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Prediction of net energy consumption based on economic indicators (GNP and GDP) in Turkey

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Abstract

The most important theme in this study is to obtain equations based on economic indicators (gross national product—GNP and gross domestic product—GDP) and population increase to predict the net energy consumption of Turkey using artificial neural networks (ANNs) in order to determine future level of the energy consumption and make correct investments in Turkey. In this study, three different models were used in order to train the ANN. In one of them (Model 1), energy indicators such as installed capacity, generation, energy import and energy export, in second (Model 2), GNP was used and in the third (Model 3), GDP was used as the input layer of the network. The net energy consumption (NEC) is in the output layer for all models. In order to train the neural network, economic and energy data for last 37 years (1968–2005) are used in network for all models. The aim of used different models is to demonstrate the effect of economic indicators on the estimation of NEC. The maximum mean absolute percentage error (MAPE) was found to be 2.322732, 1.110525 and 1.122048 for Models 1, 2 and 3, respectively. R^2 values were obtained as 0.999444, 0.999903 and 0.999903 for training data of Models 1, 2 and 3, respectively. The ANN approach shows greater accuracy for evaluating NEC based on economic indicators. Based on the outputs of the study, the ANN model can be used to estimate the NEC from the country's population and economic indicators with high confidence for planing future projections.

Keywords: Energy consumption; Economic indicator; Artificial neural network

1. Introduction

Turkey is one of the largest countries in Europe, covering an area of ~780,000 km^2, its average population density is ~80 persons per square kilometre, the annual rate of increase in population is 1.6%, the highest among IEA countries. Because of its geopolitical position, Turkey can be considered as a bridge for energy to connect Europe to Asia and Middle East (Kiliç and Kaya, 2007). Turkish economy, the world's 16th largest economy, is dynamic and emerging. Turkey will certainly play a significant role in the world's energy sector during the first decades of the 21st century (Ediger and Akar, 2007). As Turkey has improved its economic situation in recent years, the energy demand has increased.

Energy demand forecasts, which are based primarily on a realistic prediction of targeted economic growth and social development of the country in the future, are prerequisites to reach this goal (Ediger and Tatlidil, 2002). There are several factors to determine the energy policies, which are considered to be important for forecasting the future projections in each country. These factors are population growth, economic performance, technological developments, import, export and consumer tastes. Furthermore, government policies concerning the energy sector and developments in the world energy markets will play a key role in the future level and pattern of energy production and consumption (Özturk et al., 2004).

In the past, to make futuristic projections towards energy consumption, basic energy indicators have been

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Nomenclature

ANN	artificial neural network
C	coal
D	diesel
dNEC	deviations in the net energy consumption
EX	export
FO	fuel–oil
GDP	gross domestic product by production in purchasers' values
GG	gross generation
GNP	gross national product by production in purchasers' values
H	hydraulic
I	import
IC	installed capacity
L	lignite
N	natural gas
NEC	net energy consumption
O	the others
P	population
X	the general indicators (such as natural gas (N), lignite (L), coal (c), GDP, etc.)

used (Kiliç and Kaya, 2007; Ediger and Akar, 2007; Ediger and Tatlidil, 2002; Özturk et al., 2004, 2005, 2007; Dinçer and Dost, 1996; WEC-TNC, 2000; Topçu and Ülengin, 2004; Hepbasli, 2005; Demirbaş, 2002; Sözen et al., 2006; Sözen and Arcaklioğlu, 2007; Hamzaçebi, 2007; Kraft and Kraft, 1978; Hwang and Gum, 1991; Yu and Choi, 1985; Mozumder and Marathe, 2007; Say and Yücel, 2006). Therefore, the correlations between the energy indicators and their effects on the predictions of energy resources have been taken into consideration.

There is a multi-dimensional need for studying Turkey's energy situation: (i) Turkey is an important candidate for becoming an EU member in the near future. (ii) Turkey is also an important candidate to be the ''Energy Corridor'', for the transmission of the rich oil and natural gas resources of the Middle East, Caspian area and Asian Countries to the Mediterranean and to the demand centres of the West (Öztürk et al., 2007). (iii) The Turkish economy has had a boom bust structure in the recent past.

The topic of casual relationship between energy consumption and economic indicators has been well studied in the energy economics literature. Different studies have focused on different countries and time periods, and have used different proxy variables for net energy consumption (NEC) and energy indicators. These studies are given in Table 1 of Mozumder and Marathe (2007) as summary and have been varied and sometimes conflicting. The results of these studies differ even in the direction of causality and its long-term versus short-term impact on energy policies (Mozumder and Marathe, 2007). There are a few studies that investigate the relationship between economic indicators and energy consumption in Turkey using different methods and approaches (Say and Yücel, 2006; Lise and Montfort, in press; Soytaş et al., 2001; Tunç et al., 2006; Altinay and Karagöl, 2004).

Traditionally, regression analysis has been the most popular modelling technique in predicting NEC. But the importance of the artificial neural network (ANN) approach, apart from reducing the time required, is that it is possible to make energy applications more viable and thus more attractive to potential users, such as energy engineers. Also, this approach has the advantages of computational speed, low cost for feasibility and ease of design by operators with little technical experience. Therefore, the use of ANN for modelling and prediction purposes is becoming increasingly popular in recent decades. This is mainly due to the fact that ANN has very good approximation capabilities and offers additional advantages, such as short development and fast processing times. ANNs are especially useful for prediction problems where mathematical formulae and prior knowledge on the relationship between inputs and outputs are unknown.

The most important theme of this study is to develop equations of estimation of the NEC based on economic indicators (gross national product (GNP)–gross domestic product (GDP)) in order to analyse energy use and make future projections using the artificial neural network (ANN) technique. This study compares the accuracy in predicting NEC in Turkey among three different models:

- Model 1 aims to develop a formula of estimating the NEC based on energy indicators as studied in Sözen et al. (2006).
- Model 2 aims to develop a formula of estimating the NEC based on GNP.
- Model 3 aims to develop a formula of estimating the NEC based on GDP.

2. Energy and economic indicators of Turkey

Turkey's geographical location makes it a natural bridge between the energy-rich Middle East and Central Asian regions. Turkey has been one of the fastest growing power markets in the world, together with a young and growing population, rapid urbanization, strong economic growth and low per capita electricity consumption for two decades (Dinçer and Dost, 1996). Some basic data for Turkey are shown in Figs. 1–5. The relationship among the primary energy consumption, GNP, GDP, growth rate per capita, electricity generation and installed capacity in Turkey have been given in these figures. Especially, Figs. 2 and 3 show that GNP, GDP and NEC increase linearly in recent years (2001–2005).

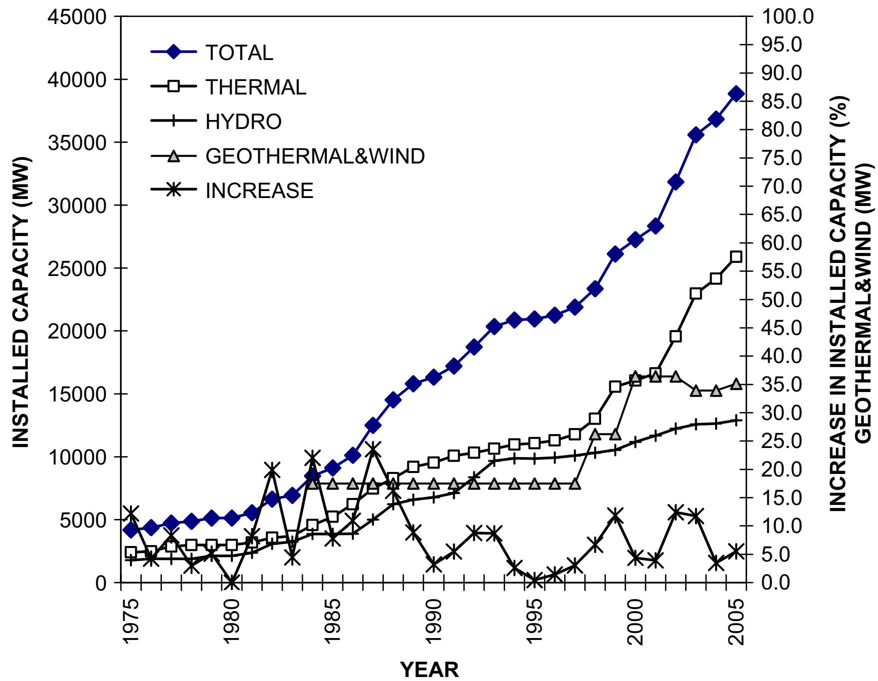

Fig. 1. Installed capacity for Turkey as energy resources.

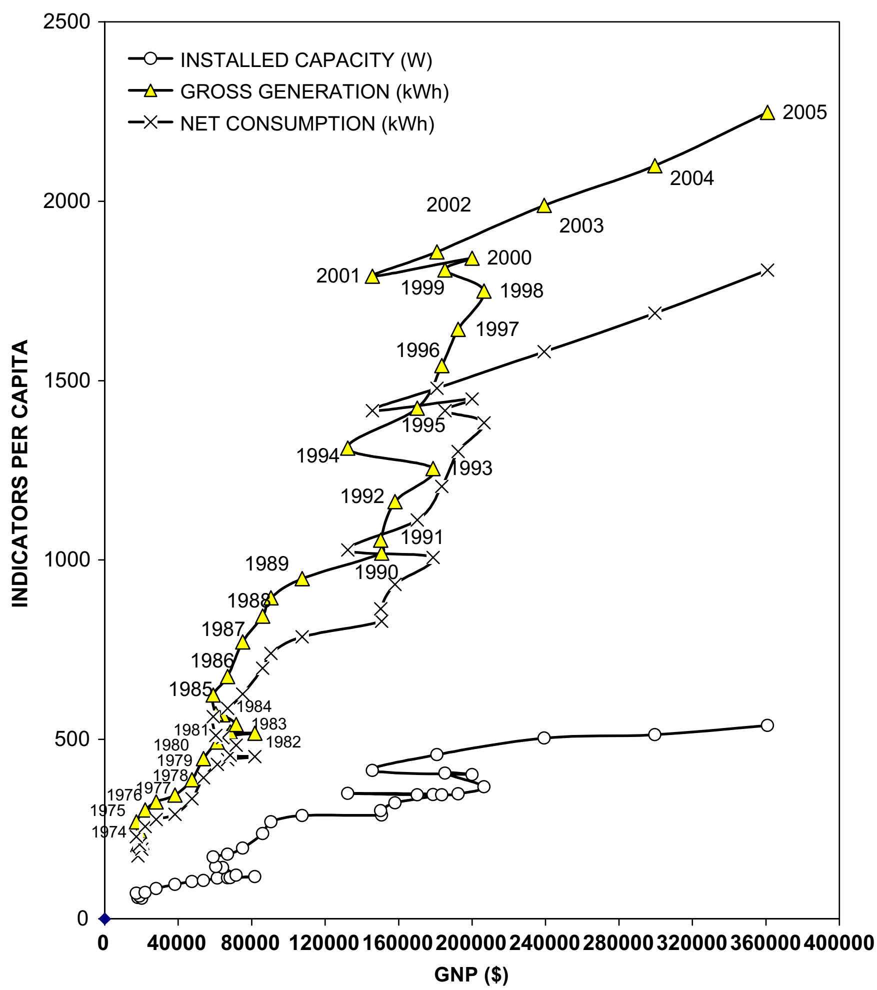

Fig. 2. The relationship between energy indicators and GNP by current prices in Turkey.

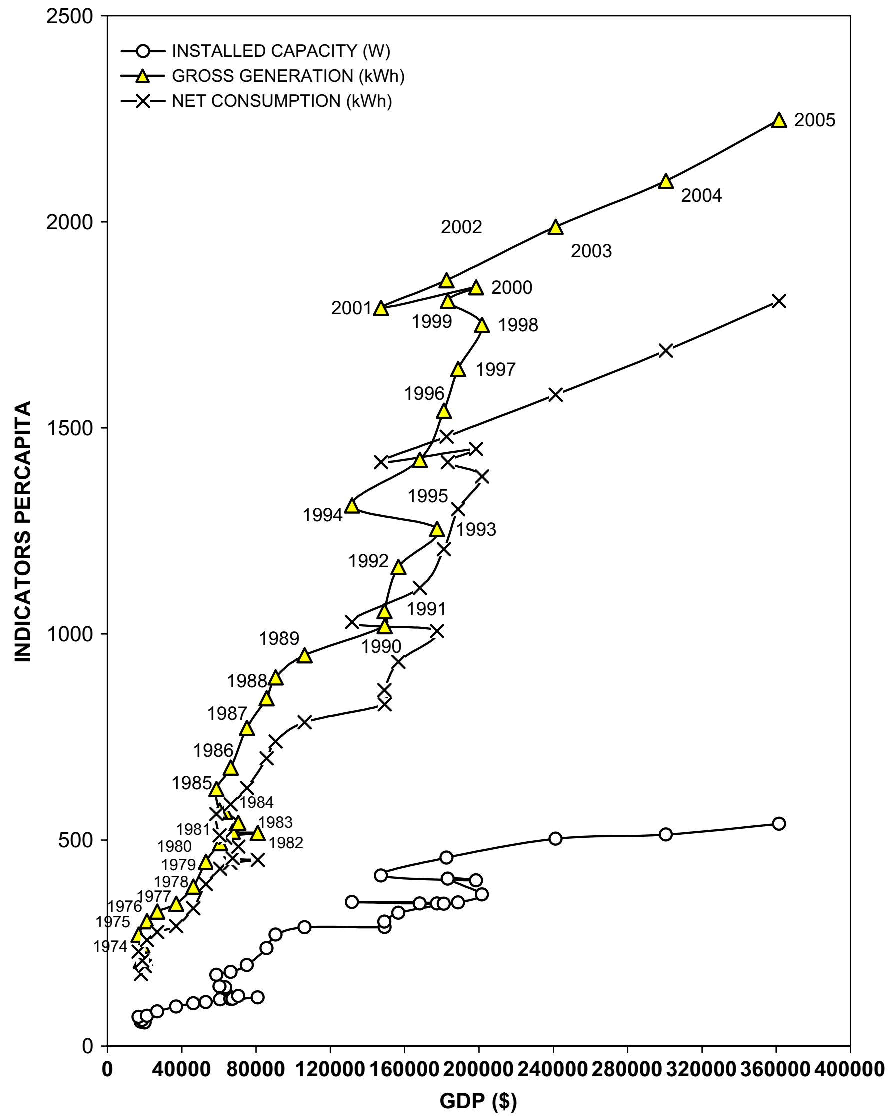

Fig. 3. The relationship between energy indicators and GDP by current prices in Turkey.

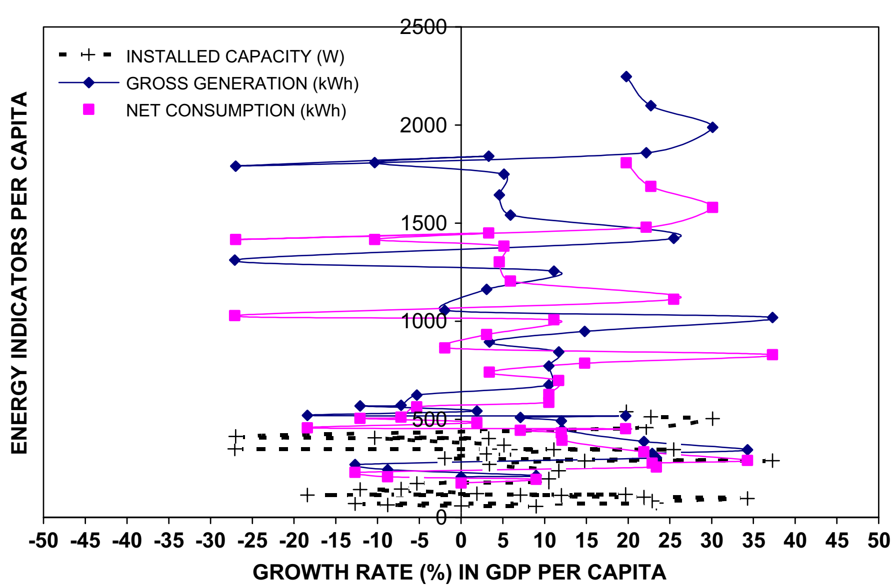

Fig. 4. The relationship between energy indicators and growth rate in GDP per capita in Turkey.

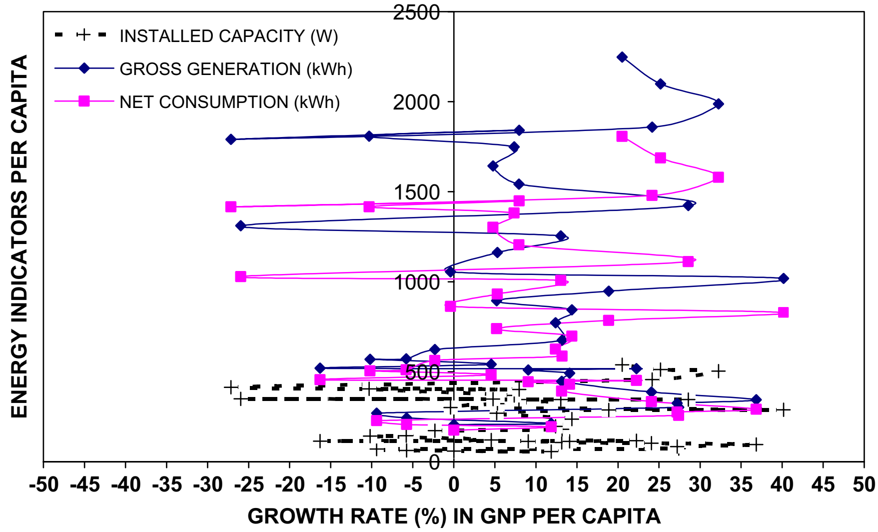

Fig. 5. The relationship between energy indicators and growth rate in GNP per capita in Turkey.

Although Turkey has many kinds of energy resources, these resources are limited. The main energy resources of Turkey are hard coal, lignite, asphaltite, petroleum, natural gas, hydroelectric energy and geothermal energy (Fig. 1). More than half (60%) of the NEC in the country is met by imports, and the share of imports continues to increase each year. Turkey's primary energy sources are based on fossil fuels. However, the level of energy production in Turkey is very low. Coal is a major fuel source for Turkey. Turkey's oil consumption has increased in recent years. Currently, half of Turkey's energy usage is oil and natural gas. Oil has the biggest share of 44% in total primary energy consumption, while natural gas has a share of 17% (Kiliç and Kaya, 2007) and is continuously increasing. Turkey's share in total OECD production is expected to rise from 2% in 1995 to 7% in the 2020s (Dinçer and Dost, 1996). The share of natural energy resources of Turkey in the world reserves are (WEC-TNC, 2000):

- coal, 0.6%
- geothermal, 0.8%
- hydro, 1%.

However, petroleum and natural gas reserves in Turkey are quite limited. Lignite has the biggest share in total primary energy production of 43%. Oil has a share of 13% and natural gas has a share of 1%. There is no nuclear power plant in Turkey as yet. The government is planning to install 33 lignite, 27 natural gas, 12 coal, two nuclear and 113 hydroelectric energy plants to fulfil this need (Kiliç and Kaya, 2007).

Rapid increases in the domestic energy demand have forced Turkey to increase its dependence on foreign energy supplies and to face the prospect of a severe energy shortage in the 21st century (WEC-TNC, 2000). Turkey maintains strong economical and political ties with the West, including membership in the OECD, a Customs Union with Europe and NATO, while simultaneously occupying a position as a leading Muslim nation. In addition, Turkey has strong historical, ethnic and linguistic ties with Central Asia's Turkic peoples. Also, Turkey's strategic location makes it a natural "bridge of energy" between major oil-producing areas in the Middle East and Caspian Sea and consumer markets in Europe (Dinçer and Dost, 1996).

GNP and GDP are two major macroeconomic indices in the system of national account. The relationship between GNP and GDP is as follows:

$$\mathrm{GNP} = \mathrm{GDP} + \text{Net factor income from abroad.} \tag{1}$$

Obviously, the extension of GNP is wider than GDP. GNP values may be bigger or smaller than GDP between years and vary from country to country. For Turkey, the relationship between GDP and GNP by production in purchasers' values is given in Fig. 6. The variation of GNP with GDP is also given in Fig. 6. Fig. 6 shows that GNP is very close to GDP in recent years (from 2001 to 2005).

3. Artificial neural network approach

Artificial intelligence (AI) systems are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems (Kalogirou, 2003). They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems, and once trained can perform prediction and generalization at high speed (Kalogirou, 2003). They have been used in diverse applications in control, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimization, signal processing and social/psychological sciences. AI systems comprise areas like expert systems, ANNs, genetic algorithms, fuzzy logic and various hybrid systems, which combine two or more techniques (Kalogirou, 2003).

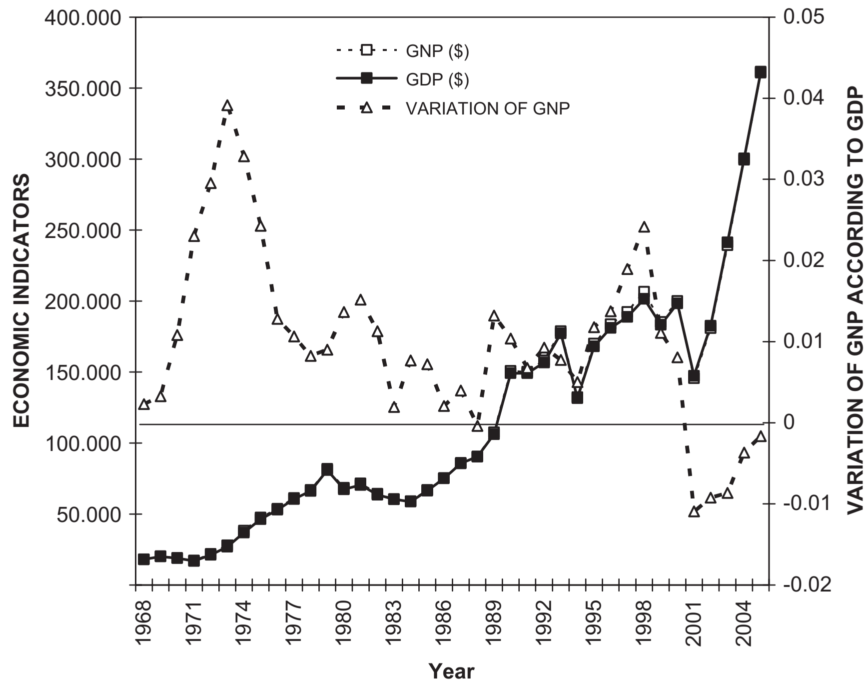

Fig. 6. The variation of GNP according to GDP and economic indicators by production in Turkey.

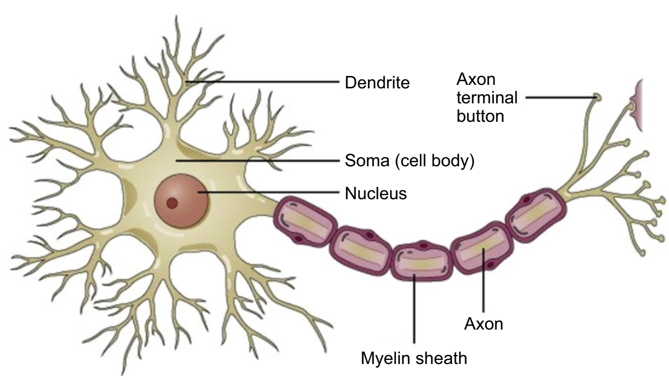

Fig. 7. A simplified model of a biological neuron (http://www.xmlann.com/index.php).

The ANN is a system loosely modelled on the human brain. A biological neuron is shown in Fig. 7. In the brain, there is a flow of coded information from the synapses towards the axon. The axon of each neuron transmits information to a number of other neurons. The neuron receives information at the synapses from a large number of other neurons. According to Haykin (1994), a neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: the knowledge is acquired by the network through a learning process and inter-neuron connection strengths known as synaptic weights are used to store the knowledge (Kalogirou, 2003). ANN is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adapting to, or learning from, a set of training patterns (Kalogirou, 2003; Haykin, 1994; Zhang, 2005; Marquardt, 1963).

A learning algorithm is defined as a procedure that consists of adjusting the weights and biases of a network, to minimize an error function between the network outputs, for a given set of inputs, and the correct outputs.

There are different learning algorithms. A popular algorithm is the back-propagation algorithm, which has different variants. Back-propagation training algorithms gradient descent and gradient descent with momentum are often too slow for practical problems because they require small learning rates for stable learning. In addition, success of the algorithms depends on the user-dependent parameters learning rate and momentum constant. Faster algorithms such as scaled conjugate gradient (SCG), quasi-Newton and Levenberg–Marquardt (LM) algorithms use standard numerical optimization techniques. These algorithms eliminate some of the disadvantages mentioned above. The LM method is in fact an approximation of Newton's method (Attiti, 1992). The algorithm uses the second-order derivatives of the cost function so that a better convergence behaviour can be obtained. In the ordinary gradient descent search, only the first-order derivatives are evaluated and the parameter change information contains solely the direction along which the cost is minimized, whereas the LM technique extracts a better parameter change vector. Suppose we have a function $E(x)$ which needs to be minimized with respect to the parameter vector x (Hagan and Menhaj, 1994; Mellit et al., 2007).

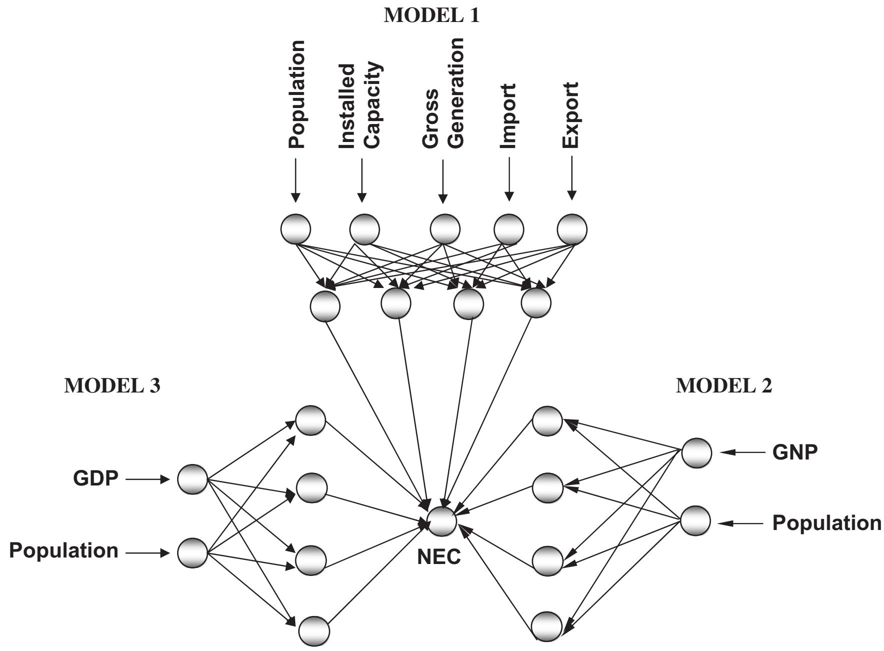

Fig. 8. ANN architecture used for estimation of the net energy consumption (NEC).

The error during the learning is called as root-mean-squared (RMS) error and is defined as follows:

$$\mathrm{RMS} = \left((1/p) \sum_j |t_j - o_j|^2 \right)^{1/2}. \tag{2}$$

In addition, absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are defined, respectively; as follows:

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right), \tag{3}$$

$$\mathrm{MAPE} = \frac{o - t}{o} \times 100, \tag{4}$$

where t is target value, o is output value and p is pattern. Input and output layers are normalized in the $(-1, 1)$ or $(0, 1)$ range.

4. Result and discussion

Analysis of examined events about scientific research made in last few years shows that simple variable analyses which are valid under the restrictive hypothesis are not enough. The most important restrictive related with simple variable analysis is that most factors in an event are kept under control, being experimental, and the affects of a simple factor are researched at each time.

In this study, taking into consideration the geographical situation of Turkey indicators that include chosen economic and energy indicators and main energy constructions are used.

Say and Yücel (2006) show that a causality relationship between GNP and NEC could be found by regression model (significance level $P = 0.001$). In this study, the significance level is 0.0007, from the statistical results obtained from regression analysis. Therefore, NEC can be explained and estimated by population and GNP or GDP with high accuracy.

A computer program has been performed under MATLAB in order to use different algorithms and neurons in the ANN. The selected different ANN structures (three types) is shown in Fig. 8. Variants of the algorithm used in the study are SCG and LM. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function has been used.

Three different models were used in order to train the neural network. In one of them, population, gross generation, installed capacity and year are used in the input layer of the network (Model 1) as in Sözen et al. (2006). In the second, GNP and population are used in the input layer of Model 2. And finally, GDP and population are used in the input layer of Model 3. The net energy consumption is in the output layer for all models. The hidden layers have four neurons. There is one output neuron. The back-propagation algorithm has been implemented to determine errors and modifications for weight of the hidden-layer neurons. The ANN structure and number of neurons have been selected using an evolutionary algorithm.

The aim of using Model 1 is to determine whether economic indicators or energy indicators are used in the estimation of NEC. So, results of Model 1 in Sözen et al. (2006) are used to test the models (Models 2 and 3) considered in this study.

4.1. Results of Model 1

The new formulation based on basic energy indicators of the output as the best algorithm SCG with four neurons, which has maximum R^2 value for testing data is given in Eq. (5). This equation can be used for the estimation of NEC in Turkey using basic energy indicators.

$$\mathrm{NEC}_{\mathrm{Model\ 1}} = \frac{1}{1+\exp(-3.4288F_1+2.1604F_2-6.3936F_3+1.6713F_4+2.3474)}, \tag{5}$$

where F_i ($i = 1, 2, 3, 4$) can be calculated according to Eq. (6). The formulation for the prediction of NEC in Turkey (Eq. (4)) is dependent on basic indicators as seen in Eq. (7).

$$F_i = \frac{1}{1+e^{-E_i}}, \tag{6}$$

where E_i ($i = 1, 2, 3, 4$) is given in Eq. (7).

$$E_i = C_{1i} \times P + C_{2i} \times GG + C_{3i} \times \mathrm{IC} + C_{4i} \times I + C_{5i} \times EX + C_{6i}. \tag{7}$$

The constants in Eq. (7) are given in Table 1. These basic energy indicators (Xs) in Eq. (7) need normalizing according to Eq. (8).

$$X = 0.8\left[\frac{X_{\mathrm{Actual}} - X_{\min}}{X_{\max} - X_{\min}}\right] + 0.1. \tag{8}$$

The $X_{\min}$ and $X_{\max}$ values for basic indicators are given in Table 2. Since the NEC values obtained by ANN is very close to the actual values, they cannot be shown together graphically. For this reason, deviation values have been calculated by the following equation (Eq. (9)), and this has been shown graphically.

$$\mathrm{dNEC} = \frac{\mathrm{NEC}_{\mathrm{Actual}} - \mathrm{NEC}_{\mathrm{ANN}}}{\mathrm{NEC}_{\mathrm{Actual}}}. \tag{9}$$

4.2. Results of model 2

The new formulation based on GNP of the output as the best algorithm LM with 4 neurons, which has maximum R^2 value for testing data is given Eq. (10). This equation can be used for estimation of NEC in Turkey using GNP and population.

$$\mathrm{NEC}_{\mathrm{MODEL\ 2}} = \frac{1}{1+\exp(2.4066F_1-0.6881F_2+0.8937F_3+0.9918F_4-1.5053)}, \tag{10}$$

where F_i ($i = 1, 2, 3, 4$) can be calculated according to Eq. (6). E_i ($i = 1, 2, 3, 4$) in Eq. (6) is given in Eq. (11).

$$E_i = C_{1i} \times \mathrm{GNP} + C_{2i} \times P + C_{3i}. \tag{11}$$

The constants in Eq. (11) are given in Table 3.

The basic economic indicators (GNP and GDP) in Eqs. (11) and (13) need normalizing according to Eq. (8) using Table 2.

4.3. Results of model 3

The new formulation dependent on GDP of the output as the best algorithm LM with four neurons, which has maximum R^2 value for testing data, is given in Eq. (12). This equation can be used for estimation of NEC in Turkey using GDP and population:

$$\mathrm{NEC}_{\mathrm{Model3}} = \frac{1}{1+\exp(2.2593F_1-0.6181F_2+0.9835F_3+1.0306F_4-1.6547)}, \tag{12}$$

Table 1
Constants in Eq. (6) obtained by SCG algorithm with four neurons

i	C_{1i}	C_{2i}	C_{3i}	C_{4i}	C_{5i}	C_{6i}
1	2.7530	5.9876	−3.7077	2.0953	4.1596	−7.2509
2	0.7058	5.6285	1.8274	0.5969	−3.9859	−2.2450
3	−6.5109	2.7931	−3.1822	0.2308	−2.2791	5.6603
4	1.8805	−1.0907	−4.9925	5.4540	0.3421	1.6137

Table 3
Constants for Eq. (11) obtained by LM algorithm with four neurons

i	C_{1i}	C_{2i}	C_{3i}
1	3.5693	22.9144	−21.6656
2	−8.1529	−48.5635	36.9050
3	6.0739	20.2442	−9.6508
4	−2.7396	32.7692	−19.0015

Table 2
Maximum and minimum values of basic indicators for normalizing according to Eq. (8)

	Model 1						Model 2		Model 3	
Indicators →	P	GG	IC	I	EX	NEC	P	GNP	P	GDP
$X_{\min}$	30,000	15,000	4000	0	0	12,500	Only divided	15,000	Only divided	15,000
$X_{\max}$	85,000	1,75,000	50,000	7500	1500	1,75,000	90,000	4,00,000	90,000	4,00,000

Table 4
Constants in Eq. (13) obtained by LM algorithm with four neurons

i	C_{1i}	C_{2i}	C_{3i}
1	3.8010	19.0049	−18.5766
2	−9.2970	−50.4544	38.6484
3	6.4832	16.5722	−7.9703
4	−2.2467	29.5083	−17.2710

where F_i ($i = 1, 2, 3, 4$) can be calculated according to Eq. (6). E_i ($i = 1, 2, 3, 4$) in Eq. (6) is given in Eq. (13).

$$Ei = C_{1i} \times \mathrm{GDP} + C_{2i} \times P + C_{3i} \tag{13}$$

The constants in Eq. (13) are given in Table 4.

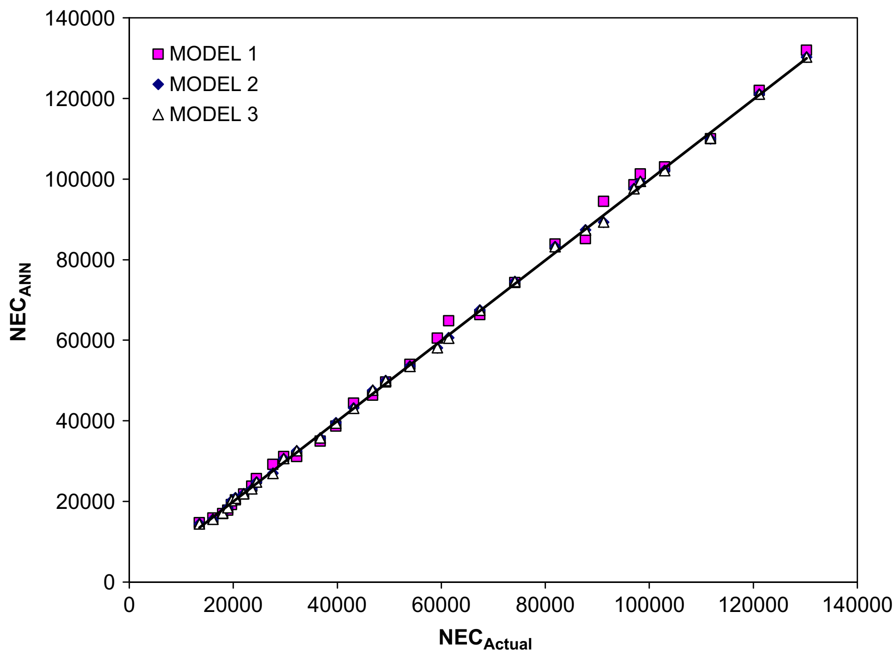

Fig. 9. Comparison of the actual data and ANN results for training in all models.

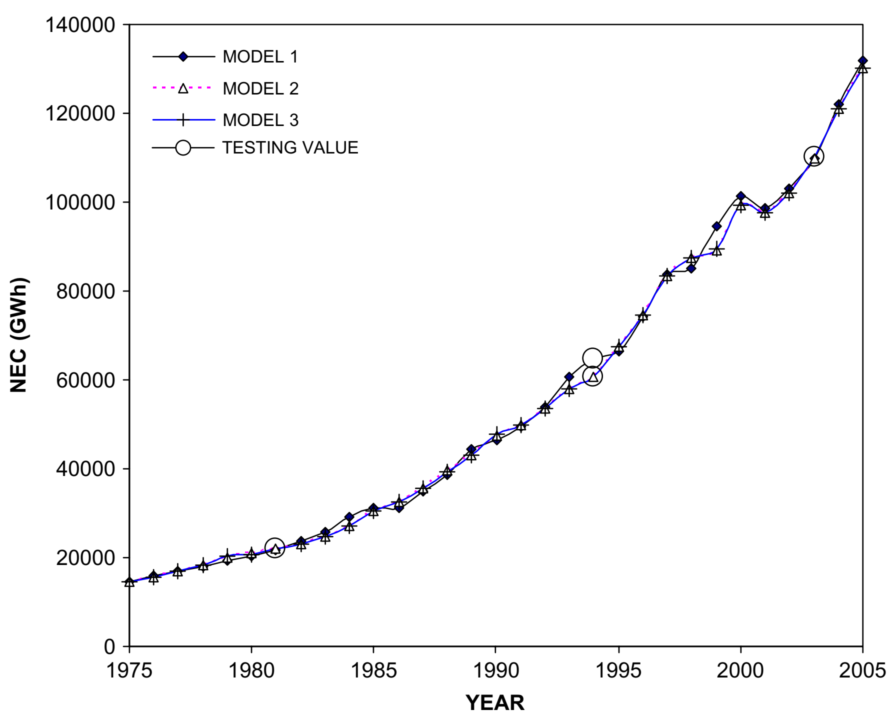

Fig. 10. Comparison of different models.

5. Comparison and conclusions

Fig. 9 for training and testing data shows the performance of the ANN for all models. Fig. 10 shows the accuracy of the ANN approach for each model. It is difficult to distinguish between the accuracies of the models selected, but numerical values show that the Model 3 gives the best accuracy as shown in the shaded cells in Table 5. In general, according to the results obtained, dNEC for training and testing years are in the range of $\pm 8\%$ for all years as shown in Fig. 11. However, NEC based on GNP and GDP is less deviated than NEC based on energy indicators. Tables 6 and 7 support this situation. In Table 6, deviations for testing years are given. Table 7 presents optimum deviations with years. The minimum deviation in NEC is obtained in Model 3 for 2005. The maximum deviation is obtained at Model 1 in Sözen et al. (2006)) for 1975. When the obtained results in this study are compare the others, the ANN approach can be used to predict the NEC. According to results ofSay and Yücel (2006) ($R^2 = 0.996$), this study can be used to predict the NEC from the country population and GNP or GDP with high confidence ($R^2 = 0.9999$).

In summary, the main goal of this study is to determinate the causality relationship between energy and economic indicators, as new numerical formulas, using the ANN approach. It is expected that this study will be helpful in

Table 6
Deviations for testing years

Testing years	Deviations (%)		
	Energy indicators Model 1	GNP Model 2	GDP Model 3
1981	−0.82	−0.533	0.6695
1994	5.5406	−1.22	1.4272
2003	1.58	−1.659	1.4497

Table 5
Statistical values for different models

Statistical values	Energy indicators, Model 1	GNP, Model 2	GDP, Model 3
RMS training	0.007439	0.003771	0.003771
R^2 training	0.999444	0.999903	0.999903
MAPE training	2.322732	1.110525	1.122048
RMS test	0.024201	0.006196	0.005806
R^2 test	0.997386	0.999834	0.999854
MAPE test	3.591475	0.903572	0.936687

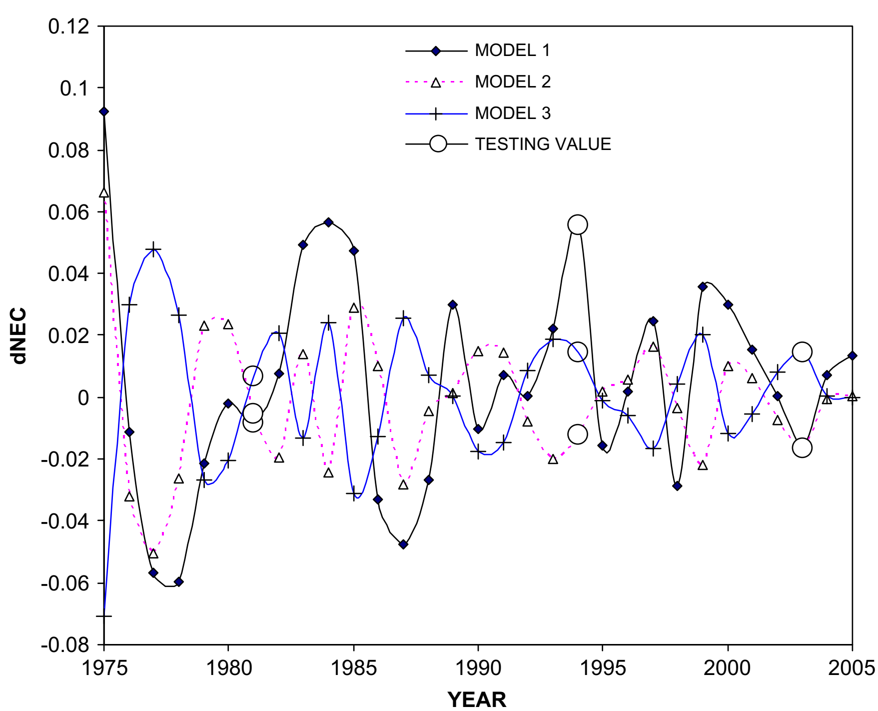

Fig. 11. Comparison of deviations for different models.

Table 7
Optimum deviations with years

	Deviations (%)		
	Energy indicators Model 1	GNP Model 2	GDP Model 3
Maximum deviation (year)	9.2348 (1975)	6.6474 (1975)	7.058 (1975)
Minimum deviation (year)	0.0311 (1992)	0.0278 (2005)	0.023 (2005)

estimating the NEC of Turkey by different indicators. The results of this study show that this estimation formula with high confidence dependent on basic economic indicators (GNP and GDP), can be used to estimate the NEC in Turkey in order to determine the future level of energy consumption in Turkey.

The results of this study show that usage of economic indicators is more appropriate than the usage of energy indicators in the estimation of NEC, because more accurate and reliable results with GDP have been obtained. Although the absolute deviation approach of Model 2 according to Model 1 is $R^2 = 0.43$, the deviation approach of Model 3 according to Model 1 is $R^2 = 0.45$. As also shown in Fig. 11, deviation values of model 3 are less than Model 2. Minimum deviations (0.023) are for Model 3 as shown in Table 7. As a general conclusion, we can say that the prediction of NEC is obtained more accurately by using the economic indicators (GNP and GDP), instead of Model 3 being better, that the prediction of NEC is obtained more accurate by using the economic indicators (GNP and GDP).

The ANN also provides prompt results for different GNP, GDP and population, speeding up the evaluation and helping us to determine the NEC. Therefore, in other applications, the use of ANNs in similar circumstances can be chosen as a test bed. Reducing the time and effort spent for the numerical studies using our approach, the NEC values can be achieved.

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