R&D EXPENDITURE AND EMISSION: ARTIFICIAL NEURAL NETWORK BASED APPROACH

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Abstract

Nowadays, energy demand increases with advanced in technology, economic growth, population and growing industrialization. The countries need more energy to produce or to import for meet to energy need. A big part of carbon emission arises from use of primary energy source. Fossil fuels are most cause carbon emissions in primary energy source. A large part of the world's energy need is met by fossil fuels. Consequently, as energy consumption increases, greenhouse gas emissions especially have increase. In recent years, environmental damage caused by carbon emissions upset balance of world and caused global warming. Therefore; technological development and R&D activites have become for reducing toxic gases such as . It is important to determine the relationship between emission and R&D expenditure negatively has affected carbon emission and R&D expenditure for policymaker and practitions. In this regard, this study, the relationship between OECD countries R&D expenditure and emission for 1996-2013 was examined using artificial neural network within the framework STIRPAT model. According to the analysis results in accordance with expectations R&D expenditure negatively has affected carbon emissions in the OECD countries.

Keywords: Artificial neural network, co2 emissions, R&D expenditure, STIRPAT.

AR-GE HARCAMALAERI VE EMİSYONU: YAPAY SİNİR AĞI YAKLAŞIMI

Öz

Günümüzde artan sanayileşme, nüfus, ekonomik büyüme ve teknolojideki gelişmeler ile enerji ihtiyacı giderek artmaktadır. Artan enerji ihtiyacını karşılamak için ülkeler daha fazla enerji üretme veya ithal etme gereksinimi duymaktadır. Karbon emisyonunun büyük bir bölümü birincil enerji kaynaklarının kullanımından kaynaklanmaktadır. Birincil enerji kaynaklarından en çok karbon emisyonuna sebep olan kaynak fosil yakıtlardır. Dünyanın enerji ihtiyacının büyük bir bölümü de fosil yakıtlardan karşılanmaktadır. Bunun sonucunda da enerji tüketimi arttıkça sera gazı emisyonlarında özellikleemisyonunda artış olmaktadır. Son yıllarda emisyonunun çevreye verdiği zararlar önemli boyutlara ulaşmıştır. emisyonundaki artış dünyanın dengesini bozmuş ve küresel ısınmaya sebep olmuştur. Bu nedenle teknolojik gelişmeler ve Ar-Ge faaliyetleri gibi zehirli gazların emisyonlarının azaltılmasına yönelik olmaya başlamıştır. emisyonu ve AR-GE harcamaları arasındaki ilişkinin belirlenmesi politikacılar ve uygulamacılar açısından önem arz etmektedir Bu bağlamda çalışmada 1996-2013 yılları arasında OECD ülkelerinin AR-GE harcamaları ile emisyonu arasındaki ilişki STIRPAT modeli çerçevesinde yapay sinir ağları kullanılarak analiz edilmiştir. Analiz sonuçlarına göre beklentilere uygun olarak OECD ülkelerinde Ar-Ge harcamaları emisyonunu negatif yönde etkilemiştir.

Anahtar Kelimeler: AR-GE harcamaları, co2 emisyonunu, STIRPAT, Yapay Sinir Ağları

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Introduction

Climate change has become one of the most global environmental problems. It is a threat to the health of ecosystems and humans (Kerr, 2007).Global warming is the most basic cause of climate change. Greenhouse gases, especially , are the main sources of global warming. Greenhouse gases released to the atmosphere are rapidly increasing with the combustion of fossil fuels, deforestation and industrialization. Also the most important factor is energy for the development of the countries. The countries have used non-renewable sources such as coal, oil and natural gas to meet the increasing demand for energy. This significantly increases emissions of greenhouse gases.(Srivastava & Oyama, 2009)

OECD countries are the highest level of energy consuming countries in the World.(IEA, 2015) Although OECD countries have gone towards renewable energy sources in recent years, they have still provided a large portion of their energy needs from non-renewable sources. emissions in OECD countries have felt 1.4% in 2014 when it has remained stable in 2013.In total emissions in OECD countries have decreased by 8%, since their pre-economic crisis in 2007(OECD/IEA, 2016)Also, the share of renewable energy consumption in total final energy consumption has exceeded 10 per cent in 2012 (World Bank , 2016).

Global agreements have been made to reduce greenhouse gas emissions so that the impact of global climate change can be minimized. Most OECD countries signed Kyoto Protocol have committed to reduce their greenhouse gas emissions by an average of 5 percent against 1990 levels over the five-year period 2008-2012 (UNFCCC, 2016). The use of renewable energy sources and the necessary infrastructure for utilization these sources are essential to achieve these goals. Greenhouse gases resulting from the use of fossil fuels is much more than the use of renewable energy(Fargione, Hill, Tilman, Polasky, & Hawthorne, 2008)

The role of the renewable energy developed as a result of these activities and R&D and innovation activities is great reducing carbon emissions. The use of R&D technologies in energy production is necessary to achieve ecological balance by reducing greenhouse gas emissions (Figueroa, Fout, Plasynski, McIlvried, & Srivastava, 2008)

The aim of this study is to examine the relationship between R&D expenditure and emission for the period of 1996-2013 from the OECD countries using artificial neural network within the framework STIRPAT model.

The rest of the study is organized as follows: In section 2; a literature review is presented. In section 3; The theoretical framework is explained. In section 4; data is defined and is discussed the methodology. Results are summarized in section 5. Finally; In section 6, the conclusions are given.

1.Literature Review

In the majority of studies, especially in countries such as OECD where greenhouse gas emissions are extremely high, R&D expenditure has contributed to reduce emissions in the literature.

Corradini, Costantini, Mancinelli, & Mazzanti (2014) innovation investments to reduce emissions for15 European Union (EU) countries and 23 manufacturing sectors in for the period between 1995– 2006 and found that emission reduction technologies are closely related to energy efficiency.

Kim (2013), analyzed on the relationship between R&D productivity of renewable energy and the Emissions Trading Scheme by using OECD's patents and R&D input data. According to the results of this analysis, Emissions trading scheme has increased the R&D productivity of renewable.

Popp, Hascic, & Medhi (2011) reported that the impact of technological change on investment in renewable energy capacity for 26 OECD countries from 1991 to 2004 and found that technological advances do lead to greater investment, but the effect is small.

Lantz & Feng (2006) examined the macroeconomic factors (GDP, population, technological change) that underlying carbon emissions from fossil fuel in Canada during 1970-2000. According to findings, technological and population changes have affectedemissions from fossil fuel use in Canada.

Ang (2009) reported that emissions are the absorptive capacity of the economy to internalize foreign technologyand negatively related to research intensity, technology transfer in China. Also, this study found thatthat more energy use, greater trade openness and higher income tend to cause more emissions.

Lindmark (2002) suggested thatthe structural change and technological development in CO2 emissions can be interpreted in relation to growth regimes.

Hang & Yuan-sheng (2011) analyzed the relationship betweenpopulation, technology, income, economic scale and emissions in China. According to the results of analysis, population income and economic scale have a positive effect on emission; the impact of technology on emission was morecomplex. While in the first stages of technology, its effect on emission was positive, at the later stage, the effect was negative through technology.

Weina, Gilli, Mazzanti, & Nicolli (2014) studied that whether a relationship exists between green technological change and both emissions and emission efficiency in framework for 95 Italian provinces in the time frame 1990-2010. Findings indicate that green technology has not yet played a significant role in promoting environmental protection, although it noteworthy improved environmental productivity.

Fischer & Newell (2008) argues that R&D focused on breakthrough technologies could be more effective in reducing long-term carbon emissions.

Goulder & Schneider (1999) investigated that the importance of technological development for reduction policies. According to the results of this study, the reduction policies have very different impacts on R&D across industries, and do not necessarily raise the economy-wide rate of technological progress.

Işık & Kılınç (2014) examined the relationship between R&D expenditures and emissions in the transport sector. According to findings, R&D expenditures has a positive impact on emissions in the selected countries and also findings indicate that there is a long-term relationship among energy consumption, R&D expenditures and emissions.

2. Theoretical framework

During the last three decades, the growth of population, wealth and technology are collectivelypresented as responsible for the environmental impact by economic and scientific researches. In this context, Ehrlich and Holdren (1971) were the first to try to explain dynamics of environmental impact, population and human well beings and they improved IPAT equation. IPAT expresses that the environmental effect (I) is multiplication of three basic driving forces. These three driving forces are population size (P), affluence (A, per capita economic activity), and technology (T, the impact of economic activity per unit). IPAT is a mathematical equation. I have been used to solve T with the known values of A and P(Ehrlich & Holdren, 1971). However, IPAT examines only a limited number of variables, thus limiting the research to energy, economy, population factors, and their ratio relationship. Also, these models do not allow hypothesis testing but the development of social ecology theory requires hypotheses about the relationship between human-driven factors and and the effects that can be tested with empirical evidence. To overcome this limitation, Dietz ve Rosa (1994) have reformulated the IPAT equtaion by converting to stochastic form. This model is STIRPAT (STochastic Impacts by Regression on Population, Affluence, and Technology) (Rosa & Dietz, 1998). STIRPAT represents the stochastic effect of the population, affluance and technology on the environment using regression methods. (York, Rosa, & Dietz, 2003)The STIRPAT model is as follows:

$$I_i = \alpha P_i^b A_i^c T_i^d e_i \quad (1)$$

taking the natural logarithm of both sides

$$In(I_{it}) = \alpha + bIn(P_{it}) + cIn(A_{it}) + In(T_{it}) + e_{it} \quad (2)$$

the error term. The subscript i denotes that these quantities (I, P, A and T) vary across observational units; t denotes the year and Equation (2) presents the linear relationship between population, affluence and technology.

T factor can not be associated only with technology in the STIRPAT model. Also, it represents everything that is not population and affluence. (York, Rosa, & Dietz, 2003)

In this study, the relationship between emission and R&D expenditure is investigated. Additional factors can be entered the basic STIRPAT model as components of the technology term (T) and T is basically considered to be the environmental impact per unit of economic activitiy. (York, Rosa, & Dietz, 2003). Thus, T is disaggregated into two variables that energy consumption and R&D expenditure in this study.

$$In\left(CO_{2_{it}}\right) = \alpha + bIn(P_{it}) + cIn(A_{it}) + In(EC_{it}) + In(R\&D_{it}) + e_{it} \tag{3}$$

where P, A, EC and R&D denote the totap population size, GDP per capita, energy consumption and R&D expenditure, respectively. E is the error term. The subscript i refers to countries and t denotes the year.

3. Data and Methodology

3.1 Data

In this study, has been used a panel data set for 26 out of 35 OECD countries for the period 1996–2013. Nine countries, Australia, Chile, Greece, Iceland, Luxemburg, New Zelland, Norway, Sweden and Switzerlandhave been dropped from the study due to non- availability of adequate data. The variables used in the study were emission, population, GDP per capita, energy consumption and R&D expenditure. Data has been obtained from theWorld Data Bank. Table 1 has been displays the variable names and their sources.

Table 1: *Variables used in the study*

Symbol	Definition	Source
Dependent variable (output)		
emissions (metric tons per capita)	World Bank Development	Indicator
Independent variable (input)		
P	Population growth (annual %)	World Bank Development Indicator
GDP	GDP per capita growth (annual %)	World Bank Development Indicator
EC	Energy use (kg of oil equivalent per capita)	World Bank Development Indicator
R&D	Research and development expenditure (% of GDP)	World Bank Development Indicator

Note: All variables in natural log form.

3.2. Artificial Neural Network

Artificial Neural Network (ANN) issimply mathematical technique developed to imitate human brain behavior. It is also tool of great importance pattern recognition, forecasting, data mining and classification (Hamzaçebi, 2007). ANNs are composed of properties that provide solutions for linear or nonlinear applications (Azadeh, Ghaderi, & Sohrabkhani, 2007). Among the applied ANNs, the multilayer feed forward neural networks (MLP) trained with the BP algorithm are the most generally used methods(Uzlu, Akpınar, Özturk, Nacar, & Kankal, 2014).MLP is consists of an input, hidden, and output layers. The component of each layer is called neuron. Each neuron in a artificial neural network is a processing unit which have a weight. At the beginning of the learning phase all weights in the network are initialized to random values(Azadeh, Ghaderi, & Sohrabkhani, 2007). Appointed weight values are regularly changed at eachiteration during a training process that compares predicted withreal outputs, and back spread any errors to determine theappropriate weight regulation that are necessary in the network to minimizeerrors (Uzlu, Akpınar, Özturk, Nacar, & Kankal, 2014). The model is achieved by minimizing the error values between the target or real data values.

The neural network architecture is composed of input neurons (corresponding to the independent variables), one output neurons (corresponding to the dependent variables), and an appropriate number of hidden neurons. The optimal number of hidden neurons is determined by trial-error (Zhang, Patuwo, & Hu, 1998). Another part that determines the structure of the network includes the selection of activation functions, the training algorithm, learning rate and performance measures. In order to train a neural network, it is necessary to choose suitable activation function and adjust all the weights in such a way that the error between the desired output and the real output is minimized(Benkachcha, Benhra, & El Hassani, 2013)

The model can be written as:

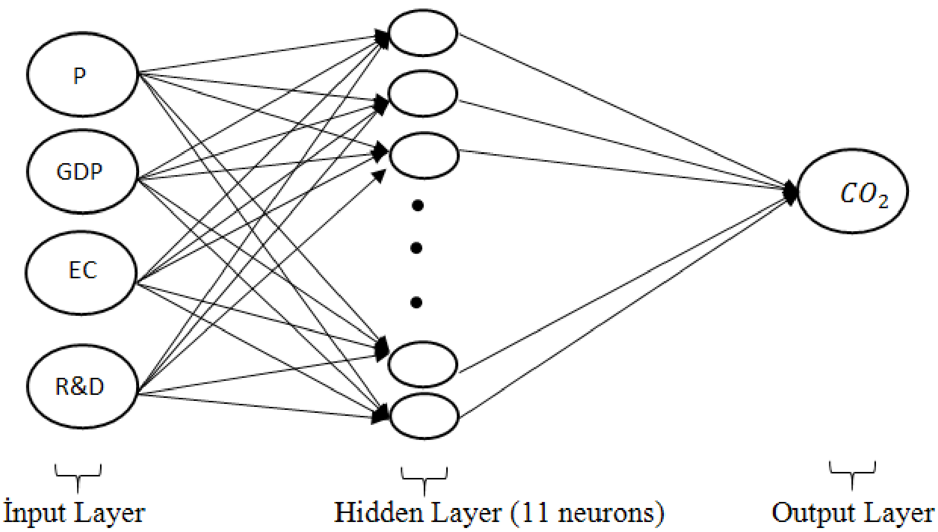
$$y_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-1} + \beta_{0j}\right) + e_t \tag{4}$$

where m is the number of input neurons, n is the number of hidden neurons, f is a sigmoid transfer function such as the logistic:, is a vektör of weights from the input to hidden neurons, are weights from the input to hidden neurons. and are bias terms.

Error estimation methods commonly used for artificial neural networks are mean absolute percentage error (MAPE), mean square error (MSE), root mean square error (RMSE) and mean absulate error (MAE). MAPE method is the most apropriate method to estimate the error because input data used for model estimation, preprocessed date and raw have different scale.(Madsen, Pinson, Kariniotakis, Nielsen, & Nielsen, 2005)

At the present study, independent variables that can be added to the model have been researched and R&D expenditures that have reached adequate numbers of past observational values have been added as independent variable in order to estimate the emission in a reliable with the model to be established with ANN. Two different ANN model based on cause-effect relationshiphas been used. The estimation of modelshas been made in the MATLAB (R2013a). The network structure of the models (ANN-1) is shown in Figure 1.

Figure 1: *The network structure of the models (ANN-1)*

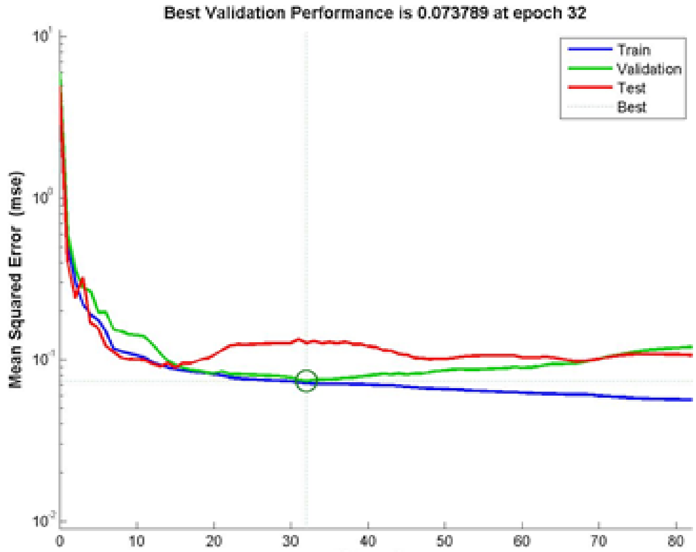


Normalization has been done for both input and output in the range [0,1]. The data has been divided into three sets: train, validation, and test. 70% of the data points have been selected for training, 15% have been selected for validation, and 15% heve been used for testing the network. The validation set has been used as a stopping criteriain this study. Because it ensures not to occur overfitting. The train test has been used to adjust the linkage weights while the test set measures the generalize capability of the model.

In studies in the literature, the only hidden layer has been generallyused for train of model since only hidden layeris sufficient for successful training (Zhang, Patuwo, & Hu, 1998). The number of neurons in the hidden layer has been determined by trial and error. This study the number of the most suitable neurons in the hidden layer has been determined to be 11 in many trial results. Logistic sigmoid transfer function (logsig) have been used in the hidden layerof the network as an activation function. Linear transfer function (purelin) have been used in the output layer. The back-propagation algorithm has been used for optimizing the connection weights, while the Levenberg-Marquardt (LM) algorithm has been used as a learning rule. It is one of the most appropriate algorithms used for minimizing the error of a neural network (Tarawneh & Imam, 2014)

During network traning, one of the performance criterion which is named mean absolute percentage error (MAPE) has been used aim of comparing the success of the ANN model established. The other performance criterion, the mean squared error (MSE), measures the error performance of the ANN model. The ANN model has been trained for 1000 iteration. The ANN model showed the best performance in the 32th iteration. The graph of the MSE function has been shown in Figure 2.

Figure 2:*The graph of the MSE function*



The MAPE values of the model have been given in Table 2. 4,23 % error value obtained for the training set indicates that the training has been carried out quite successfully. Also, the error value of 4.46 % for the validation set indicates that the network is correctly trained and does not memorize. The 4,68 % mape value obtained in the test set indicates that the network can make successful predictions.

Table 2. *MAPE results for ANN-1 model.*

	MAPE
Train set	4,23%
Validation set	4,46%
Test set	4,68%

ANN-2 model with only GDP, population and energy consumption variables has been established in order to determine whether the contribution to the estimation performance of the R&D expenditures variable in the ANN-1 model. As in the ANN-1 model, the only hidden layer has been preferred in the phase of setting model. The optimum number of neurons in the hidden layer has been determined using the trial and error. When using the sigmoid function in the hidden layer, the identity function has been used in the output layer. Levenberg-Marquardt backpropagationalgorithm has been used as learning method. The MAPE values of the ANN-2 model and ANN-1 model have been compared in Table 3. As seen in table 3, there is no memorization problem when the validation set values of both models has been examined. The ANN-1 model performed more successfully than the ANN-2 model. The ANN-1 model estimated the test set with fewer errors with the weight values obtained. Thus, in addition to the variables used in the ANN-2 model, it can be argued that the R&D expenditures variable added to the ANN-1 model have contributed significantly to explain emission model.

Table 3: *The MAPE values of the ANN-2 model and ANN-1 model*

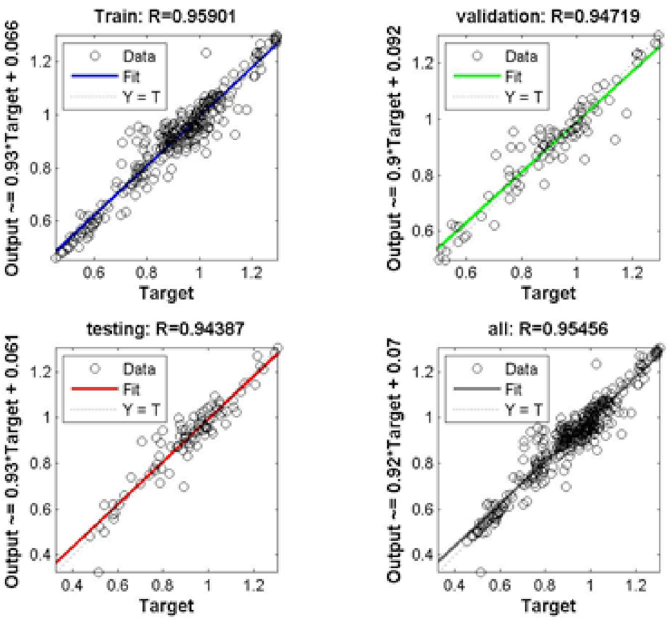
	ANN-1 MODEL MAPE	ANN-2 MODEL MAPE
Train sets	4,23%	6,61%
Validation sets	4,46%	6,76%
Tests sets	4,68%	6,60%

4.Results

At the end of the comparison made, Since the ANN-1 model has been identified as the best estimator, the emission estimate has been based on this model.

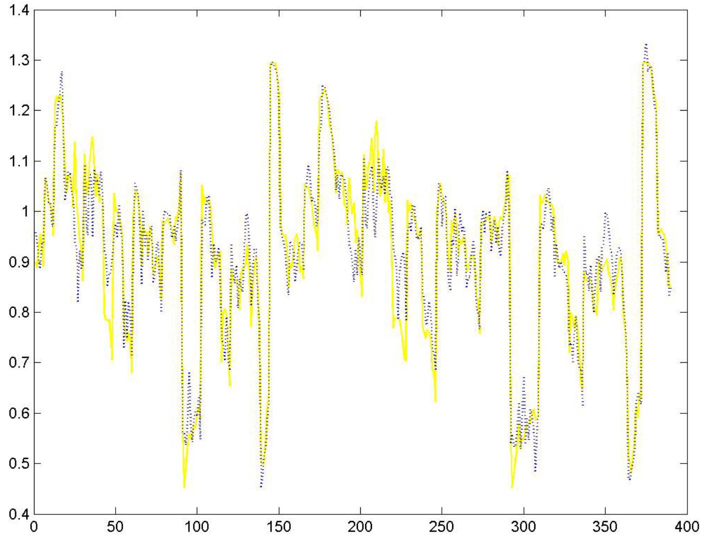
The regression curves of the ANN-1 model have been given in Fig.3.The difference between regression curves and the observation points is called error.

Figure 3: *Model of Regression Graph*



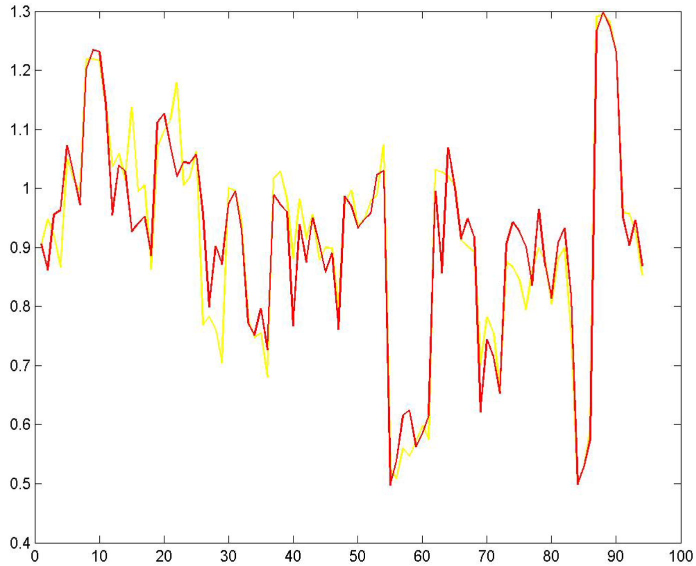
As shown in Figure 3, the training, validation and test sets of the ANN-1 model have quite high regression values. These graphs show that network training is successful and that the network produces values are very close to real values. ANN-1 Model as a whole is successful with a 0.95456 regression value. The graph of the values produced by the artificial neural network with the real values of the data in the training set has been given in Fig.4. The values produced by the network in the training set have been overlapped with the real values. This indicates that the artificial neural network succesfully learns the relationship between emission and R & D expenditure.

Figure 4: *Graph of the value produced by the real values of the data in the training set*



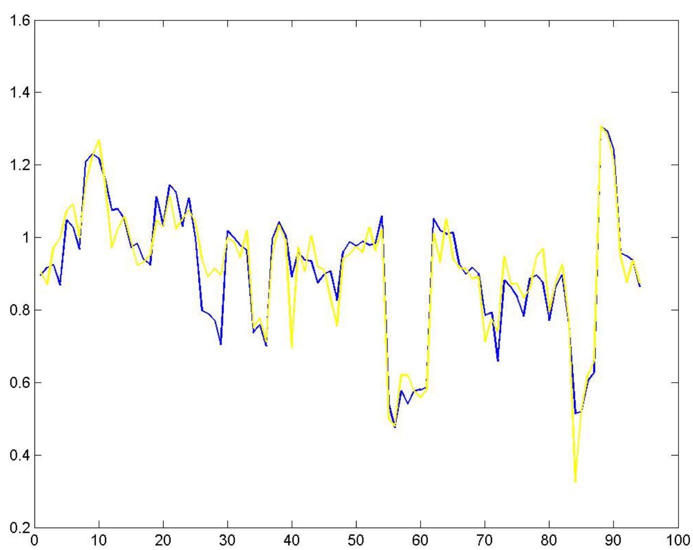
The graph of the values produced by the artificial neural network with the real values of the data in the validation set has been given in Fig.5 The values produced by the network in the training set have been overlapped with the real values. This shows that the network learned not to memorize during training.

Figure 5: *Graph of Value Generated by Real Values of Validation Set Data*



The ANN-1 model needs to be tested in order to see the model in which correct estimation. The graph of the values produced by the artificial neural network with the real values of the data in the test set has been given in Fig.6

Figure 6: *Graph of Value Generated by Real Values of Test Set Data*



The ANN-1 model has been tested with the MAPE and performance criterion. It has been seen that this model made successful predictions. The MAPE values obtained in the test set indicate that the model can make successful predictions. Because the error between the real values of the test set and the predicted values obtained is very low. The Performance criterions of the ANN-1 model have been shown in Figure 2.

Table 4: *Performance criterions of the ANN-1 model*

	MAPE	
Train set	4,23%	0,91970
Validation set	4,46%	0,89716
Test set	4,68%	0,89089

The model based on R&D expenditure variableof the output as the best algorithm LM with tenneurons, which has minumum MAPE andmaximum valuefor testing datais given in Eq. (5). This equation can be used forthe estimation of emissionwithR&D expenditure variable in OECD countries.

$$CO_{2_{ANN-1}} = 1{,}2946 + 2{,}2256F_1 + 0{,}6644F_2 + 2{,}7527F_3 - 0{,}2037F_4 + 0{,}5021F_5 - 0{,}1578F_6 - 1{,}2494F_7 + 0{,}2695F_8 - 0{,}1396F_9 + 0{,}3820F_{10} \quad (5)$$

where F_i (i = 1, 2, …, 10) can be calculated according to Eq. (6). The model the prediction of CO_2 emission in OECD countriesis dependent on indicators as seen in Eq. (7).

$$F_i = \frac{1}{1+e^{-E_i}} \quad (6)$$

where E_i(i=1,2, …,10) is given in Eq.(7)

$$E_i = \alpha_{0i} + \alpha_{1i}P + \alpha_{2i}GDP + \alpha_{3i}EC + \alpha_{4i}R\&D \quad (7)$$

The constants in Eq. (7) are given in Table 5.

Table 5: *Constants in Eq. (7) obtained LM algorithm with ten neurons.*

i					
1	-2,0036	1,2161	-1,5964	1,1790	1,5772
2	-5,8066	5,4185	0,0358	1,3503	1,5372
3	1,7840	-1,4611	1,2399	-0,9459	-1,2077
4	-0,3709	1,5162	0,8041	-0,7092	4,4990
5	0,2094	-2,1441	0,6040	-4,5103	-1,3438
6	4,7359	-1,0252	-1,3968	-12,4101	0,9191
7	1,8643	-0,9231	0,3745	0,2768	0,2596
8	-2,9096	-3,3383	3,6826	-1,7638	0,5054
9	-2,6114	-2,2674	0,9966	2,5021	1,6919
10	4,3260	-3,5004	0,3842	0,2237	6,1953

5.Conclusion

The main goal of this study is to determinate the causality relationship between emission and R&D expenditure in OECD countriea using the ANN approach.

The results of this study show that this estimation formula with quite reliable dependent on R&D expenditure can be used to estimate the emission in OECD countries in order to determine the future level of emission in OECD countries.

The OECD countries have the highest share of carbon dioxide released to the environment the results of this study, which examines the effect of R&D expenditure on reducing emissions, show that R&D expenditure is very important for OECD countries in reducing toxic gas emissions.

Nowadays, it has become a necessity rather than a need to do R&D activities in order to ensure sustainability and reduce the level of carbon emissions reaching dangerous dimensions for countries. In this regards, it is recommended that countries in the supply of sustainable development and clean environment allocate more resources to R&D expenditures.

Sosyal Bilimler Dergisi
ICEBSS Özel Sayısı

References

Ang, J. B. (2009). CO2 emissions, research and technology transfer in China. *Ecological Economics*.

Azadeh, A., Ghaderi, S. F., & Sohrabkhani, S. (2007). Forecasting electrical consumption by integration of Neural Network, time series and ANOVA. *Applied Mathematics and Computation*.

Benkachcha, S., Benhra, j., & El Hassani, H. (2013). Causal Method and Time Series Forecasting model based on Artificial Neural Network . *International Journal of Computer Applications*.

Corradini, M., Costantini, V., Mancinelli, S., & Mazzanti, M. (2014). Unveiling the dynamic relation between R&D and emission abatement. *Ecological Economics*.

Dietz, T., & Rosa, E. A. (1994). Rethinking the Environmental Impacts of Population, Affluence and Technology. *Human Ecology Review*.

Ehrlich, P. R., & Holdren, J. P. (1971). Impact of Population Growth. *Science*.

Fargione, J., Hill, J., Tilman, D., Polasky, S., & Hawthorne, P. (2008). Land Clearing and the Biofuel Carbon Debt. *Science*.

Figueroa, J. D., Fout, T., Plasynski, S., McIlvried, H., & Srivastava, R. D. (2008). Advances in CO2 capture technology—The U.S. Department of Energy's Carbon Sequestration Program. *international journal of greenhouse gas control*.

Fischer, C., & Newell, R. G. (2008). Environmental and Technology Policies for Climate Mitigation. *Journal of environmental economics and management*.

Goulder, L. H., & Mathai, K. (2000). Optimal CO2 Abatement in the Presence of Induced. *Journal of Environmental Economics and Management*.

Goulder, L. H., & Schneider, S. H. (1999). *Induced technological change and the attractiveness of CO abatement policies.* Resource and Energy Economics.

Hamzaçebi, C. (2007). Forecasting of Turkey's net electricity energy consumption on sectoral bases. *Energy Policy*.

Hang, G., & Yuan-sheng, J. (2011). The Relationship between CO2 Emissions, Economic Scale,Technology, Income and Population in China. *Procedia Environmental Sciences*.

IEA. (2015, 10 28). *Excerpt From Energy Balances Of Oecd Countrıes.* Excerpt From Energy Balances Of Oecd Countrıes: https://www.iea.org/publications/freepublications/publication/EnergyBalancesofOECDcountries2015editionexcerpt.pdf

Işık, N., & Kılınç, E. C. (2014). Ulaştırma Sektöründe CO2 Emisyonu ve Enerji Ar-Ge Harcamaları İlişkisi. *Sosyo Ekonomi*.

Kerr, R. A. (2007). Global warming is changing the world. *Science*.

Kim, S. (2013). The Analysis on the Relationship between R&D Productivity of Renewable Energy and Emission Trading Scheme; Using OECD Patent Data. *Korean Resource Economics Association*.

Lantz, V., & Feng, Q. (2006). Assessing income, population, and technology impacts on

CO2 emissions in Canada: Where's the EKC? *Ecological Economics*.

Lindmark, M. (2002). An EKC-pattern in historical perspective: carbon dioxide emissions, technology, fuel prices and growth in Sweden 1870–1997. *Ecological Economics*.

Madsen, H., Pinson, P., Kariniotakis, G., Nielsen, H. A., & Nielsen, T. S. (2005). Standardizing the Performance Evaluation of ShortTerm Wind Power Prediction Models. *Wind Engineering Volume*.

OECD/IEA. (2016, 10 29). *International Energy Agency* . http://www.iea.org/newsroom/news/2016/november/world-energy-outlook-2016.html

Popp, D., Hascic, I., & Medhi, N. (2011). Technology and the diffusion of renewable energy. *Energy Economics*.

Rosa, E. A., & Dietz, T. (1998). Climate Change and Society Speculation, Construction and Scientific Investigation. *International sociology*.

Srivastava, D. C., & Oyama, T. (2009). Evaluating the emission reduction targets in UNFCCC Kyoto Protocol by applying primary energy data analyses. *Journal of Asian Public Policy*.

Tarawneh, B., & Imam, R. (2014). Regression versus artificial neural networks: Predicting pile setup from empirical data. *KSCE Journal of Civil Engineering*.

UNFCCC. (2016, 11 03). United Nations Framework Convention on Climate Change: https://unfccc.int/kyoto_protocol/items/2830.php

Uzlu, E., Akpınar, A., Özturk, H. T., Nacar, S., & Kankal, M. (2014). Estimates of hydroelectric generation using neural networks with the artificial bee colony algorithm for Turkey. *Energy*.

Weina, D., Gilli, M., Mazzanti, M., & Nicolli, F. (2014). Green inventions and greenhouse gas emission dynamics:A close examination of provincial Italian data. *SEEDS Working Paper Series*.

World Bank . (2016, 11 03). The world bank: http://data.worldbank.org/

York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*.

Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks:: The state of the art. *International Journal of Forecasting*.