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ESTIMATION OF FAST VARIED WIND SPEED BASED ON NARX NEURAL NETWORK BY USING CURVE FITTING

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Abstract

In this study, a Nonlinear AutoRegressive eXogenous (NARX) neural network is used to estimate the wind speed on three monthly data sets taken from the wind central in Zonguldak province in Turkey. In the estimation study, the first and second order curve fitting coefficients of the measured temperature, pressure, humidity and solar radiation parameters together with the wind speed are used. In the estimation process, before these coefficients are applied directly to the NARX network structure, the most suitable features are selected with ReliefF method to minimize the MSE value. The number of delay steps in the NARX network structure is varied from 3 to 15 and the number of hidden neurons is varied from 3 to 15 to obtain model parameters that give the least estimation error. In order to determine the performance of the obtained model, the model is evaluated in terms of statistical error criteria such as MAE, MSE and RMSE. The model parameters and features matrix giving the least estimation error for the wind speed estimation of the NARX network structure are determined. It has been observed that this approach provides a high performance for estimating the wind speed with related to other measured parameters.

Key words: *Wind speed, Estimation, NARX, Curve fitting, ReliefF method*

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1. Introduction

The rapid decline of fossil fuel reserves (petroleum, coal and natural gas) in recent years [1] and the adverse impacts of these energy sources on the environment clearly set out the necessity and use of renewable and clean energy resources [2]. The hydraulic, wind, solar, geothermal and biomass energy are used commonly as renewable energy sources today. The demand for these energy sources is increasing day by day due to the fact that it does not cause environmental problems during the production and conversion of energy. Among these energy sources, wind energy stands out because it is clean, sustainable and less costly than other sources [3].

Due to the solar radiation, different warming of the ground surface causes difference of air temperature, humidity and pressure. These pressure differences cause the movement of the air, and the wind is generated by the movement of air from high pressure to low pressure. The electricity generation from wind energy is realized by wind turbines [4]. In order to benefit technologically from wind energy, it is important to know the possibilities of utilization, to identify location with high wind energy potential, to predict wind characteristics and wind speeds [5]. It is stated that the estimated economic wind energy potential of Turkey is about 50.000 MW and the installed system capacity is about 10% of this value. In terms of wind potential, it is obtained from the wind map that the average wind speed in coastal areas of the Western Black Sea region is 6-7 m/sec [6]. In this study, wind speed estimation is performed by obtaining a model with minimum error for different hidden layer neurons and delay steps in one minute time scale with Nonlinear AutoRegressive eXogenous (NARX) artificial neural network on three monthly data set taken from wind central established in Zonguldak province in Turkey.

In [7], the wind speed estimation were made with Artificial Neural Network (ANN) based model by using measured wind speed data from 11 different locations. In their study, the values of temperature, air pressure, solar radiation and altitude were applied to the ANN model input and the average wind speed was estimated and the model performance was measured. The model was confirmed by data sets obtained from different regions, Mean Absolute Percentage Error (MAPE) was 6.489% and correlation coefficient was 0.99. In [8], the short-time wind speed estimate was made using the Unscented Kalman Filter (UKF) based on the state-space Support Vector Regression (SVR) method. The authors compared the method they proposed with other methods (ANN, AR, AR-Kalman, SVR). The proposed method has shown that it provides high performance in estimating one step ahead and multi-step-ahead wind speed on data collected from different locations. In [9], short time wind speed estimation application was done by using the algorithm of coral reefs optimization and Extreme Learning Machine (ELM) with meteorological data. The feature selection was made by using coral reef optimization method on prediction variables. The selected features have been applied to ELM and it has been shown that this method was very successful for wind speed estimation problem. In [10], the selection of meteorological variables was made by NBTree method which was composed of C4.5 tree and Naive Bayes methods. The authors were shown that the proposed method was more successful than C4.5 and NB methods in the selection of variables. The estimation of the next wind speed was made for two different locations with Auto-Regressive Integrated Moving Average (ARIMA) and NARX artificial neural network model approaches [11]. In their study, the mean values of temperature, pressure, solar radiation and humidity except wind speed from meteorological data were used for both locations. It was determined that the NARX method used improved the MSE value according to the ARIMA method by 10.6% for the first location and 12.8% for the other location.

In this study, NARX neural network is used to estimate wind speed on three monthly data sets taken from the wind central. The first and second order curve fitting coefficients of measured meteorological parameters together with the wind speed are used in the estimation process. The features are determined by curve fitting method for obtained other measurements including wind speed. The most suitable features are selected with ReliefF method to minimize the MSE value. The selected features are applied directly to NARX network structure. The features matrix obtained according to weight coefficients and the model parameters for the wind speed estimation of the NARX network structure are determined to minimize MSE value. The statistical error criteria in terms of MAE, MSE and RMSE are calculated to measure performance of obtained model. This article is organized as follows: the modelling and prediction method is presented in Section 2. Simulation and experimental results are given in Section 3. Conclusions are finally discussed in Section 4.

2. Modelling and Prediction Method

In this study, one step ahead wind speed estimation is predicted by using three monthly wind speed data which consists of one minute time series from the wind central established in Zonguldak province in Turkey. The average wind speed distribution according to wind direction from the obtained data is shown in Fig. 1-3. For the data set obtained, the statistical values such as the highest, lowest, mean and standard deviation value of wind speed, temperature, humidity, pressure and solar radiation variables used in this study are given in Table 1. Month-I, Month-II and Month-III are expressed the values measured in the same month of different years.

In Fig. 1, the dominant wind direction is from 31.24% East-Southeast (E-SE), 17.27% SE and 10.75% E. In Fig. 2, the dominant wind direction is from 29.42% E-SE, 14.61% E and 11.40% SE. In Fig. 3, the dominant wind direction is from 25.56% SE, 19.83% E-SE and 10.27% E.

Table 1. Wind speed statistical values.

Parameters	Month	Max.	Min.	Mean	Std. Dev.
Wind speed (m/s)	I	13	0	2.22	2.09
	II	14.3	0	2.35	2.40
	III	12.5	0	1.91	2.00
Temperature (℃)	I	23.2	3.3	11.98	4.21
	II	28.4	2.1	12.38	6.14
	III	21	2.5	10.46	4.26
Humidity (gr/m^3)	I	100	18	67.25	17.88
	II	99	15	69.74	19.50
	III	100	35	71.32	16.68
Pressure (mbar)	I	1035	1001	1020	6.92
	II	1033	999	1021	6.55
	III	1045	1010	1027	8.06
Solar radiation (W/m^2)	I	490	0	39.56	81.76
	II	570	0	43.57	95.28
	III	570	0	50.03	99.30

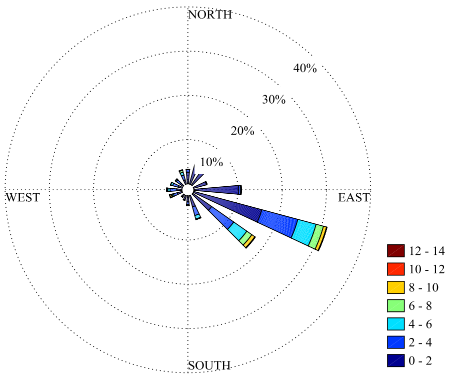

Fig. 1. Wind rose of the studied month-I.

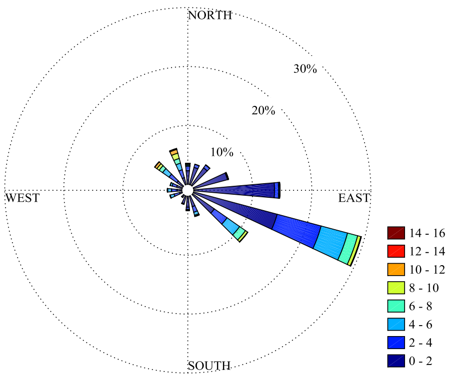

Fig. 2. Wind rose of the studied month-II.

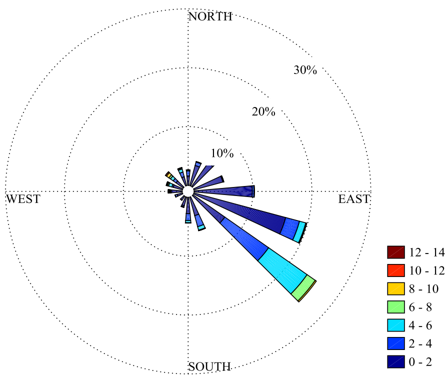

Fig. 3. Wind rose of the studied month-III.

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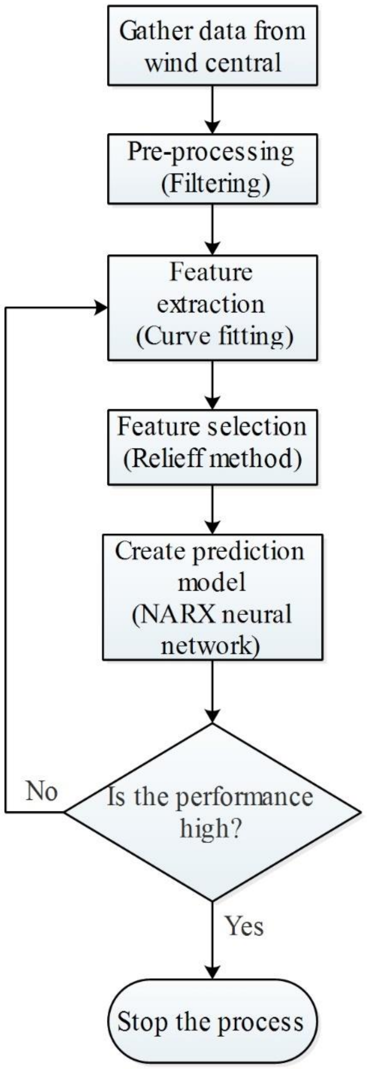

Fig. 4. Wind speed prediction flow chart.

The steps followed in the study are seen in the flow chart in Fig. 4. In the preliminary processing phase, three monthly wind speed, temperature, humidity, pressure, solar radiation data from the wind central are filtered with 3-day average filter. The curve fitting coefficients are determined as a feature by applying curve fitting method in first and second order to the values obtained after filtering process. With the ReliefF method, the most suitable features are selected and the estimation process is completed with the NARX neural network. The network which estimates the actual wind speed with minimum error is obtained and the estimation process is concluded.

2.1. Model

In this study, variables such as temperature, pressure, humidity, solar radiation are used in addition to the wind speed for NARX artificial neural network entry. The nonlinear f (.) function calculates the value of the one step ahead wind speed which depends on the d step previous values of the input and output signals by Equation (1). Using the parameters in Table 2, NARX neural network model is shown in Fig. 5.

$$y(n+1) = f\left(y(n),\ldots,y(n-d),u(n),\ldots,u(n-d)\right) \qquad (1)$$

Table 2. Model parameters.

Features	Values
Layer number	3
Time delay number (d)	from 3 to 15
Hidden layer neuron number (N)	from 3 to 15
Weight (w) and biases (b)	Random
Activation functions	Tan-Sigmoid, Pure linear
Training algorithm	Levenberg-Marquardt
Epoch	1000

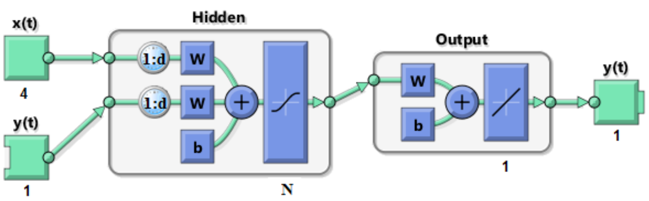

Fig. 5. NARX neural network model.

2.2. Curve Fitting and Determination of Features

For the values of wind speed, temperature, humidity, pressure and solar radiation values in the past d step, first and second order curve fitting are performed by using Equation (2) and Equation (3). The features are labelled as wind speed F1, temperature F2, humidity F3, pressure F4 and solar radiation F5.

$$y_1 = a_1 x + b_1 \qquad (2)$$

$$y_2 = a_2 x^2 + b_2 x + c_2 \qquad (3)$$

The coefficients of a1 and b1 in the first order linear function and the coefficients a2, b2 and c2 in the second order quadratic function generated for each feature are determined as the feature vector extracted from each feature. The extracted features and their labels are given in Table 3.

Table 3. Extracted features and their labels.

Parameters	Features	Feature label
Wind speed	[a_1, b_1, a_2, b_2, c_2]	F6, F7, F8, F9, F10
Temperature	[a_1, b_1, a_2, b_2, c_2]	F11, F12, F13, F14, F15
Humidity	[a_1, b_1, a_2, b_2, c_2]	F16, F17, F18, F19, F20
Pressure	[a_1, b_1, a_2, b_2, c_2]	F21, F22, F23, F24, F25
Solar radiation	[a_1, b_1, a_2, b_2, c_2]	F26, F27, F28, F29, F30

2.3. Normalization and Feature Selection with ReliefF Method

The wind speed data collected to obtain the best prediction result is normalized [12]. The min-max normalization is performed by using Equation (4), taking into consideration the statistical properties in Table I together with wind speed, temperature, humidity, pressure, solar radiation values.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (4)$$

Relief method is used in the selection of features in classification and regression analysis applications in data mining [13]. This method has applications in different areas, such as estimation of unfamiliar person's height [14], estimation of fraudulent financial statements [15] and estimation of electricity price one day later [16]. In this study, those that minimize the prediction error from the features in Table 3 are selected.

2.4. Training Phase

Table 4. Data set used for model.

Month	Training Set (%70)	Validation Set (%15)	Test Set (%15)	Total Data (%100)
I	29912	6410	6410	42732
II	29557	6333	6333	42223
III	25538	5472	5472	36483

The generated NARX neural network model is used 70% of the data set during the training phase, 15% of the data set during the validation phase and 15% of the data set during the test phase. The data numbers corresponding to these ratios are given in Table 4.

2.5. Statistical Error Criteria

Table 5. Statistical error criteria.

Performance Metrics	Statistical Error Criterion Formula
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n} \lvert e_t \rvert$
Mean Squared Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n} e_t^2$
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_t^2}$

In the estimation of wind speed, the statistical error criteria given in Table 5 are used to calculate the model error by comparing the response of the obtained model with the actual data. The error is expressed:

$$e_t = r_t - p_t \qquad (5)$$

where r_t is observed for a given time t and p_t is the predicted time series [17].

3. Simulation and Experimental Results

In the study, three monthly data are taken from 1-minute time series from wind central. The features based on the curve fitting method are used to estimate the wind speed from the wind central data. Then, the NARX neural network for different hidden layer neuron numbers and delay step numbers is created by selecting feature based on ReliefF method. The data are randomly divided into %70 training, %15 validation and %15 testing. The number of delay steps in the NARX network structure is varied from 3 to 15 and the number of hidden neurons is varied from 3 to 15 to obtain model parameters that give the least estimation error. The representation of features which selected with ReliefF method from the most significant to the least significant is shown in Fig. 6 for the three monthly data set. The weight coefficients which is sorted from maximum to minimum according to this method are shown Fig. 7.

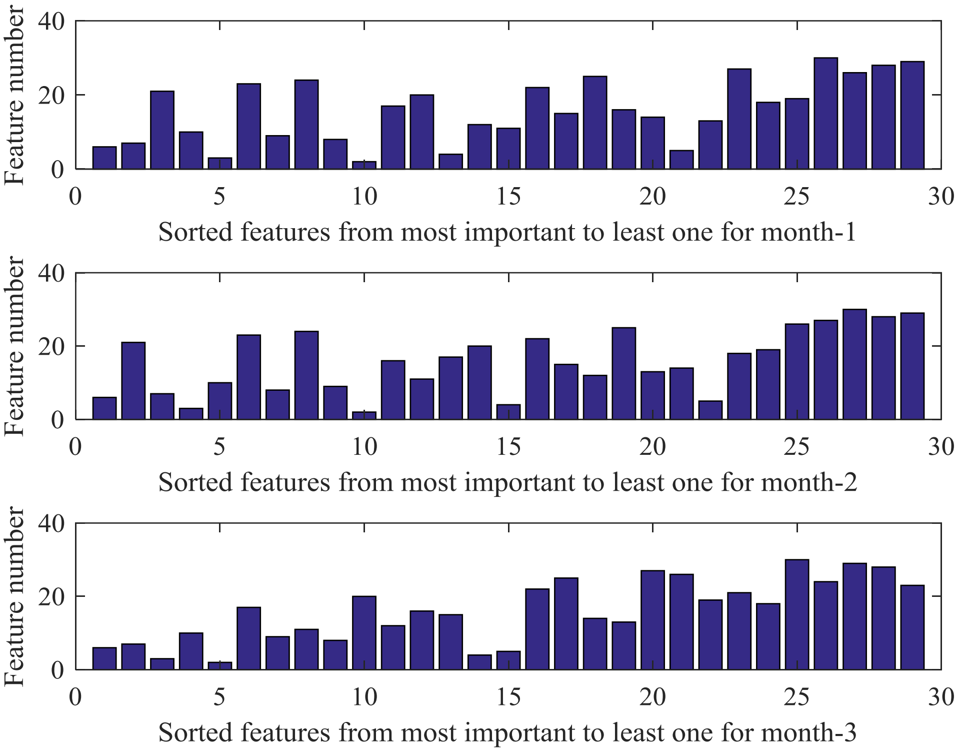

Fig. 6. Features sorted by weight coefficients with the ReliefF method.

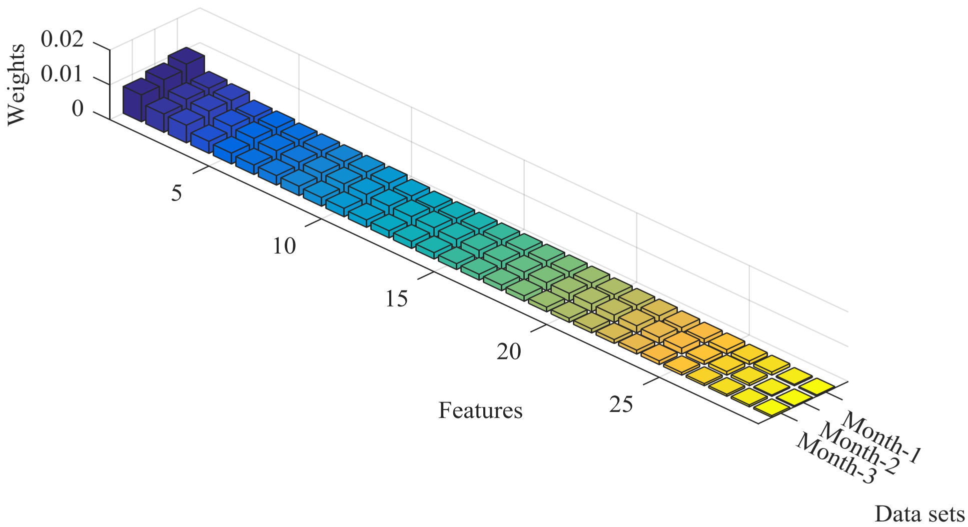

Fig. 7. Features change of weight coefficients according to the features for the data set.

The MSE change graph for the variable parameters of the NARX neural network generated in the step of estimating the wind speed is given in Fig 8-10. The error value decreases gradually as the number of delay steps increases, and the model prediction performance increases. The model performance is increased directly proportional to the number of neurons for the fixed number of delay steps.

In the training, validation and test phases, the frequency of the error between the actual wind speed and the estimated wind speed is shown in Fig. 11. The model performance graph for the lowest training, validation, and test error at a short iteration value (for epoch 34) is shown in Fig. 12.

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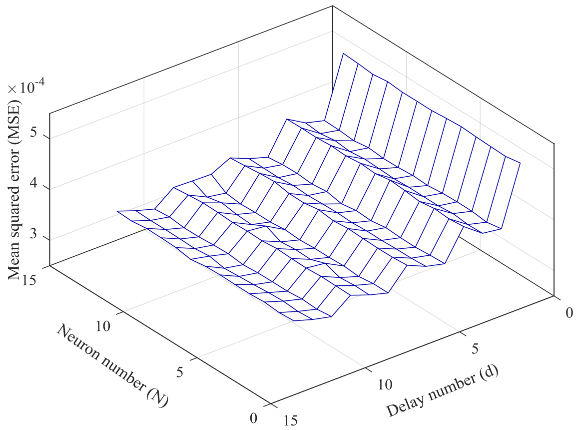

Fig. 8. MSE change for different number of neurons and number of delay steps (Month-I).

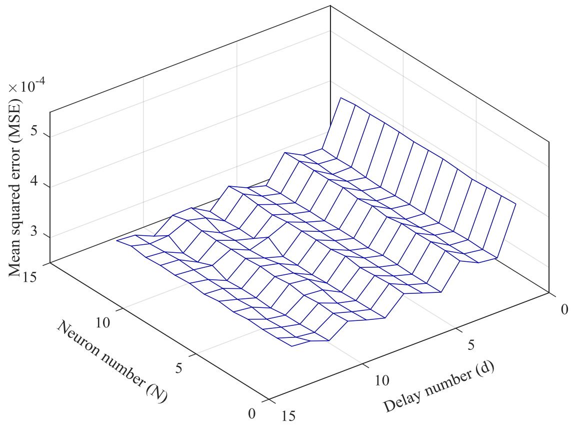

Fig. 9. MSE change for different number of neurons and number of delay steps (Month-II).

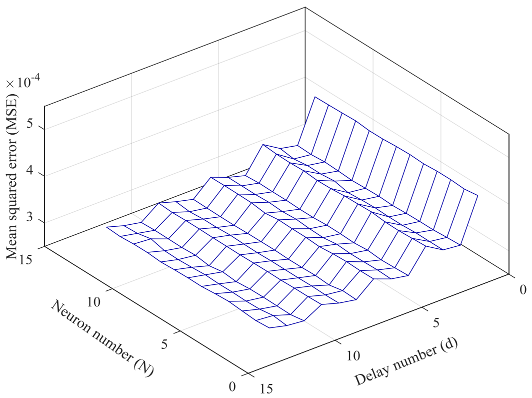

Fig. 10. MSE change for different number of neurons and number of delay steps (Month-III).

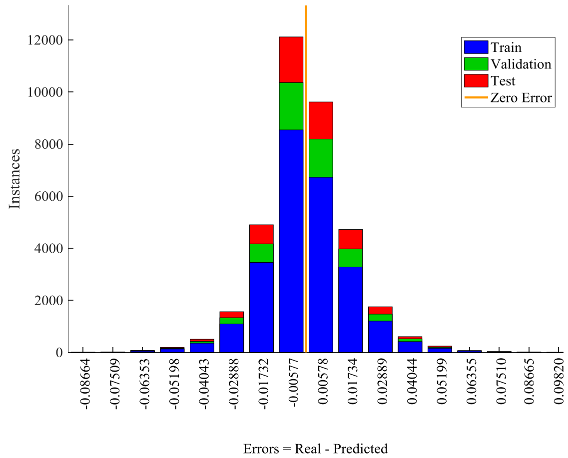

Fig. 11. Error histogram for training, validation and testing phases.

For the three monthly data set, the selected features with ReliefF method and the corresponding parameters of the most appropriate prediction model with the MAE MSE and RMSE values are shown in Table 6-7, respectively.

Table 6. Applied model parameters and their inputs.

Data sets	Inputs	Parameters
Month-I	F6,F7,F21,F10	d=13, N=9
Month-II	F6,F21,F7,F3	d=13, N=15
Month-III	F6,F7,F3,F10	d=13, N=10

Table 7. Error values for the applied models.

	MAE	MSE	RMSE
Month-I	0.013227	0.000340	0.018448
Month-II	0.012106	0.000283	0.016815
Month-III	0.012276	0.000279	0.016697
Average	0.012536	0.000300	0.017320

For month I, the features F6, F7, F21 and F10 are selected and the MSE value for the number of 13 delay steps and 9 hidden layer neurons is 3.4x10-4. For month II, the features F6, F21, F7 and F3 are selected and the MSE value for the number of 13 delay steps and 15 hidden layer neurons is 2.83x10-4. For month III, the features F6, F7, F3 and F10 are selected and the MSE value for the number of 13 delay steps and 10 hidden layer neurons is 2.79x10-4. The overall model error rate is 3.00x10-4 in terms of MSE.

The R-value is shown that the relationship between the outputs and targets. The training, validation and test phase for the best model is shown in Fig. 13 with R-value 0.91, 0.92 and 0.91, slope 0.91, 0.91 and

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0.89, respectively. It is seen that R-value is close to 1 from the obtained results. In this case there is linear relationship between the outputs and the targets.

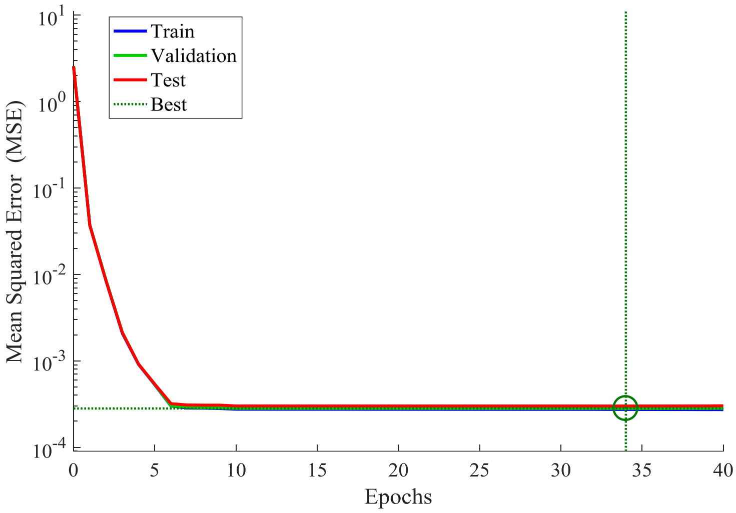

Fig. 12. Performance plot.

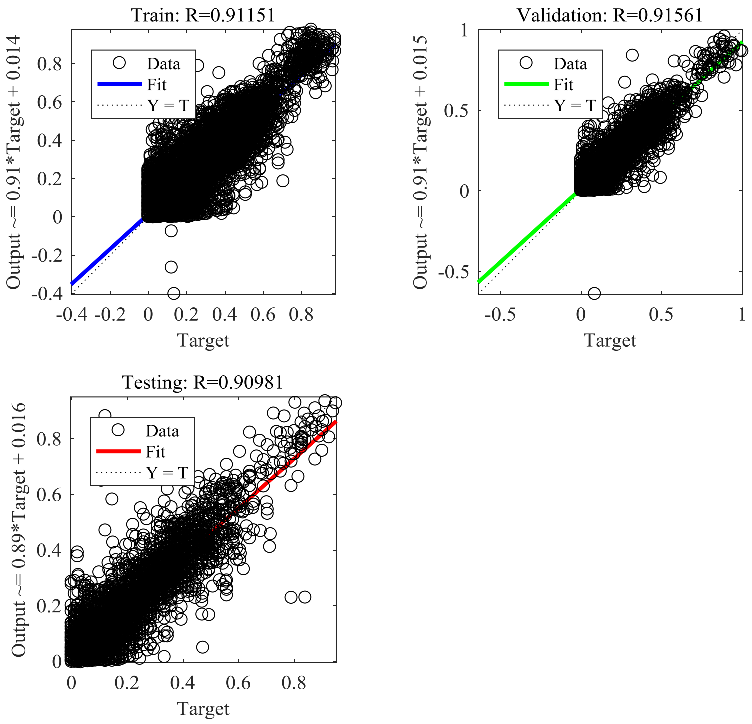

Fig. 13. Regression plot for training, validation and testing phases.

The predicted wind speed versus real wind speed for the minimum error model is given in Fig. 14-16, respectively. With the model obtained, it is observed that the predicted wind speed overlap the real wind speed. It is also seen that the obtained model predicts wind speed with high performance.

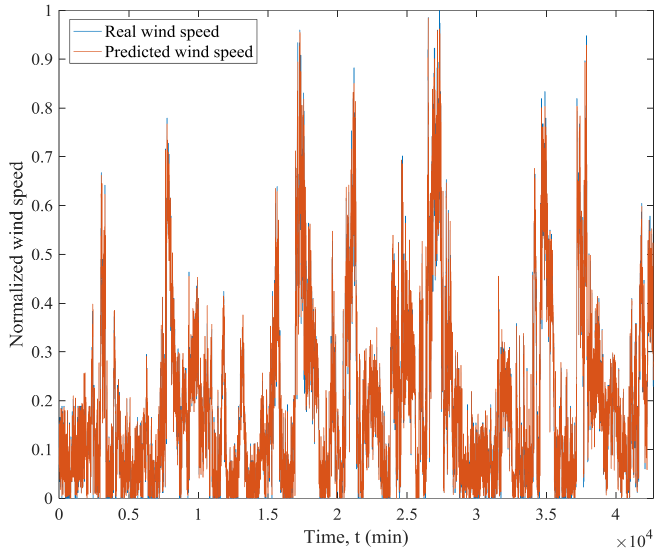

Fig.14. Wind speed prediction graph with NARX neural network model (for Month I).

5. Conclusions

In this article, one step ahead wind speed estimation is performed with NARX neural network model using three monthly wind speed, temperature, pressure, humidity and solar radiation data set obtained from wind central. The features are determined by curve fitting method for obtained other measurements including wind speed. The most suitable features are selected with ReliefF method to minimize the MSE value. The number of delay steps and the number of hidden layer neurons in the NARX neural network directly affect the prediction performance of wind speed. For this reason, the most suitable model parameters are obtained after the feature selection step. The most suitable features which are determined with curve fitting method are selected with ReliefF method and model is obtained by training NARX neural network for estimation of wind speed. It is seen that the performance of the obtained model is high. It is thought that the used method is shown high performance and will give light to future studies.

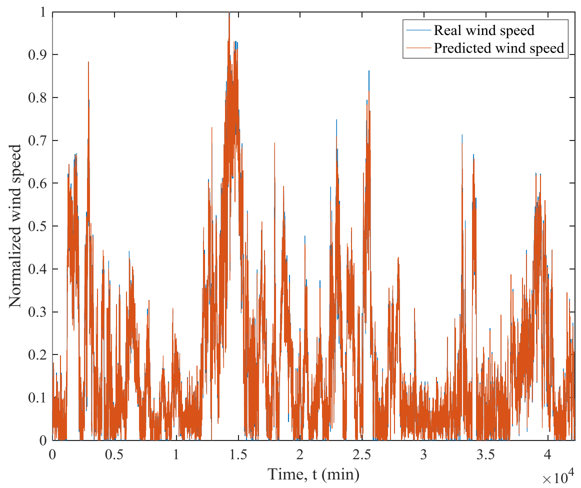

Fig.15. Wind speed prediction graph with NARX neural network model (for Month II).

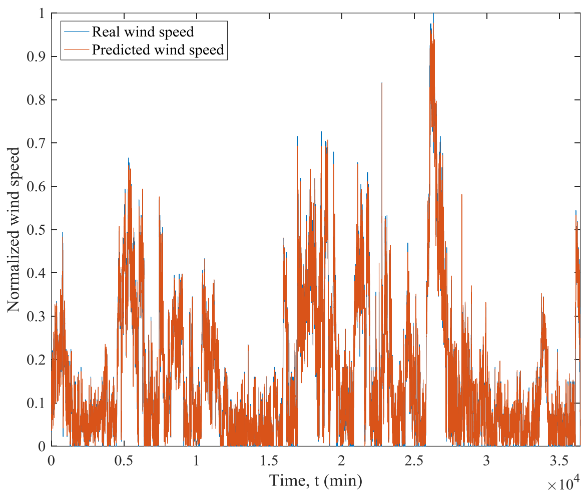

Fig.16. Wind speed prediction graph with NARX neural network model (for Month III).

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