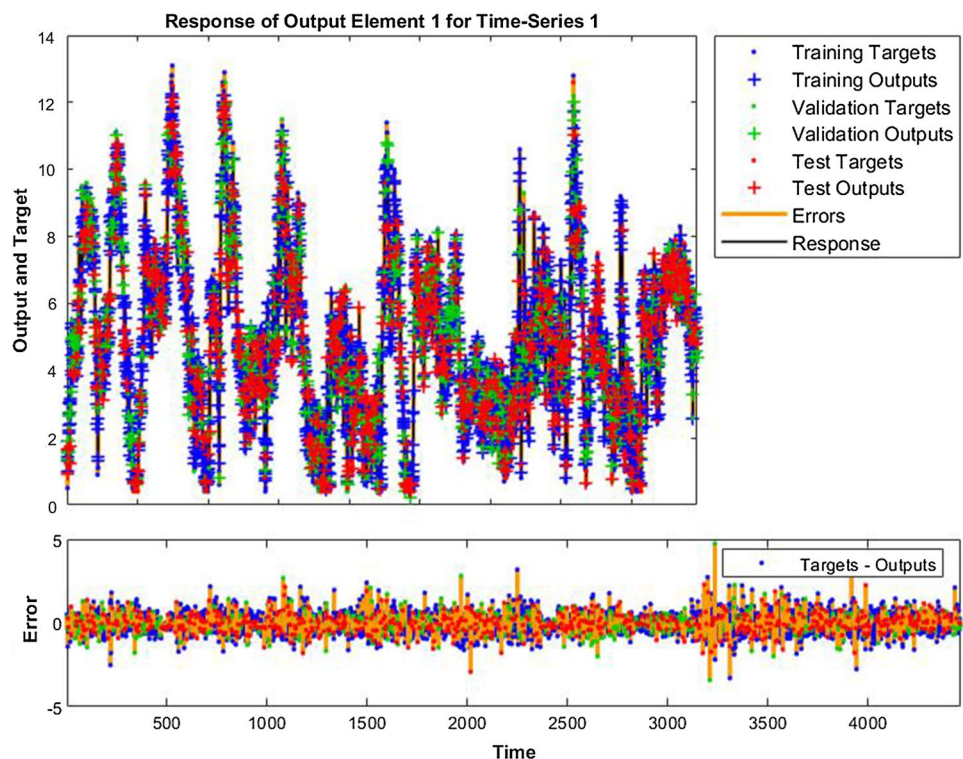
The performance of the NARX model depends on the statistics of MSE, RMSE, and R. The number and length of the time series and the correlations between time series determine the ANN model of a time series. If these parameters are reasonable, ANN is the right choice; otherwise, the classical time series approach will give better results.

Correlations between data points in wind speed prediction are more revealing in daytime measurements. Therefore, it may be more useful to test the model on intraday data. In this case, we can examine whether the model’s long-term learning ability is even more valuable.

Table 4 Regression equations

Training	Output = 0.96 target + 0.22
Validation	Output = 0.96 target + 0.22
Test	Output = 0.96 target + 0.21
All	Output = 0.96 target + 0.22

Fig.9 The Response of NARX prediction model for wind speed data (trained by the Levenberg Marquardt algorithm)



Acknowledgement This research was support by the Scientific Research Grant of Istanbul University-Cerrahpasa, [Grant number: 2071]

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