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Forecasting of Electricity Generation Shares by Fossil Fuels Using Artificial Neural Network and Regression Analysis in Turkey

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Abstract

This study is conducted to get predictions for the generation of electricity by annual production shares and decide the most suitable method for future periods. Between 2010-2017 in Turkey, the relation of generation shares of coal, natural gas, liquid fuels with the greenhouse gas is examined with the artificial neural network and the regression analysis. The input “greenhouse gas” to explain the effect in the using the energy sources for the electricity generation is searched. Artificial neural network (ANN) and regression analysis methods are used in the study. As a result, ANN gives better results than the regression analysis.

Keywords: “Fossil Fuels, Greenhouse gas, Regression Analysis, Feed Forward Neural Networks”

1. Introduction

Our world faces the problems because of the fossil fuels and its harmfull effects. This makes clean or green energy using important. Renewable energies such as solar energy, wind energy, jeotermal energy, hydrogen etc. are called green energy and they should be criticially our main energy sources for the next generation. Modern world try to solve the fossil fuels problems by using technical solutions; but these are not enough to reduce the rate of the greenhouse gas.

Energy is vital for the development of any nation. In the last decade, energy consumption has increased exponentially. Energy management is crucial for future economic prosperity and environmental security. Energy management is necessary for proper use of available resources [1]. Turkey's energy demand has increased rapidly as a result of social and economic development [2]. Modern statistical methods of planning and forecasting future energy demand are used officially since 1984 in Turkey [3].

The use of artificial neural networks for estimation has increased substantially in recent years [4]. ANNs present different ways of solving complex problems [5],[6]. ANNs have been accepted as an important method [7] and emerged as an important way between traditional statistical estimation methods [8]. ANN is preferred because of its ability to predict future values with more than one variable and to model nonlinear relations in data structure [9].

In this study, ANN and the regression analysis are used for the prediction of the electricity generation shares by energy sources as the output. For three types of the energy sources (coal, liquid fuels, and natural gas) are considered. The data is taken from the Turkish Statistical Institute (TSI). The input is greenhouse gas and the output is the generation share of the fossil fuels.A feed forward neural network is used for forecasting three energy sources in Turkey. ANN model uses the Levanberg-Marquadt learning algorithm for training data by MATLAB software package.

Various energy demand forecasting models are presented. In addition to traditional methods such as time series, regression, econometric, ARIMA, fuzzy logic, genetic algorithm and artificial neural networks are used [1]. Electricity sector is investigated by ANN as a means of prediction [9]. To determine the future level of energy consumption in Turkey, ANN technique has been preferred for energy consumption [2],[10],[11],[12],[13]. The impact of energy use on the efficiency of Turkey's agriculture is reported by results of the regression analysis, the relationship between energy uses and agricultural productivity is examined [14]. ANN to estimate the electrical loads in Japan until the year 2020 are used [15]. In order to predict energy demand

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efficiently for South Korea, an artificial neural network model is developed [16]. The relationship between electricity demand and temperature in the European Union is presented [17].

Natural gas that is 5% of the total consumption is very important for Turkey. The forecasting accuracy of natural gas consumption is one of the important factors influencing the energy sector for investments and natural gas agreements. In recent years, new techniques such as artificial neural networks and fuzzy systems have been widely used in predicting natural gas consumption in addition to classical time series analyzes [18] and gas demand is forecasted by ANN [19]. Artificial neural networks have also been used to predict natural gas [18],[20]. Forecasts for the future by using artificial neural networks for natural gas consumption are proposed [21]. An integrated particle swarm optimization (PSO) and artificial neural network (ANN) are presented to analyze fossil fuels (oil, natural gas, coal etc.) and green energy consumption [22]. The analysis of green energy consumption through artificial neural networks is presented. In addition, world's primary energy sources such as coal, oil and natural gas are analysed [23]. Analysis of greenhouse gas emissions due to global warming in the world is an important issue [24]. Greenhouse gas emissions by fossil fuel sources and the energy crisis caused by environmental concerns, sustainable need to energy resources has rised [6]. Greenhouse gas emissions can be estimated using a meta-regression analysis (MRA) [25] and by artificial neural networks [26],[27]. A time series analysis model to estimate greenhouse gas emissions is used [24].In this context, it is envisaged that the interlock system to be used in the accelerator will come to 3 subsystems. These are FPGA, PLC and software interlock systems.

2. Material and Method

The data taken from the TSI is as bellows [28]. Generation shares of electiricty by coal between 2010-2017 is Table 2.1. The biggest share is in 2016 and the lowest share is 2010.

Table 2.1. Generation shares of electiricty by coal between 2010-2017

Year	Actual Generation Shares by Coal
2010	26,1
2011	28,8
2012	28,4
2013	26,6
2014	30,2
2015	29,1
2016	33,7
2017	31

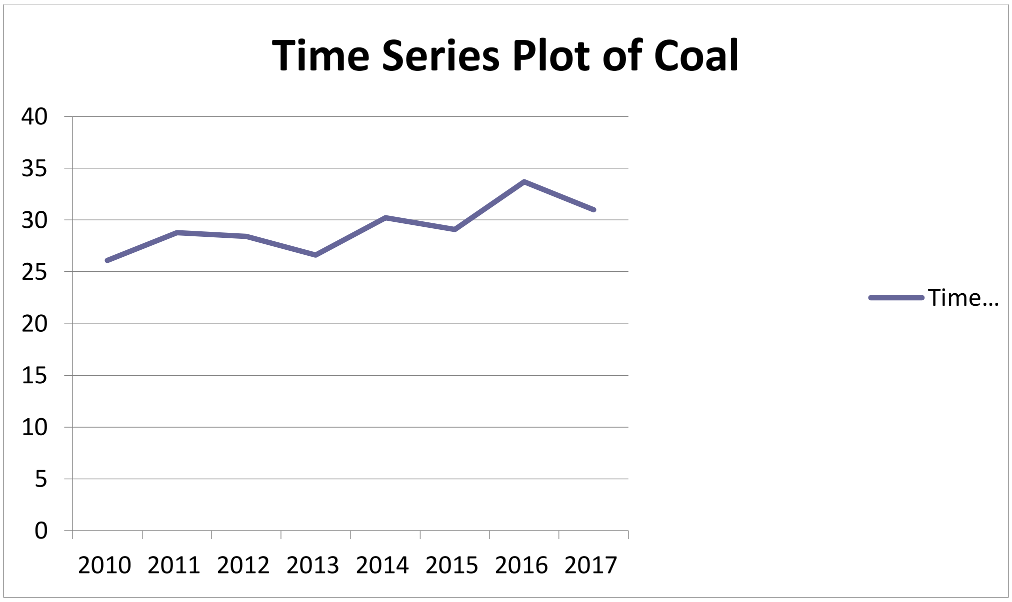

Fig 2.1. Time series plot of coal between 2010-2017

Coal share between 2010-2017 in Figure 2.1. shows an increasing pattern. Generation shares of electiricty by liquid fuels between 2010-2017 is Table 2.2. The biggest share is in 2017 and the lowest share is 2011.

Table 2.2. Generation shares of electiricty by liquid fuels between 2010-2017

Year	Actual Generation Shares by Liquid Fuels
2010	1
2011	0,4
2012	0,7
2013	0,7
2014	0,9
2015	0,9
2016	0,7
2017	3

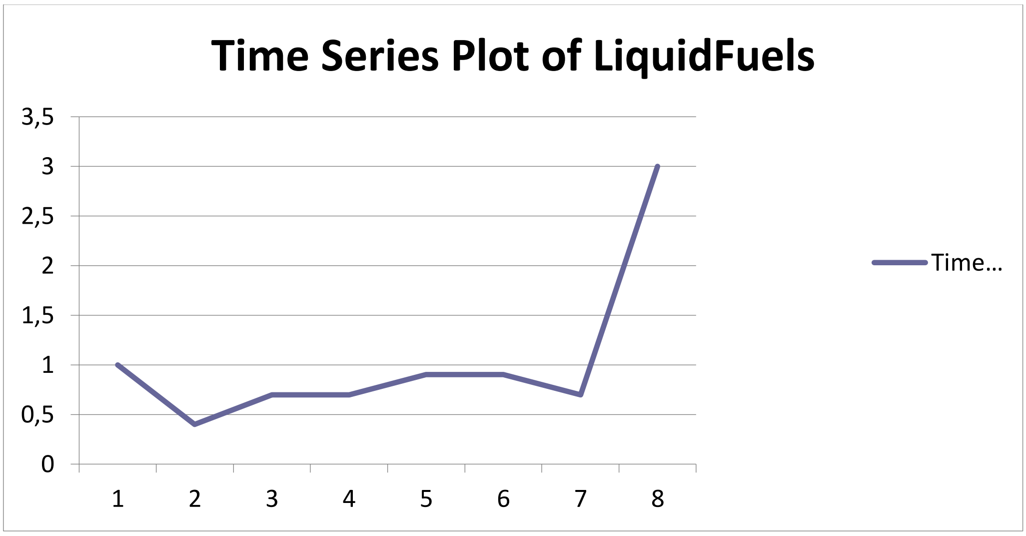

Fig 2.2. Time series plot of liquid fuels between 2010-2017

Liquid fuel share between 2010-2017 in Figure 2.2. shows an increasing pattern.

Generation shares of electiricty by natural gas between 2010-2017 is Table 2.3. The biggest share is in 2014 and the lowest share is 2016.

Table 2.3. Generation shares of electiricty by natural gas between 2010-2017

Year	Actual Generation Shares by Natural Gas
2010	46,5
2011	45,4
2012	43,6
2013	43,8
2014	47,9
2015	37,9
2016	32,5
2017	34

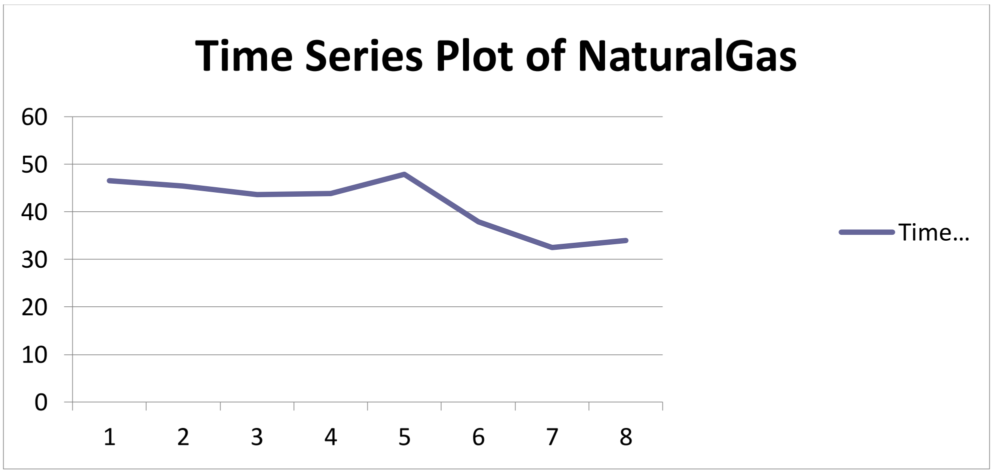

Fig 2.3. Time series plot of natural gas between 2010-2017

Natural gas share between 2010-2017 in Figure 2.3. shows an decreasing pattern.

Table 2.4. Greenhouse gas values between 2010-2017

Year	Period	Greenhouse gas
2010	1	406,8
2011	2	436,4
2012	3	448,9
2013	4	442,2
2014	5	455,6
2015	6	475,1
2016	7	490,6
2017	8	482,85

The data of the greenhouse gas between 2010-2016 is get from TSI in Table 2.4. The greenhouse gas value for 2017 is not documented; so, 2017 value is predicted by moving average method.

3. Results

The results for three type of fossil energies used for electricity generation are given in this section. Artificial neural network and linear regression results are compared with each other.

R square value, a measure of goodness of fit of linear regression, is found as 0.73 in Table 2.5.

Table 2.5. Regression Model Summary

Regression Statistics	
R square	0,73681952
Adjusted R Square	0,69295611
Standart error	1,46814884
count	8

The linear regression results for the coal are given in Table 2.6. The proposed linear regression model can be used (significance value 0.006<0.05). The linear regression equation is given in Eq 1.

Table 2.6. Linear regression results

	df	SS	MS	F	Sig
Regression	1	30,69498013	30,69498013	16,7980433	0,0063678
Residual	6	10,96376987	1,827294978		
	7	41,65875			

Coal generation share = -5, 31778119 + 0,07597803* greenhouse gas Eq 1

R square value, a measure of goodness of fit of linear regression, is found as 0.14 in Table 2.7.

Table 2.7. Regression Model Summary

Regression Statistics	
R square	0,1455652
Adjusted R Square	0,0031594
Standart error	0,8127637
count	8

The linear regression results for the coal are given in Table 2.8. The proposed linear regression model can not be used (significance value 0.35>0.05). The linear regression equation is given in Eq 2.

Table 2.8. Linear regression results

	df	**SS**	**MS**	**F**	**Sig**
Regression	1	0,6752407	0,6752407	1,0221862	0,3510213
Residual	6	3,9635093	0,6605849		
	7	4,63875			

Liquid Fuels generation share = -4,086409 + 0,011266* greenhouse gas Eq 2

R square value, a measure of goodness of fit of linear regression, is found as 0, 70 in Table 2.9.

Table 2.9. Regression Model Summary

Regression Statistics	
R square	0,7097133
Adjusted R Square	0,6613322
Standart error	3,4150771
count	8

The linear regression results for the coal are given in Table 2.10. The proposed linear regression model can be used (significance value 0.008<0.05). The linear regression equation is given in Eq 3.

Table 2.10. Linear regression results

	df	**SS**	**MS**	**F**	**Sig**
Regression	1	171,08349	171,08349	14,669222	0,0086587
Residual	6	69,976508	11,662751		
	7	241,06			

Natural gas generation share = 123,00981 -0,179326* greenhouse gas Eq 3

Learning, validation, test ve system performance are investigated for different neuron numbers the best performance is obtained with 16 neuron numbers. The results obtained for the 16 neuron numbers for energy generation share by coal are showed in Figure 2.4.

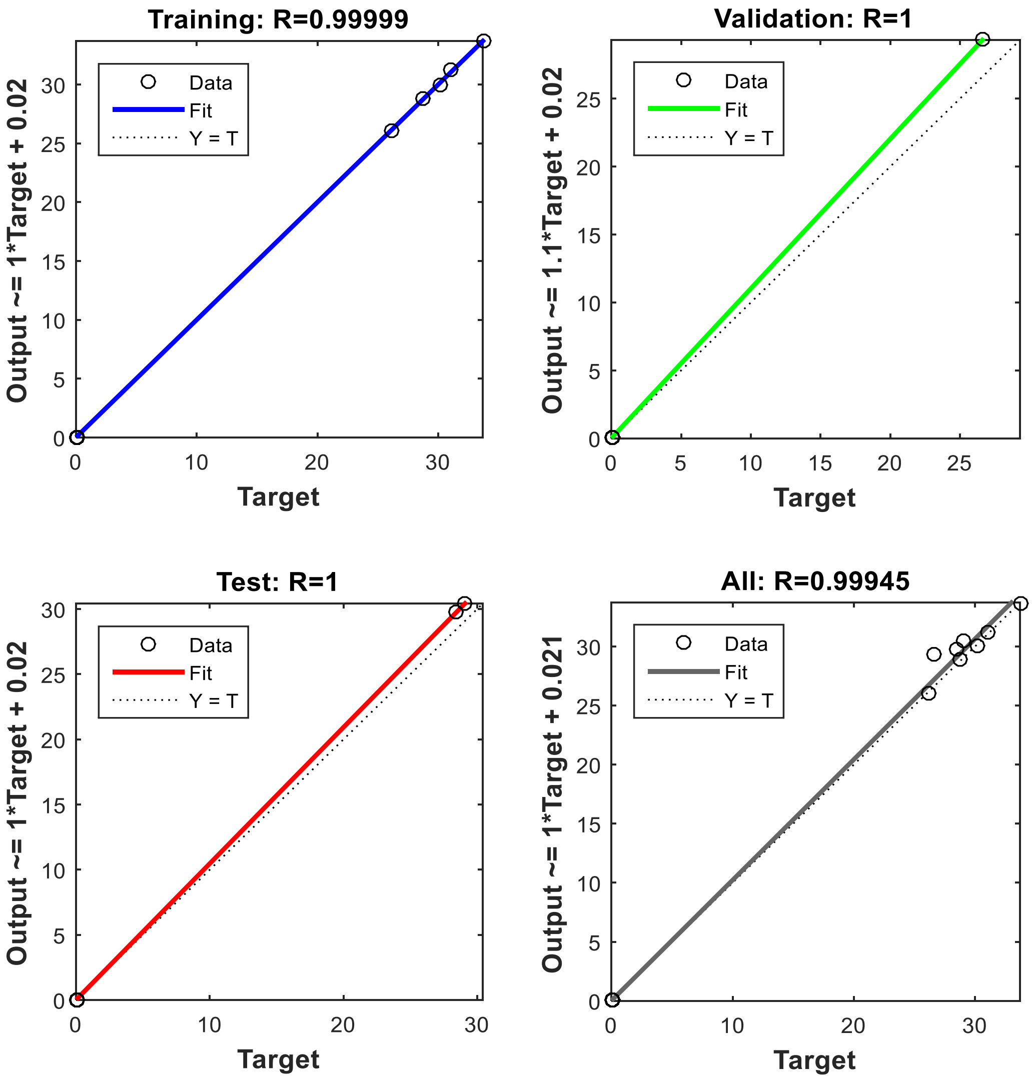

Fig 2.4. The performance values for 16 number of hidden neurons

The neural network model used for the generation by coal is achieved 99 percent shown in Figure 2.4. The neural network results are compared with the linear regression model. R square value,a measure of goodness of fit of linear regression, is found as 0.73 in Table 2.5.

The results obtained for the 16 neuron numbers for energy generation share by liquid fuels are showed in Figure 2.5.

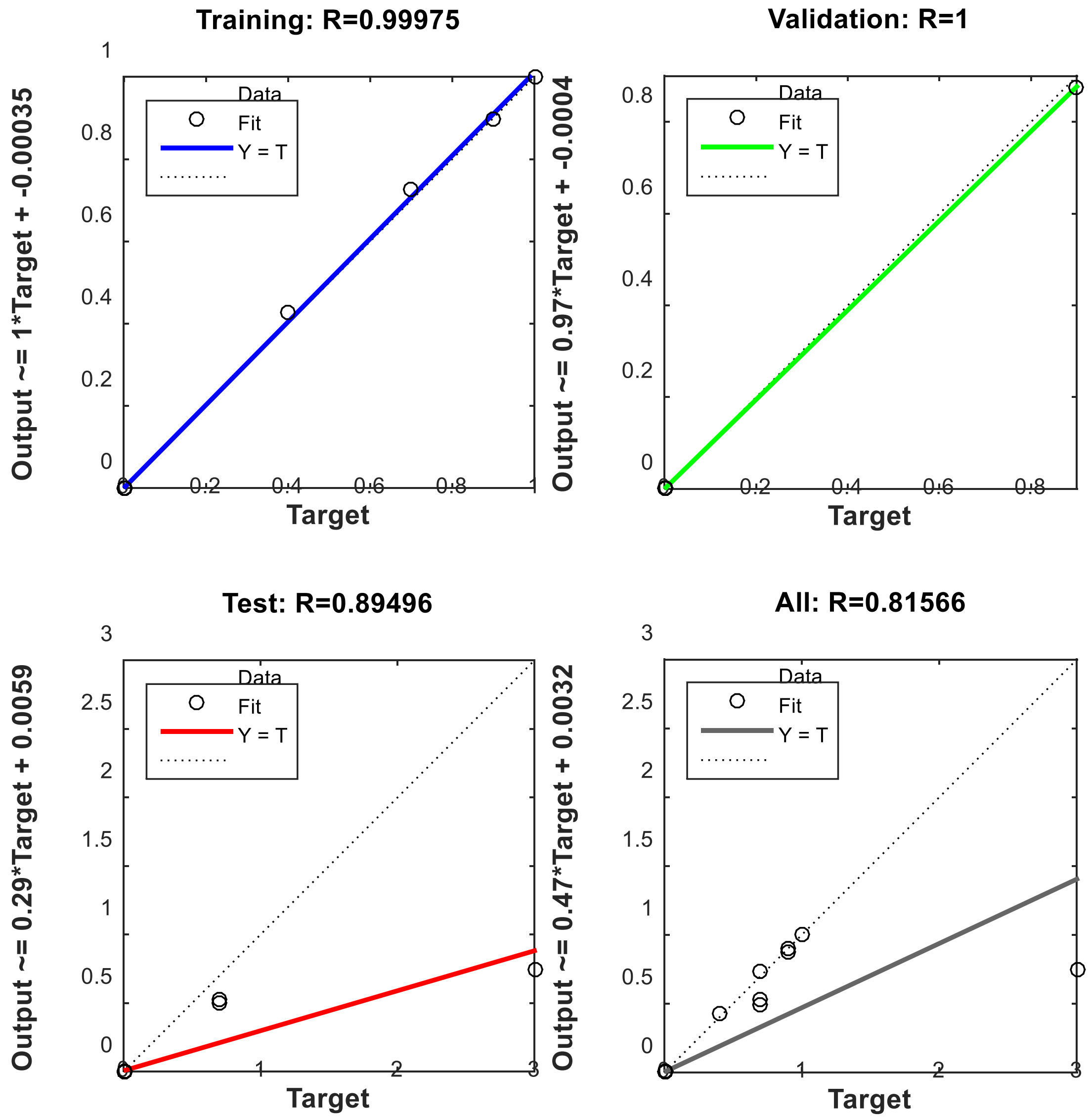

Fig 2.5. The performance values for 16 number of hidden neurons

The neural network model used for the generation by coal is achieved 81 percent shown in Figure 2.5. The neural network results are compared with the linear regression model. R square value, a measure of goodness of fit of linear regression, is found as 0.14 in Table 2.7.

The results obtained for the 16 neuron numbers for energy generation share by natural gas are showed in Figure 2.6.

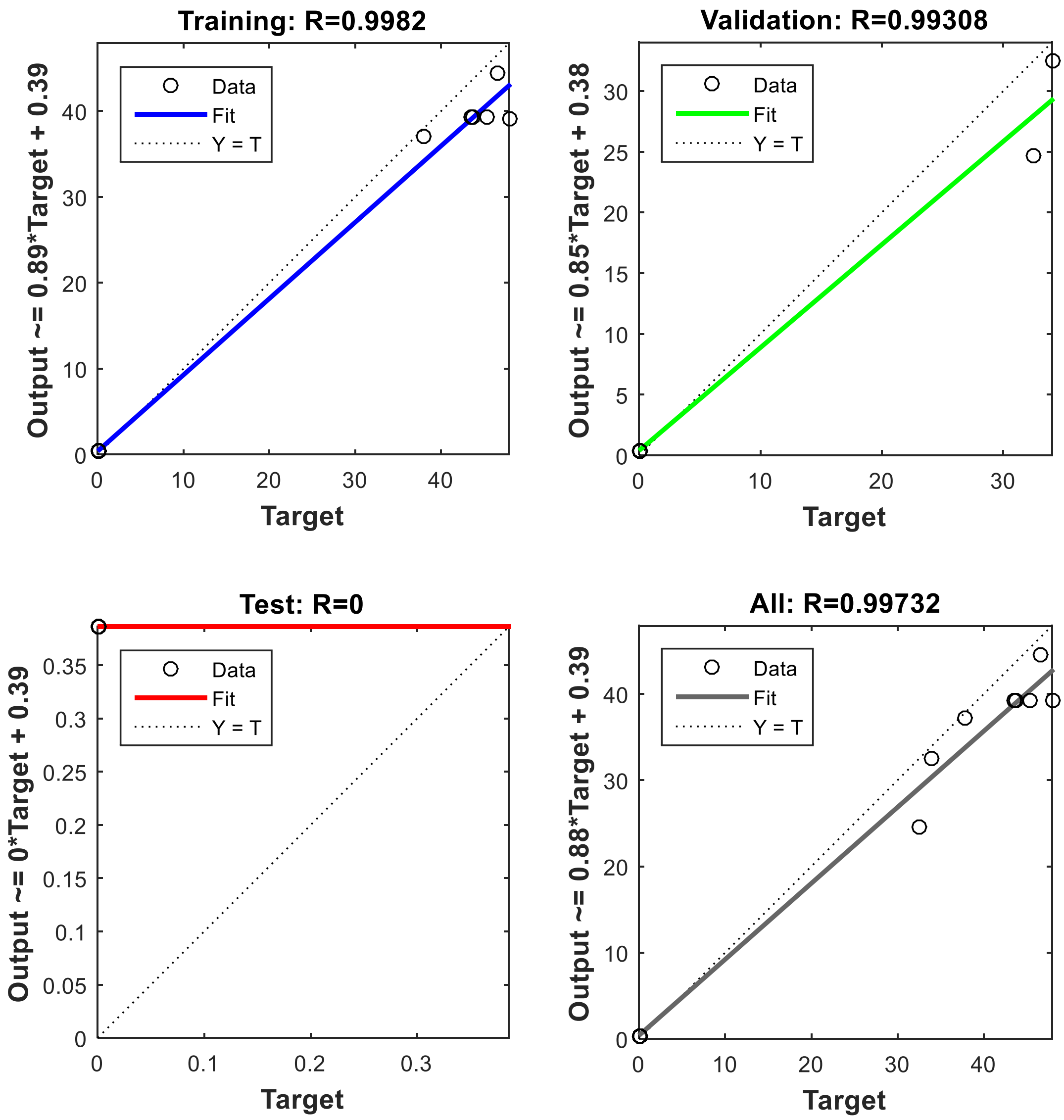

Fig 2.6. The performance values for 16 number of hidden neurons

The neural network model used for the generation by the natural gas is achieved 99 percent shown in Figure 2.6. The neural network results are compared with the linear regression model. R square value, a measure of goodness of fit of linear regression, is found as 0.70 in Table 2.9.

According to these results;

- The relation is higher between coal and greenhouse gas than the other energies.
- The relation is lower between liquid fuels and greenhouse gas than the other energies.
- Artifical neural network gives better results than the linear regression analysis for three types of energy sources.
- The regression analysis gives worse results for the liquid fuels than the other sources.

4. Conclusion

The next generation will face the problems of the fossil fuels until using of renewable energies completely all over the world. Renewable energies such as solar energy, wind energy, jeotermal energy, hydrogen etc. are green energy and they should be evaluated as main energy sources. The fossil fuels damage not only the human but also the ecological life. So, effective precautions should be taken. In this study, electricity generation shares by the energy sources are examined and the relation of these fossil energies with the greenhouse gas is investigated. Results show that the coal energy is related mostly according to the other energy sources. To reduce the greenhouse gas effects on our world, the fossil fuels should be disused and renewable energies should be accepted for main energy sources. For future studies, both of fossil fuels and renewable energies may be examined with different inputs. The other time series analysis methods may be used to compare with ANN.

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