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# Forecasting based on sectoral energy consumption of GHGs in Turkey and mitigation policies

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## Abstract

Recently, global warming and its effects have become one of the most important themes in the world. Under the Kyoto Protocol, the EU has agreed to an 8% reduction in its greenhouse gas (GHG) emissions by 2008–2012. The GHG emissions (total GHG, $CO_2$, CO, $SO_2$, $NO_2$, E (emissions of non-methane volatile organic compounds)) covered by the Protocol are weighted by their global warming potentials (GWPs) and aggregated to give total emissions in $CO_2$ equivalents. The main subject in this study is to obtain equations by the artificial neural network (ANN) approach to predict the GHGs of Turkey using sectoral energy consumption. The equations obtained are used to determine the future level of the GHG and to take measures to control the share of sectors in total emission. According to ANN results, the maximum mean absolute percentage error (MAPE) was found as 0.147151, 0.066716, 0.181901, 0.105146, 0.124684, and 0.158157 for GHG, $SO_2$, $NO_2$, CO, E, and $CO_2$, respectively, for the training data with Levenberg–Marquardt (LM) algorithm by 8 neurons. $R^2$ values are obtained very close to 1. Also, this study proposes mitigation policies for GHGs.


*Keywords:* Greenhouse gas emissions; Sectoral energy consumption; Mitigation

## 1. Introduction

Global warming and climate change are the most difficult problems facing the world today. The risk of climate change due to emissions of greenhouse gas (GHG) from fossil fuels is considered to be the main environmental threat from the existing energy system (Demirbaş, 2003). The accelerating use of fossil fuels since the Industrial Revolution and rapid destruction of forests cause a significant increase in the anthropogenic GHGs (Tunç et al., 2007). The Kyoto Protocol can be cited as the most important agreement that tries to limit the countries' emissions within a time horizon (Tunç et al., 2007). The Kyoto marks an important turning point in efforts to promote the use of renewable energy as a key strategy for reducing GHG emissions worldwide.

Estimating GHG emissions plays an important role in decision making and planning of the share of energy consumption by sectors. Recently, there have been a few studies that investigated the relationship between energy indicators and GHG emissions in Turkey using different methods and approaches (Demirbaş, 2003; Tunç et al., 2007; Conzelmann and Koritarov, 2002; Bilgen et al., 2007). These researches give a general perspective and future projections on global warming and GHG emissions. One of them (Conzelmann and Koritarov, 2002) is a forecasting study based on modeling the energy sector developed by the Argonne National Laboratory.

The main objective of this study is to develop equations for the estimation of GHG emissions in Turkey using the artificial neural network (ANN) approach in order to plan the use of energy by sectors. This study also compares the

*Abbreviations:* I; Industry; T; Transport; H; Household; A; Agriculture; S; Services; O; Other; GHG; Greehouse gas; $CO_2$; Emission of $CO_2$; CO; Emission of CO; $SO_2$; Emission of $SO_2$; $NO_2$; Emission of $NO_2$; Emission of $NO_2$; E; Emission of non-methane volatile organic compound; TEC; Total energy consumption

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accuracy in predicting GHG emissions in Turkey with values found in the literature. The importance of the 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. Therefore, the use of ANN for modeling and prediction purposes is becoming increasingly popular in recent decades (Sözen et al., 2006; Sözen and Arcaklioğlu, 2007a; Reddy and Ranjan, 2003; Mellit et al., 2007; Yücesu et al., 2007; Mohandes et al., 1998). 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.

Moreover, the purpose of this study is to assist Turkey's future energy politics in its interactions with the United Nations Framework Convention on Climate Change.

## 2. General perspective

### 2.1. Sectoral energy consumption in Turkey

Turkey's geographical location makes it a natural bridge between the energy-rich Middle East and Central Asian regions. Turkey's demand for energy is increasing rapidly. Energy consumption has increased at an annual average rate of 4.3% since 1990 (Ediger and Tatlidil, 2002). The use of basic energy sources in Turkey is shown in Fig. 1. Turkey has many kinds of energy resources, but 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) (Sözen and Nalbant, 2007). More than half (60%) of the net energy consumption in the country is met by imports, and the share of imports continues to increase each year. Turkey's primary energy sources are based primarily on fossil fuels. However, the level of energy production in Turkey is very low. Coal is a major fuel source for Turkey. In recent years, Turkey's oil consumption has increased. 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 2020s (Dinçer and Dost, 1996). The

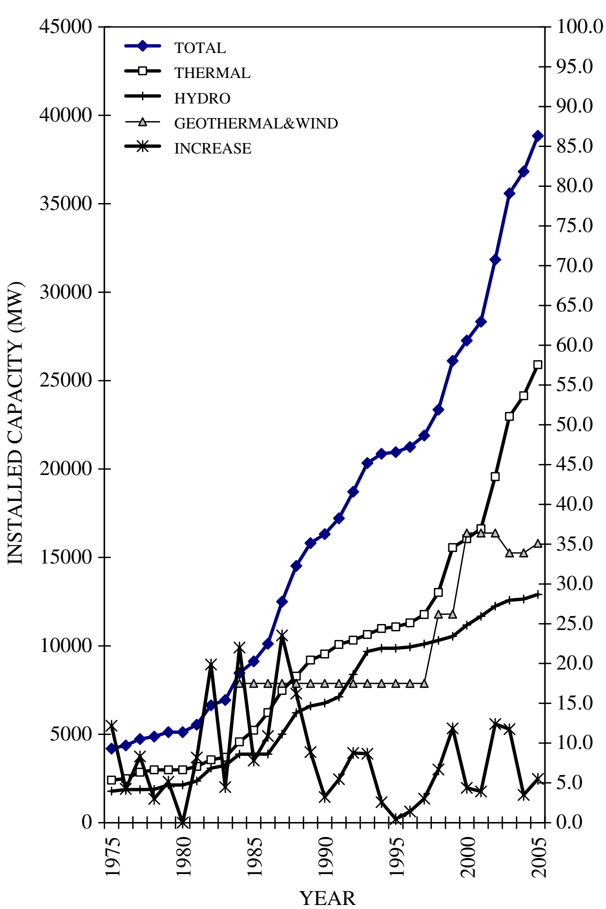


Fig. 1. Installed capacity for Turkey as energy resources.

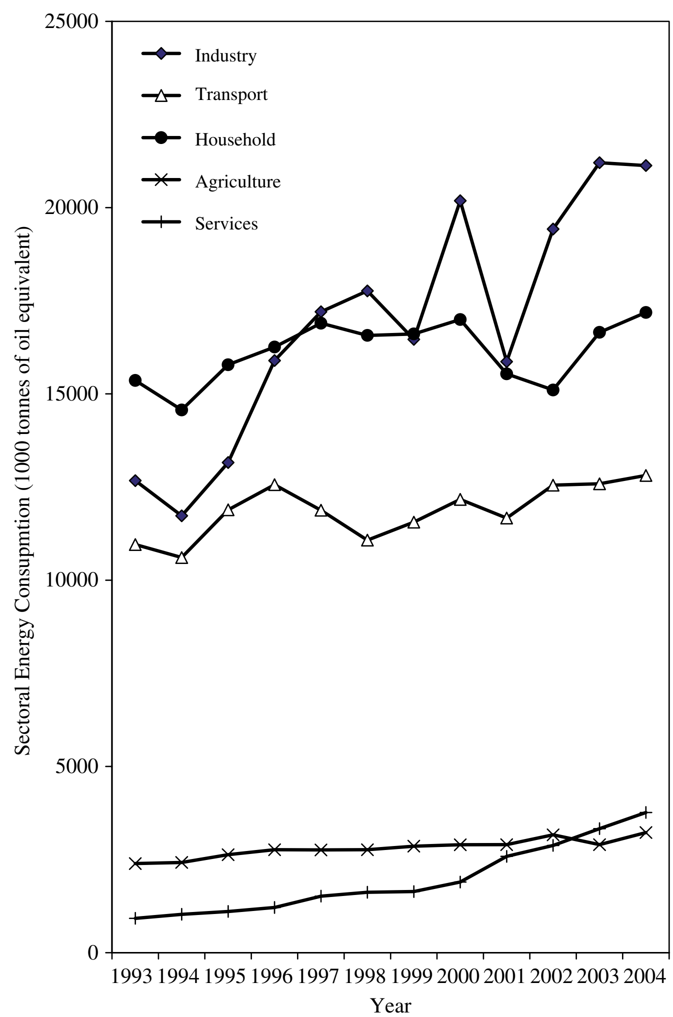


Fig. 2. Sectoral energy consumption in Turkey (*Source*: http://www.ec.europa.eu/eurostat).

share of natural energy resources of Turkey in the world reserves are (WEC-TNC, 2000)

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

Petroleum and natural gas reserves in Turkey are quite limited. Lignite has the biggest share in the 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 also planning to install 33 lignite, 27 natural gas, 12 coal, two nuclear, and 113 hydroelectric energy plants (Kiliç and Kaya, 2007).

The variation of sectoral energy consumption in Turkey is given in Fig. 2 (*Source*: http://www.ec.europa.eu/eurostat). It is the sum of energy consumption in industry, transport, households, services, agriculture, etc. The housing sector had the highest energy consumption until 1990, and then has gradually decreased. While this consumption is 36.29% of the total energy consumption in 1993, this share is 29.56% in 2004 (Türkeş, 2002). Similarly, while energy consumptions of industry, transport, agriculture and services are 29.9%, 25.88%, 5.65%, and 2.18% in 1993, these shares are 36.3%, 22%, 5.54%, and 6.47% in 2004, respectively (Fig. 3). While transport energy consumption is decreasing, the others are increasing in this time period. Based on demand forecasts from the Model for Analysis of Energy Demand, total energy consumption grows at an average rate of 5.9% per year from 65.5 mtoe (2000) to 273.5 mtoe (2025). The other models in the literature (Ediger and Akar, 2007; Sözen and Arcaklioğlu, 2007b; Sözen et al., in press) are estimating similar results. Average annual growth rates vary by sector, with industry having the highest rate at 7.6%, followed by the transportation sector with 5% (Conzelmann and Koritarov, 2002). In terms of final energy by fuel, hard coal/coke increase their share slightly from 13% to 18%, lignite holds steady at 6%, electricity grows from 17% to 24%, oil products decline from 42% to 29%, and natural gas increases from 7% to 17% between 2000 and 2025 (Conzelmann and Koritarov, 2002).

### 2.2. Greenhouse gas emissions in Turkey

The rapid expansion of energy consumption has brought with it a wide range of environmental issues at the local, regional, and global levels. Countries must reduce emissions of 6 GHGs by at least 5% compared with 1990 levels over 2008–2012 according to the Kyoto Protocol.

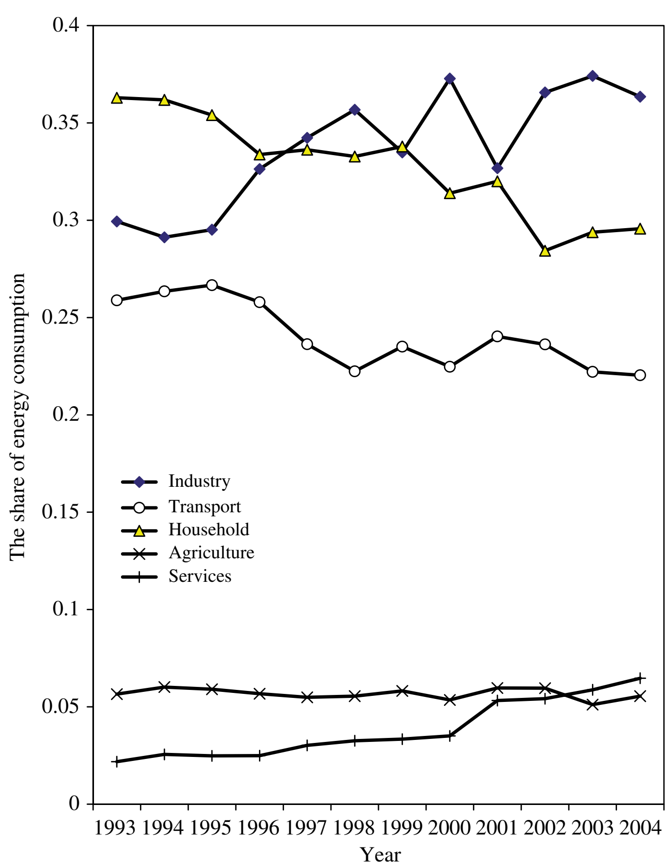


Fig. 3. The share of energy consumption.

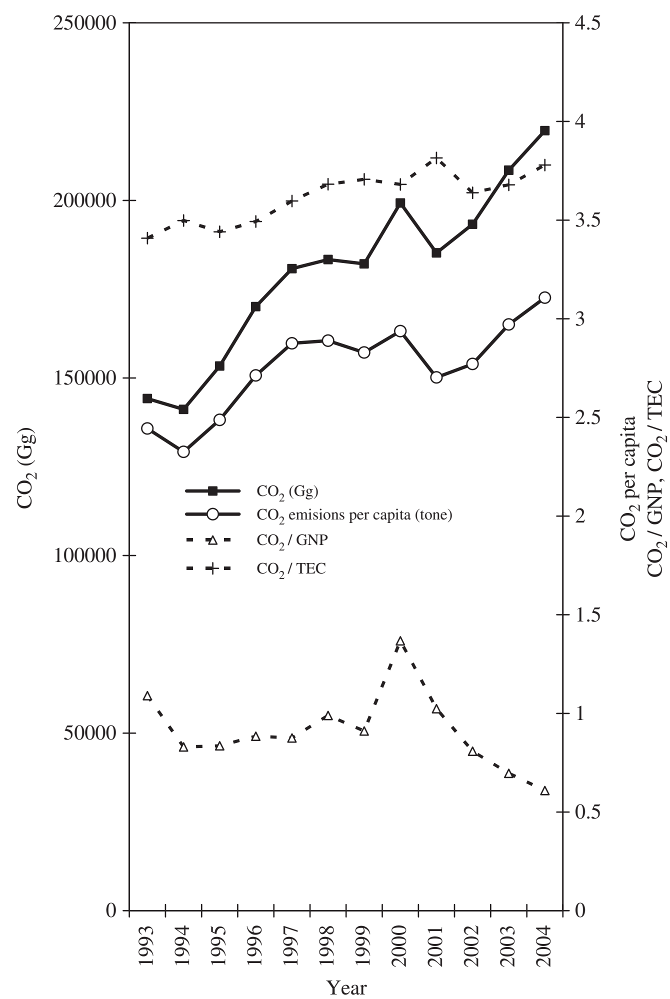


Fig. 4. $CO_2$ emission for Turkey.

The main gaseous pollutants in the atmosphere are CO, $CO_2$, $CH_4$, NO, $NO_2$, $N_2O$, $SO_2$, CHCs, and $O_3$. $CO_2$ and CO are the main GHGs associated with global warming. It is predicted that $CO_2$ contributes ~50% to the anthropogenic greenhouse effect (Demirbaş, 2003). Turkey's GHG emissions (especially $CO_2$) have grown along with its energy consumption. GHG emissions in 2000 reached 211 million metric tons in Turkey (Conzelmann and Koritarov, 2002). All energy consumption sectors (power, industrial, residential, and transportation) will contribute to this increased GHG emissions burden. Table 2 shows Turkey's GHGs in $CO_2$ equivalents per capita compared with EU countries (*Source*: http://www.ec.europa.eu/eurostat).

Though the energy consumption of the country increases rapidly, Turkey's contribution to GHG emissions is definitely below the average of EU countries. Table 2 shows Turkey's GHG emission per capita compared with other EU countries. Although the energy demand of the country increases rapidly, Turkey's contribution to global GHG emissions is considerably below the average of EU countries. Figs. 4–8 show GHG emissions in $CO_2$ equivalents: $CO_2$ (Gg), $SO_2$, $NO_2$, CO, and E, respectively, in Turkey (*Source*: http://www.tuik.gov.tr). Also, these figures show GHG emissions based on economical and energy indicators and per capita. But, according to $CO_2$ emission per capita, Turkey has lower GHG emissions than the other countries. Sectoral distribution of $CO_2$ emissions per year is given in Table 1 by the Turkish Statistical Institution (Akcasoy et al., 2000).

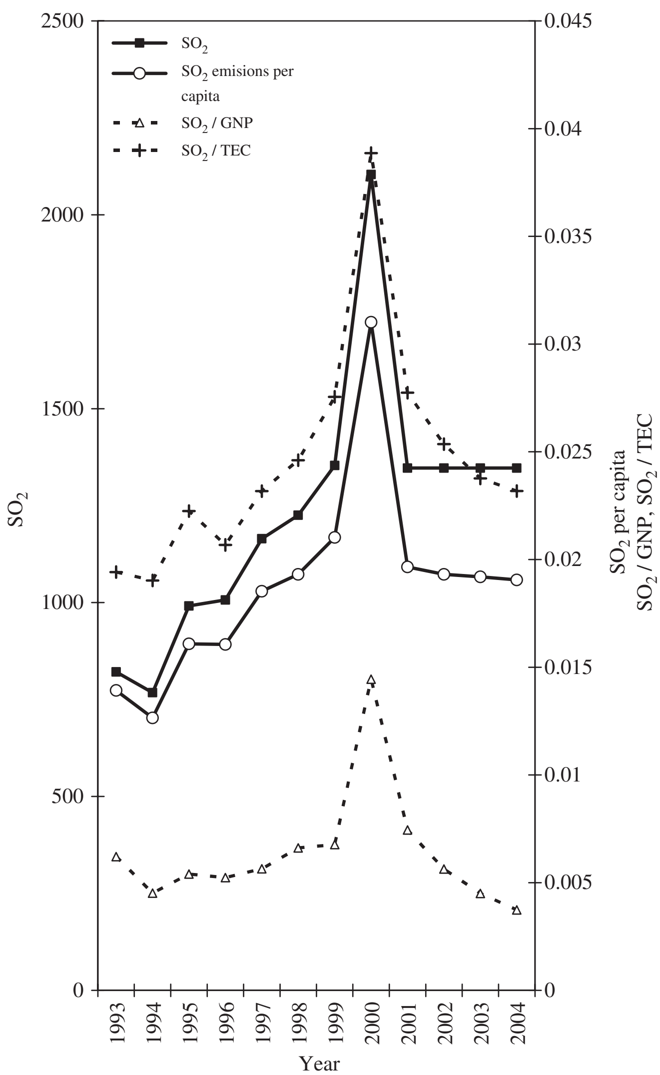


Fig. 5. $SO_2$ emission for Turkey.

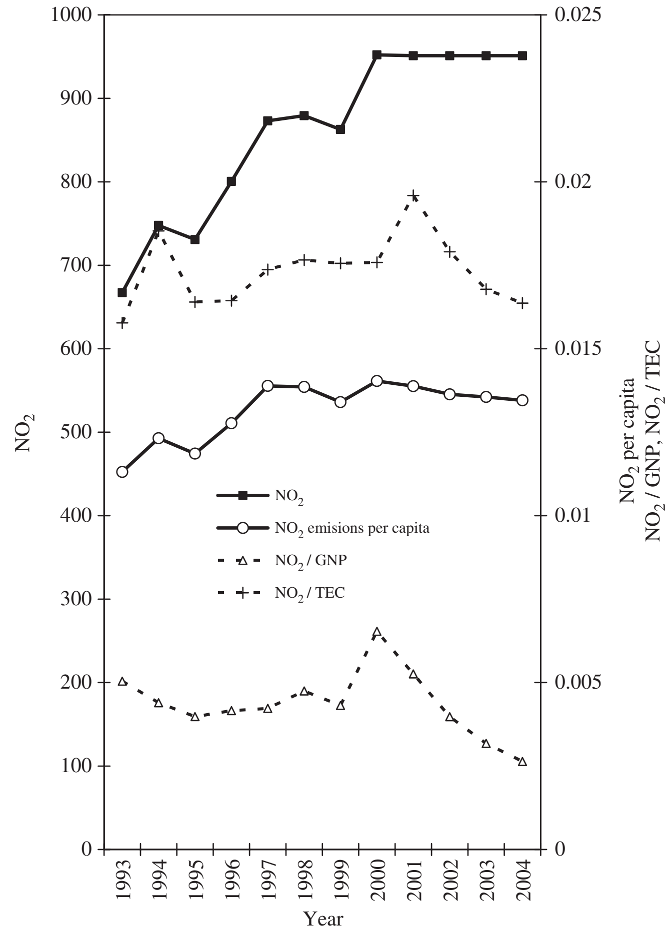


Fig. 6. $NO_2$ emission for Turkey.

## 3. Artificial neural network approach

ANNs are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy-efficient packages. This brain modeling also promises a less technical way to develop machine solutions. This new approach to computing also provides a more graceful degradation during system overload than its more traditional counterparts (Anderson and McNeil, 1992).

The individual neurons are complicated. They have a myriad of parts, sub-systems, and control mechanisms.

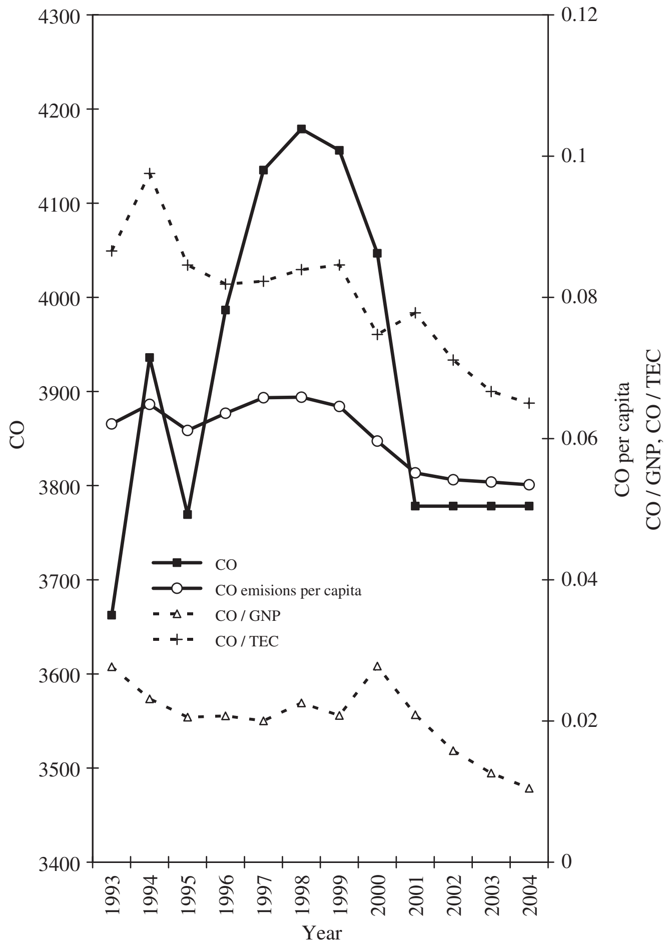


Fig. 7. CO emission for Turkey.

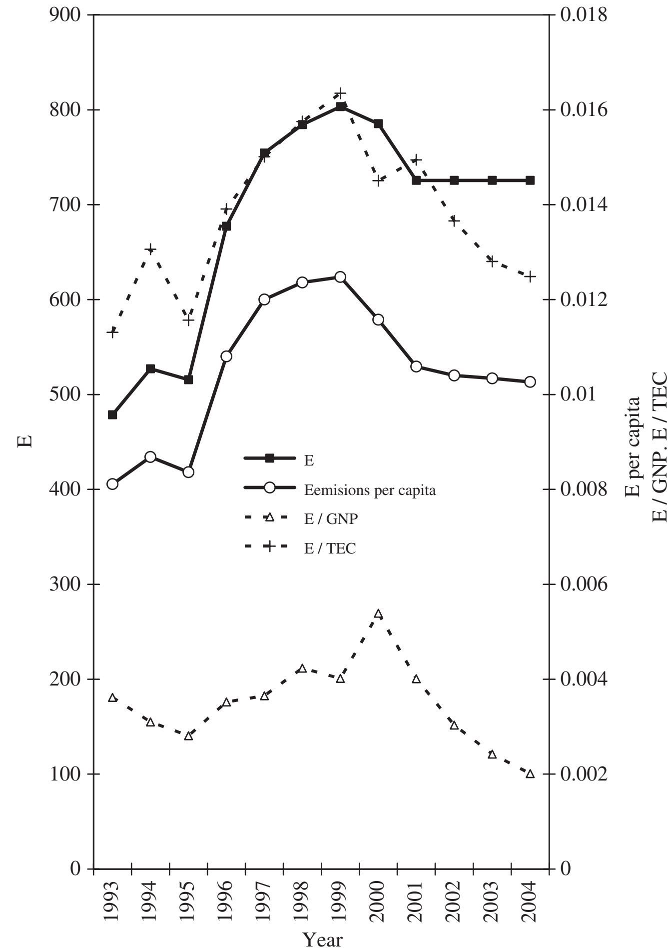


Fig. 8. E emission for Turkey.

They convey information via a host of electrochemical pathways. There are over 100 different classes of neurons, depending on the classification method used. Together, these neurons and their connections form a process that is not binary, not stable, and not synchronous. In short, it is nothing like the currently available electronic computers, or even ANNs. These ANNs try to replicate only the most basic elements of this complicated, versatile, and powerful organism. They do it in a primitive way. But for the software engineer who is trying to solve problems, neural computing was never about replicating human brains. It is about machines and a new way to solve problems (Anderson and McNeil, 1992). Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then outputs the final result. Fig. 9 shows the relationship of these four parts (http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html). 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 (Anderson and McNeil, 1992). 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: 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 (Kalogiro, 2003). 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 (Anderson and McNeill, 1992; Haykin, 1994; Kalogiro, 2003; 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. Faster algorithms such as conjugate gradient, quasi-Newton, and Levenberg–Marquardt (LM) use standard numerical optimization techniques. The LM method is in fact an

Table 1
$CO_2$ (Gg)[a] distribution as sectoral energy consumption

| Sector | 1970 | 1975 | 1980 | 1985 | 1990 | 1995 | 2000 | 2005 |
|---|---|---|---|---|---|---|---|---|
| Energy | 11,560 | 16,496 | 20,437 | 33,279 | 51,094 | 61,271 | 100,119 | 150,180 |
| Industry | 10,628 | 17,673 | 20,864 | 24,573 | 37,385 | 41,560 | 54,170 | 83,276 |
| Transportation | 10,116 | 15,967 | 16,025 | 18,885 | 26,443 | 33,665 | 53,211 | 62,800 |
| Others | 9277 | 15,072 | 18,361 | 24,530 | 27,805 | 32,686 | 46,078 | 51,593 |

[a]Gg means $10^9$ times (Say and Yücel, 2006).

Table 2
Comparison of GHG emission per capita between EU states and Turkey

| Country | Year | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 |
| Belgium | 0.010236 | 0.0105 | 0.009901 | 0.010204 | 0.009791 | 0.009806 | 0.009743 | 0.009583 | 0.009695 | 0.009686 | 0.008855 |
| Bulgaria | 0.007452 | 0.007287 | 0.007002 | 0.006278 | 0.005905 | 0.005933 | 0.00618 | 0.005955 | 0.006526 | 0.006537 | 0.011854 |
| Czech Republic | 0.007616 | 0.007683 | 0.007896 | 0.007428 | 0.007036 | 0.007394 | 0.007422 | 0.007192 | 0.00737 | 0.007335 | 0.009001 |
| Denmark | 0.021109 | 0.024624 | 0.021857 | 0.02068 | 0.019761 | 0.018443 | 0.018788 | 0.018516 | 0.019838 | 0.018193 | 0.014599 |
| Germany | 0.001092 | 0.001109 | 0.001071 | 0.001044 | 0.001014 | 0.001013 | 0.001022 | 0.001004 | 0.001009 | 0.001 | 0.000958 |
| Estonia | 0.035633 | 0.037679 | 0.038193 | 0.03503 | 0.032483 | 0.032942 | 0.033065 | 0.033353 | 0.036652 | 0.037008 | 0.068274 |
| Ireland | 0.029353 | 0.03011 | 0.031163 | 0.031947 | 0.032367 | 0.032612 | 0.033003 | 0.031719 | 0.030931 | 0.030464 | 0.027499 |
| Greece | 0.009618 | 0.009847 | 0.0102 | 0.010566 | 0.010505 | 0.010877 | 0.010978 | 0.010922 | 0.01123 | 0.011222 | 0.011279 |
| Spain | 0.002793 | 0.002721 | 0.002897 | 0.002977 | 0.003211 | 0.003316 | 0.003283 | 0.003391 | 0.003384 | 0.003493 | 0.002672 |
| France | 0.001671 | 0.001712 | 0.001684 | 0.00172 | 0.001666 | 0.001637 | 0.001627 | 0.001602 | 0.001605 | 0.0016 | 0.0016 |
| Italy | 0.001803 | 0.001778 | 0.001799 | 0.001836 | 0.001857 | 0.001874 | 0.001896 | 0.001897 | 0.001938 | 0.001936 | 0.001599 |
| Cyprus | 0.185156 | 0.190614 | 0.189854 | 0.200089 | 0.198272 | 0.205069 | 0.20172 | 0.20567 | 0.213676 | 0.202912 | 0.20022 |
| Latvia | 0.018835 | 0.019478 | 0.018733 | 0.018135 | 0.017006 | 0.016081 | 0.017426 | 0.017435 | 0.017714 | 0.017894 | 0.039888 |
| Lithuania | 0.01765 | 0.015794 | 0.013935 | 0.012043 | 0.011848 | 0.011645 | 0.011471 | 0.011077 | 0.009761 | 0.011579 | 0.026859 |
| Luxembourg | 0.193739 | 0.193878 | 0.177501 | 0.156835 | 0.168694 | 0.176199 | 0.178815 | 0.194551 | 0.200981 | 0.222099 | 0.158242 |
| Hungary | 0.006608 | 0.006811 | 0.006669 | 0.006693 | 0.006681 | 0.006486 | 0.006715 | 0.006496 | 0.006714 | 0.006722 | 0.009309 |
| Malta | 0.331258 | 0.332705 | 0.320856 | 0.323772 | 0.332629 | 0.339295 | 0.302504 | 0.354283 | 0.35263 | 0.364871 | 0.362582 |
| Netherlands | 0.006814 | 0.007029 | 0.00679 | 0.006778 | 0.006383 | 0.00631 | 0.006311 | 0.006228 | 0.006207 | 0.006249 | 0.005765 |
| Austria | 0.01279 | 0.013303 | 0.01322 | 0.013122 | 0.012816 | 0.012859 | 0.01344 | 0.013639 | 0.014465 | 0.014214 | 0.010601 |
| Poland | 0.001913 | 0.002005 | 0.001957 | 0.001847 | 0.001836 | 0.001764 | 0.00177 | 0.001713 | 0.001771 | 0.001791 | 0.002462 |
| Portugal | 0.011859 | 0.011381 | 0.011973 | 0.01276 | 0.013903 | 0.013448 | 0.013611 | 0.014241 | 0.013413 | 0.013461 | 0.012062 |
| Romania | 0.002968 | 0.003054 | 0.002732 | 0.002455 | 0.002192 | 0.00224 | 0.002323 | 0.002492 | 0.002604 | 0.002717 | 0.004248 |
| Slovenia | 0.046092 | 0.047731 | 0.048566 | 0.047861 | 0.046555 | 0.046836 | 0.049093 | 0.049448 | 0.048772 | 0.049689 | 0.046055 |
| Slovakia | 0.01361 | 0.01373 | 0.013702 | 0.01329 | 0.01296 | 0.012484 | 0.01333 | 0.012828 | 0.012976 | 0.012955 | 0.017085 |
| Finland | 0.019711 | 0.021224 | 0.020809 | 0.019739 | 0.019556 | 0.019028 | 0.020459 | 0.020982 | 0.023145 | 0.021936 | 0.019096 |
| Sweden | 0.011569 | 0.012107 | 0.011374 | 0.011427 | 0.010899 | 0.010653 | 0.010729 | 0.010854 | 0.01095 | 0.01074 | 0.011541 |
| United Kingdom | 0.001583 | 0.00163 | 0.001575 | 0.001557 | 0.001473 | 0.00147 | 0.001481 | 0.001434 | 0.001442 | 0.001439 | 0.001457 |
| Croatia | 0.014739 | 0.015771 | 0.0169 | 0.017045 | 0.017751 | 0.017778 | 0.019132 | 0.019959 | 0.021116 | 0.021298 | 0.021378 |
| Turkey | 0.002106 | 0.002611 | 0.002948 | 0.002976 | 0.002808 | 0.002684 | 0.002469 | 0.002651 | 0.002725 | 0.002971 | 0.003002 |
| Iceland | 0.355056 | 0.363806 | 0.380882 | 0.378488 | 0.393906 | 0.36129 | 0.340861 | 0.333217 | 0.325477 | 0.333138 | 0.374689 |
| Norway | 0.023043 | 0.024256 | 0.024108 | 0.024063 | 0.02434 | 0.023981 | 0.024404 | 0.02374 | 0.023966 | 0.024096 | 0.021926 |

approximation of Newton's method (Attiti, 1992; Hagan and Menhaj, 1994).

Artificial intelligence systems are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems (Kalogiro, 2003). ANNs are attractive because of at least four reasons:

1. They are weighted connections and massively parallel processes with fault tolerance, so that they can automatically learn from experience.
2. They have the generalization capability to learn complex patterns of inputs and provide meaningful solutions to problems even when input data contain errors, or are incomplete, are not presented during training.
3. They are distribution free because no prior knowledge is needed about the statistical distribution of the classes in the data sources in order to apply the method for classification. This is an advantage over most statistical methods that require modeling of data. Neural networks could avoid some of the shortcomings of the currently used statistically or empirically based techniques.
4. They take care of determining how much weight each data source should have in the classification, which remains a problem for statistical methods. The nonlinear learning and smooth interpolation capabilities give the neural network an edge over standard computers and rule-based systems for solving certain problems.

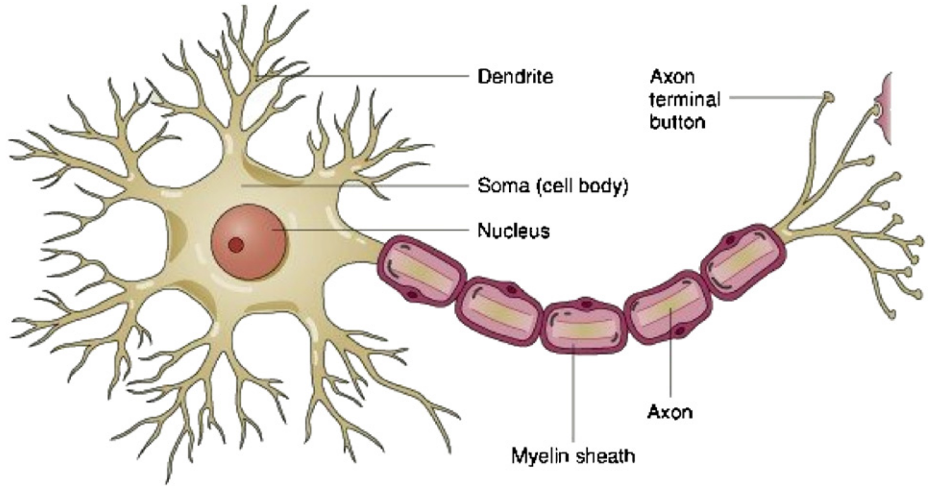


Fig. 9. A simplified model of a biological and artificial neuron (Anderson and McNeil, 1992).

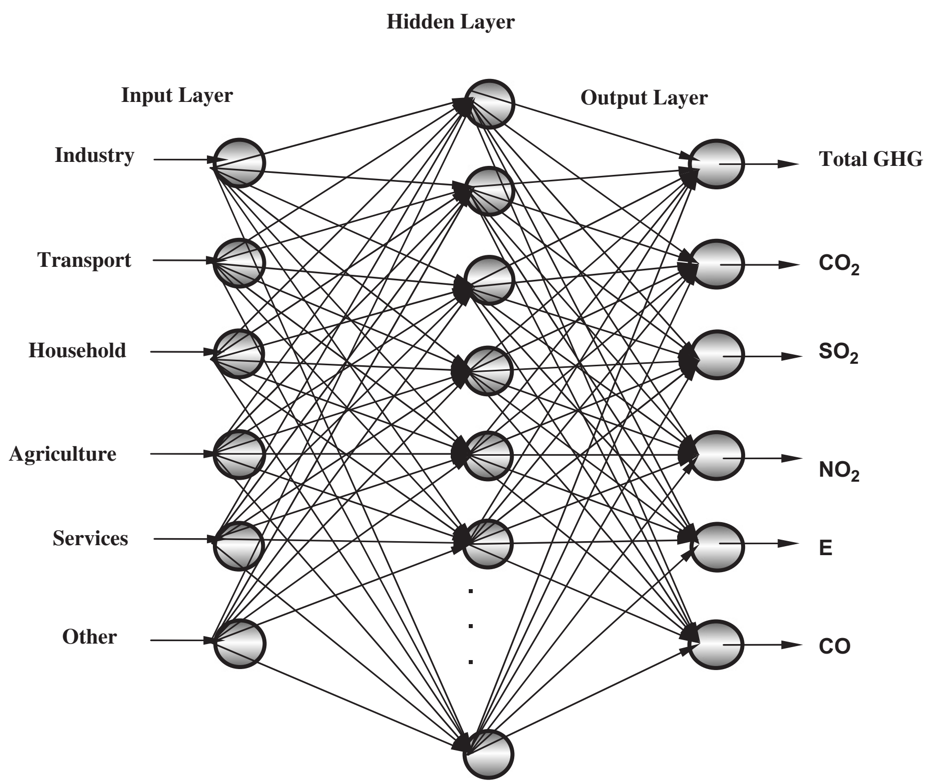


Fig. 10. ANN architecture used for the estimation of GHG emissions.

Table 3
Statistical values for outputs in ANN

| Statistical values | GHG emissions | | | | | |
|---|---|---|---|---|---|---|
| | GHG | $SO_2$ | $NO_2$ | CO | E | $CO_2$ |
| RMS training | 0.001162 | 0.000408 | 0.001849 | 0.001075 | 0.001143 | 0.001326 |
| $R^2$ training | 0.999997 | 0.999999 | 0.999995 | 0.999998 | 0.999997 | 0.999997 |
| MAPE training | 0.147151 | 0.066716 | 0.181901 | 0.105146 | 0.124684 | 0.158157 |
| RMS test | 0.493215 | 0.137817 | 0.006763 | 0.012671 | 0.042496 | 0.038166 |
| $R^2$ test | 0.989278 | 0.923079 | 0.999924 | 0.999737 | 0.996232 | 0.997397 |
| MAPE test | 2.424228 | 28.23405 | 0.79656 | 1.451238 | 6.25854 | 3.030889 |

Table 4
Constants in Eq. (12) obtained by LM algorithm with 8 neurons

| $i$ | $C_{1i}$ | $C_{2i}$ | $C_{3i}$ | $C_{4i}$ | $C_{5i}$ | $C_{6i}$ | $C_{7i}$ |
|---|---|---|---|---|---|---|---|
| 1 | 2.4281 | 1.7733 | 2.5283 | −4.5980 | −1.4819 | 2.8233 | −10.4189 |
| 2 | −0.2592 | −5.7661 | 1.6461 | −1.6836 | 7.9695 | −1.5040 | 6.4563 |
| 3 | 3.8851 | 0.6926 | −2.9626 | −5.2433 | 0.3997 | 3.4768 | −2.0377 |
| 4 | 1.2739 | 3.3547 | 5.3905 | 1.6390 | −0.3526 | 2.9301 | −5.06 |
| 5 | −4.3032 | 5.2610 | −3.7533 | 0.3291 | 8.4522 | 1.7946 | −3.1585 |
| 6 | 0.5627 | 7.1679 | −7.5427 | −4.6784 | 10.9228 | 0.7586 | −0.3196 |
| 7 | −3.9810 | 0.1076 | 0.3519 | −3.9812 | −9.1057 | 0.4462 | 5.0888 |
| 8 | −2.7088 | −2.1773 | −5.5119 | 2.9109 | 1.3231 | 0.7224 | 2.6009 |

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

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

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

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

$$\mathrm{MAPE} = \frac{o - t}{o} \times 100, \quad (3)$$

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. Application of ANN and results

The selected ANN structure is shown in Fig. 10. Variants of the algorithm used in the study are scaled conjugate gradient and LM. Inputs and outputs are normalized in the (0, 1) range. Neurons in input layer have no transfer function. Logistic sigmoid transfer function has been used. Each input is multiplied by a connection weight. In the simplest case, products and biases are simply summed, then transformed through a transfer function to generate a result, and finally the output is obtained. The back-propagation algorithm has been implemented to determine errors and modifications for weight of the hidden-layer neurons. In order to avoid undesirably long training times or the network being trapped in local error minima, various learning rates have been tried.

Table 5
Normalizing values

| Inputs/outputs | For normalizing |
|---|---|
| Industry (I) | Divided 25,000 |
| Transport (T) | Divided 15,000 |
| Household (H) | Divided 20,000 |
| Agriculture (A) | Divided 4000 |
| Services (S) | Divided 4500 |
| Other (O) | Use of Eq. (12) |
| GHG | Multiplied 250 |
| $CO_2$ | Multiplied 250,0000 |
| CO | Multiplied 5000 |
| $SO_2$ | Multiplied 2500 |
| $NO_2$ | Multiplied 1100 |
| E | Multiplied 1000 |

The new formulation dependent on sectoral energy consumption of the output (GHG emissions) as the best algorithm LM with 8 neurons, and which has a maximum $R^2$ value for testing data (see Table 3) are given in Eqs. (4)–(9). These equations can be used for the estimation of GHG emissions in Turkey using sectoral energy consumptions.

$$\mathrm{GHG} = \frac{1}{1 + e^{-(-1.9495F_1 - 3.3054F_2 - 2.1248F_3 - 0.3029F_4 + 3.7607F_5 - 4.16F_6 - 4.9847F_7 - 8.1703F_8 + 6.8931)}}, \quad (4)$$

$$CO_2 = \frac{1}{1 + e^{-(0.8585F_1 + 3.5537F_2 + 3.7976F_3 - 2.2132F_4 - 0.2257F_5 + 1.154F_6 - 0.6379F_7 - 3.7614F_8 - 0.884)}}, \quad (5)$$

$$SO_2 = \frac{1}{1 + e^{-(-1.8724F_1 - 1.6628F_2 + 2.2837F_3 - 3.3763F_4 - 7.8749F_5 + 12.6757F_6 + 5.579F_7 - 0.1096F_8 - 0.669)}}, \quad (6)$$

$$NO_2 = \frac{1}{1 + e^{-(-3.1248F_1 + 3.6212F_2 + 0.1119F_3 - 2.378F_4 - 1.293F_5 + 2.8223F_6 - 0.7438F_7 + 0.2463F_8 - 1.0741)}}, \quad (7)$$

$$\mathrm{CO} = \frac{1}{1 + e^{-(1.1262F_1 + 1.9526F_2 + 0.1005F_3 + 0.4408F_4 - 0.2069F_5 - 1.1877F_6 - 2.3613F_7 - 0.2767F_8 + 0.1142)}}, \quad (8)$$

$$E = \frac{1}{1 + e^{-(-1.2875F_1 + 3.6058F_2 + 3.2441F_3 + 4.3003F_4 - 1.0511F_5 - 0.1462F_6 - 4.2469F_7 + 2.2754F_8 - 6.4159)}}, \quad (9)$$

where $F_i$ ($i=1,2,\ldots 8$) can be calculated according to Eq. (10). The formulation for the prediction of GHG emissions in Turkey (Eqs. (4)–(9)) is dependent on sectoral energy consumption as seen in Eq. (11). In Eqs. (4)–(9), $E_i$ ($i=1,2,\ldots 8$) is given in Eq. (11), which is sectoral energy consumption data.

$$F_i = \frac{1}{1+e^{-E_i}} \tag{10}$$

by

$$E_i = C_{1i}I + C_{2i}T + C_{3i}H + C_{4i}A + C_{5i}S + C_{6i}O + C_{7i}, \tag{11}$$

where the constants in Eq. (11) are given in Table 4. The inputs and outputs in ANN need normalizing according to Table 5. The other energy indicators ($O$) need normalizing

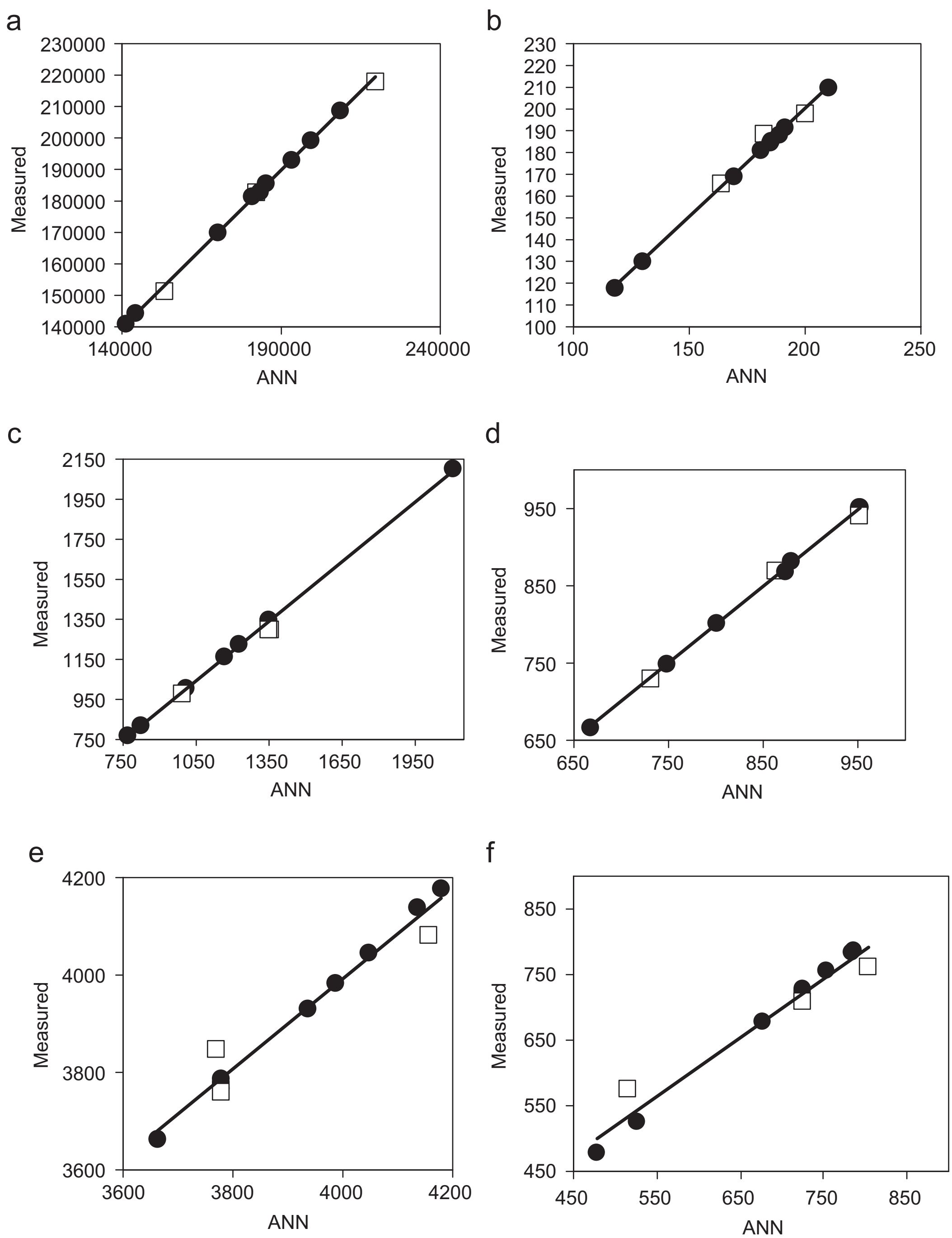


Fig. 11. Comparison of the measured data and ANN results for training and testing data in emissions of GHG (□: testing value). (a) $CO_2$; (b) GHG; (c) $SO_2$; (d) $NO_2$; (e) CO; (f) E.

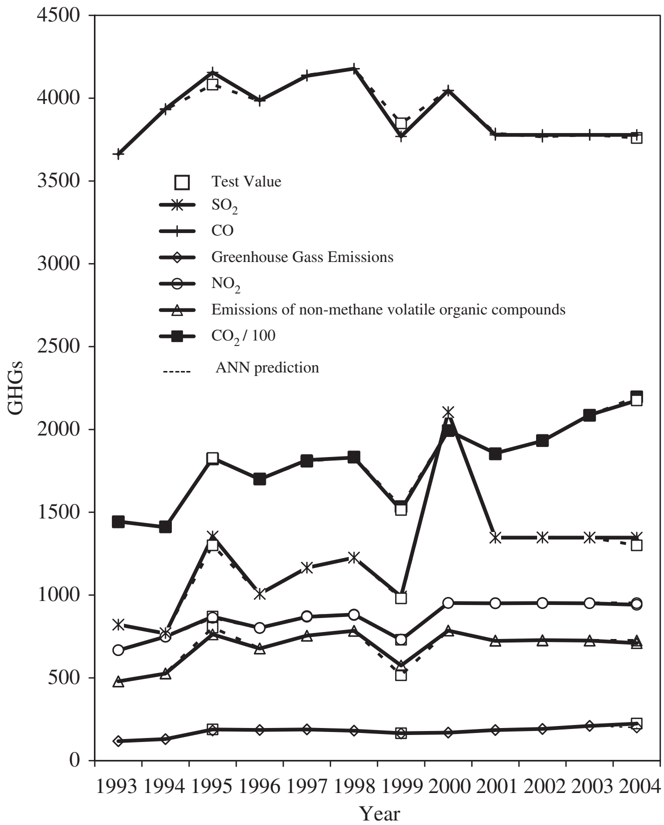


Fig. 12. Variation of the measured data and ANN results for training and testing data in emissions of GHG.

according to Eq. (12).

$$O = 0.8 \times \left[\frac{O_{\text{Actual}} - (-100)}{50 - (-100)}\right] + 0.1. \qquad (12)$$

Fig. 11 shows the performance of the ANN for training and testing data for all emissions of GHG. Also, Fig. 12 shows the accuracy of the ANN approach for each GHG emission. As seen in Fig. 12, the difference between actual data and that predicted by ANN, both training and testing data, is negligible. Fig. 13 shows the prediction of GHG emission up to 2020 by the ANN approach. As seen in Fig. 13, the ANN model projects total $CO_2$ emissions to increase at an average rate of 5.4%/yr. Similarly, the ANN model projects the other emissions of GHG, $SO_2$, $NO_2$, CO, and E to increase at an average rate of 7.16%, 7.05%, 4.8%, 0.57%, and 5.94%, respectively. For the $CO_2$ emission, the industrial contribution changes the most noticeably, rising from 36% to 43% driven by the high growth in industrial energy as well as the continued reliance on solid and liquid fuels in this sector. The majority of the $SO_2$ emissions' growth can be attributed to an increase in industrial solid fuel and fuel oil combustion.

In Table 6, a comparison is given of the published literature for similar studies in which ANN and other methods are used in order to predict the future projection of $CO_2$ emissions. According to the results of Say and Yücel (2006) ($R^2 = 0.998$), this study can be used to predict the $CO_2$ emissions from the sectoral energy consumption with high confidence ($R^2 = 0.999997$). To verify the estimation of the ANN approach, statistical error values (i.e. $R^2$ and RMS) of training and testing data can be evaluated. $R^2$ values in this study are much higher than other studies and the values are in the acceptable range. Therefore, the results of the validation and comparative study indicate that the ANN-based prediction approach for GHG emissions is more suitable than the classical regression and other models proposed by other researchers for Turkey. In other words, when the obtained results in this study are compared with the others, the ANN approach can be used to predict the GHG emissions based on sectoral energy consumption.

Fig. 14 shows the share of sectoral energy on GHG emissions. As seen in Fig. 14, the sectoral energy contributions of agriculture, transport, and household are projected to fall while industry and services increase. This projection is similar to the results of Conzelmann and Koritarov (2002) and Bilgen et al. (2007).

## 5. Mitigation policies for GHGs in Turkey

The introduction of the Kyoto Protocol represents a very important step in the effort for the limitation of the emissions of GHG, so that negative impacts from human activities on global climate can be anticipated (Georgopoulou et al., 2003). GHG emissions can be estimated based on the energy usage for the period of 2007–2020 by using the equations derived in Section 4. In addition, the sectoral share of the effect of energy usage on environment can be determined with the derived equations for this period. So, with this study, it is proposed to prepare a base for GHG reduction by planning the distribution of energy usage to the sectors, inspiring to the usage of energy sources decreased the GHG emissions, planning the usage of macro-energy sources such as utilizing the renewable energy resources.

After the evaluation of the share of energy sector in Turkey and future predictions, the fundamental planning criteria for GHG reduction is developed as depicted in Fig. 15. The proposed mitigation criterions to reduce GHG emissions can be evaluated under four topics as follows:

- increasing the use of renewable energy,
- decreasing the energy losses,
- improving the fuel quality,
- using the technology preventing the GHG.

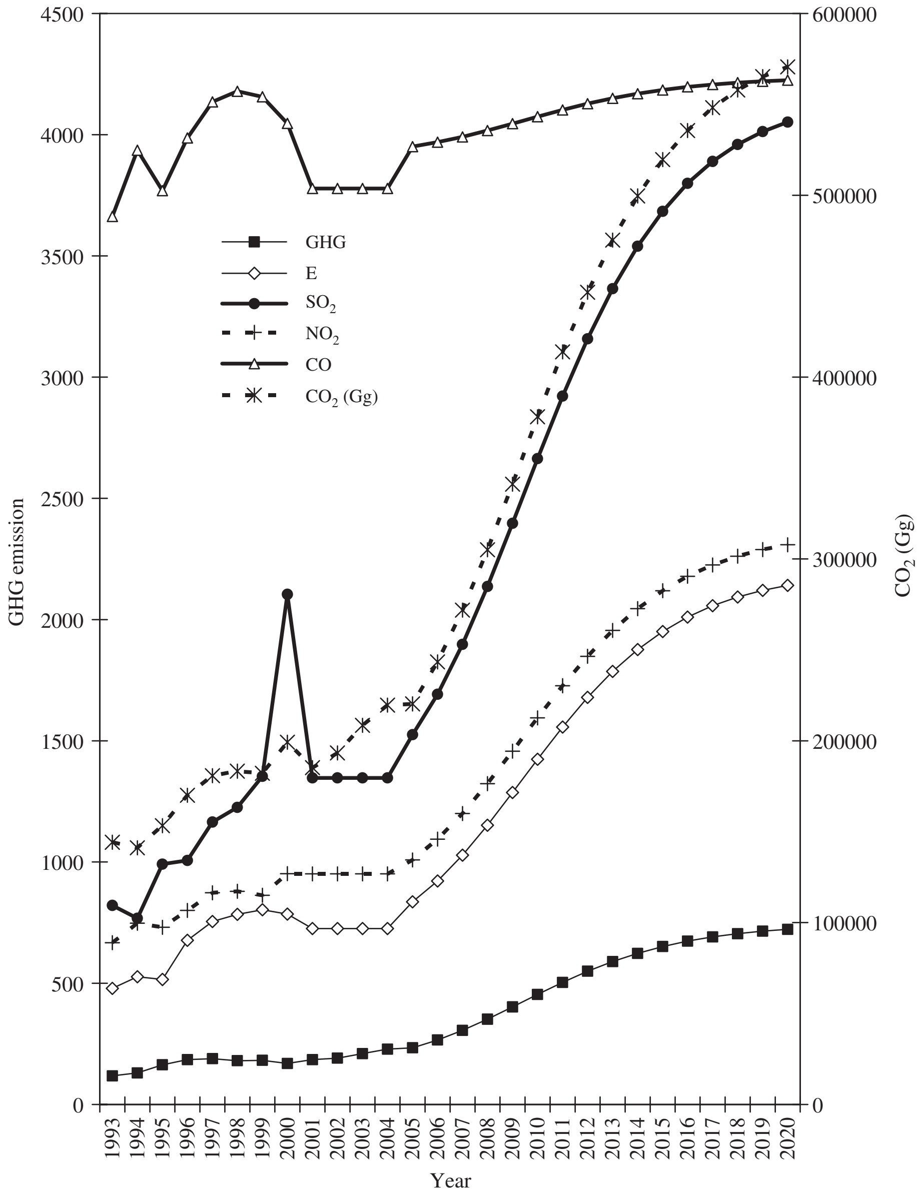


Fig. 13. Prediction of GHG emissions from 2007 to 2020 with ANN.

Table 6
Comparison of estimated $CO_2$ emission (Gg)

| Studies | Estimation of $CO_2$ (Gg) 2010 | 2015 |
|---|---|---|
| Say and Yücel (2006) (Regression model) | 363,769 | 522,427 |
| Say and Yücel (2006) (IPCC model) | 480,244 | 631,781 |
| Akcasoy et al. (2000) | 535,985 | – |
| Demirbaş (2003) (Projections based on the case of energy pattern in 1992) | ~500,000 | – |
| Demirbaş (2003) (Projections based on the case of energy pattern in 1996) | ~410,000 | – |
| Bilgen et al. (2007) | 535,985 | – |
| SPO (2000) | 403,653 | 768,942 |
| Türkeş (2002) | 347,850 | 486,465 |
| Conzelmann and Koritarov (2002) | ~380,000 | ~650,000 |
| This study (ANN model) | 378,182 | 570,653 |

### 5.1. Increasing the use of renewable energy

- Renewable energy sources should be utilized as much as possible.

The energy sector in Turkey is dependent on fossil resources. The share of the fossil resources in total electricity consumption was 85% in 2005. The main fossil resources are petroleum and coal. Recently, it is seen that natural gas use was markedly increased especially after the year 1995. Turkey has a significant coal potential. But, about 90% of this potential is low-calorie lignite and this reserve is mostly used in thermic plants as fuel. The risk of climate change due to emissions of $CO_2$ from fossil fuels is considered to be the main environmental threat from the existing energy system. Supplies of such energy resources as fossil

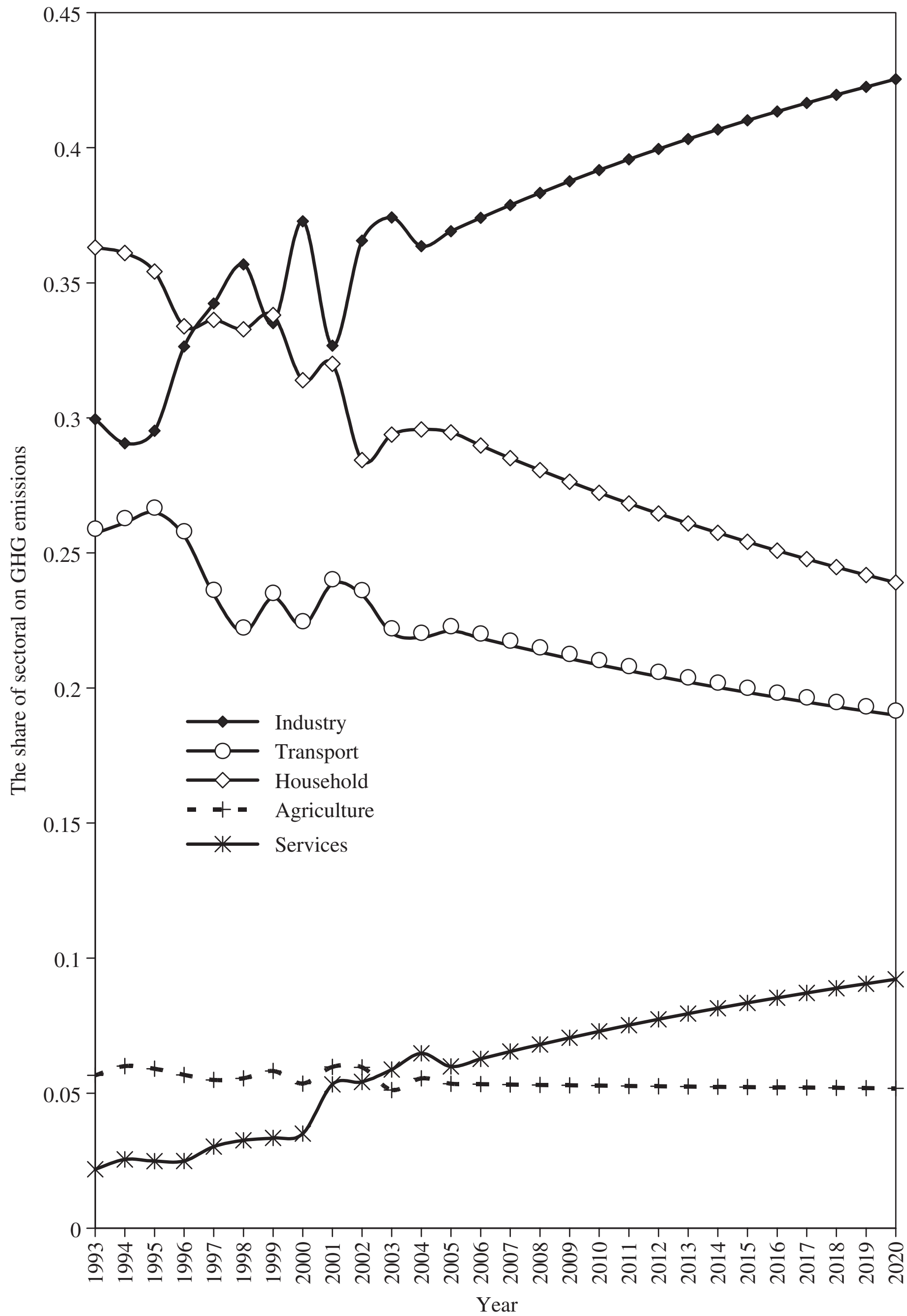


Fig. 14. The share of sectoral energy on GHG emissions.

fuels and nuclear fuels are acknowledged to be finite, but other sources such as solar, hydropower, biomass, geothermal, and wind are considered renewable and, therefore, sustainable over the relatively long term (Demirbaş, 2003).

- Turkey must increase rapidly the usage of renewable energy source. For this aim, the government must encourage the usage of renewable energy source.
- Nuclear power plants must be put into use by increasing in variety the usage of energy source.
- More extensive use of solar PVs, wind energy, and mini-hydroelectric plants.
- The carbon tax leads to a change in the dispatch of some fossil fuel plants and in the overall fuel mix.

### 5.2. Decreasing the energy losses

- Upgrading of power transmission lines.
- Promoting the diffusion and efficiency of central heating systems (Demirbaş, 2003).

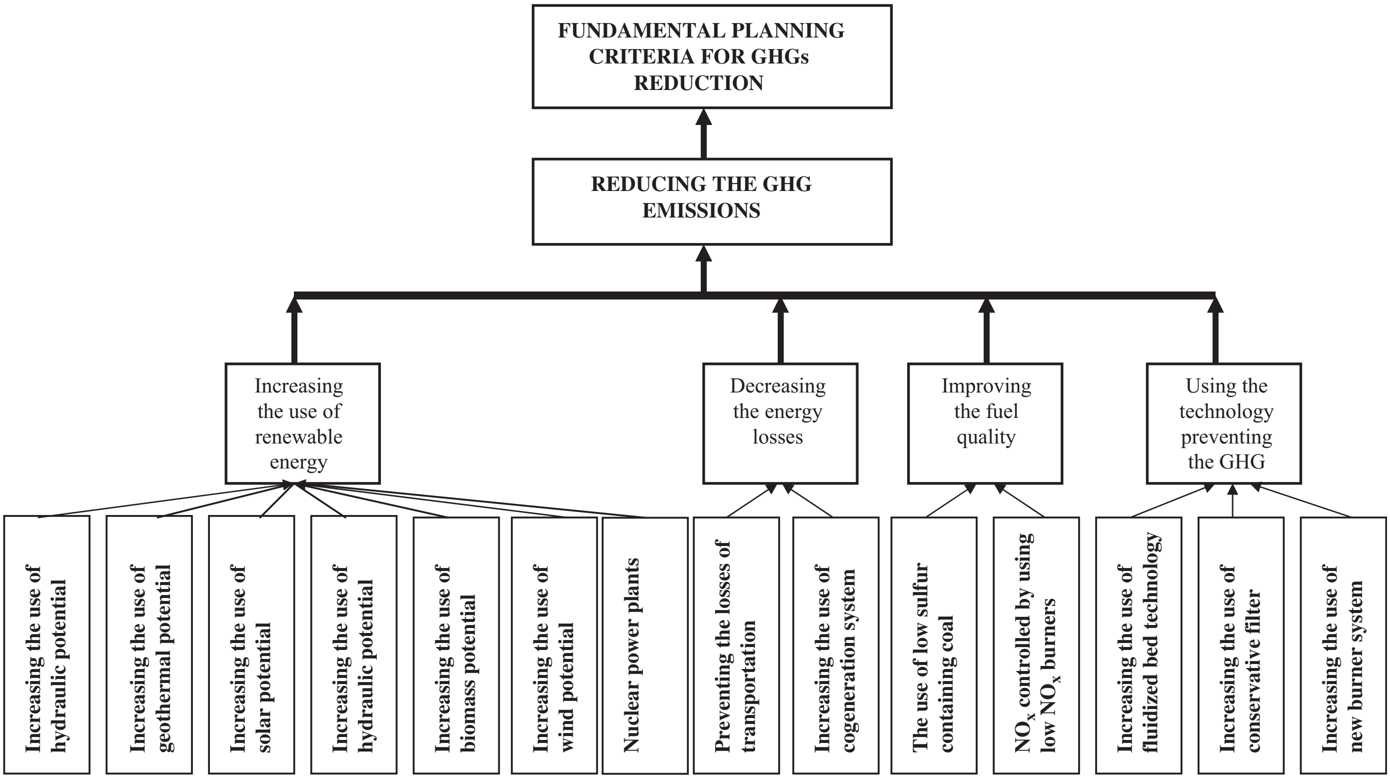


Fig. 15. The flowchart for fundamental planning criteria for GHG reduction.

- Increasing the use of process energy such as co-generation systems.
- Supporting energy-efficient technology transfer in energy field.
- Upgrading of techniques for energy consumption in buildings.

### 5.3. Improving the fuel quality

- Promoting the scientific founding for their work regarding increase in fuel quality.
- Making legal the cooperation of industry with universities with regard to fuel and combustion efficiency.
- Constrained gas supply combined with the use of sub-critical and super-critical coal-fired power plants.
- Upgrading petroleum product quality.

### 5.4. Using the technology preventing the GHG

- Increasing the use of fluidized bed combustion systems.
- Encouraging the development of techniques that increase energy efficiency and the use of high-efficiency–low-emission stove and boiler systems (Demirbaş, 2003).
- Encouraging the scientific research and development of the usage of emission trappers in fuels.
- Technical efficiency improvements of existing power stations.

After the evaluation of the share of energy sector in Turkey and future predictions from Fig. 14, the GHG reduction as a flowchart of mitigation criteria can be seen as dotted lines in Fig. 16. Otherwise, the full line in Fig. 16 is valid. In general, the proposed mitigation criteria to reduce GHG emissions can be decreased by approximately 10%.

## 6. Conclusion

The main goal of this study is to predict GHG emissions in Turkey using sectoral energy consumption by the ANN approach. The results of this study show that this prediction formula with high confidence dependent on sectoral energy consumption can use GHG emissions in Turkey in order to determine the future level. It is shown that estimation capability of the ANN is very excellent when the test values that are not used for training the ANN are denoted on the graphs with different symbols. The analytical equivalent of this situation is given in Table 3. Straightness of prediction methods given in the literature is understood with error values.

Renewable energy and nuclear energy have a role to play in GHG reduction policy; mini-hydro and windmills are the most promising and offer an attractive GHG mitigation. Also, cogeneration in industry and improved technical efficiency in the power sector appear to be clearly essential ingredients of future climate change policies.

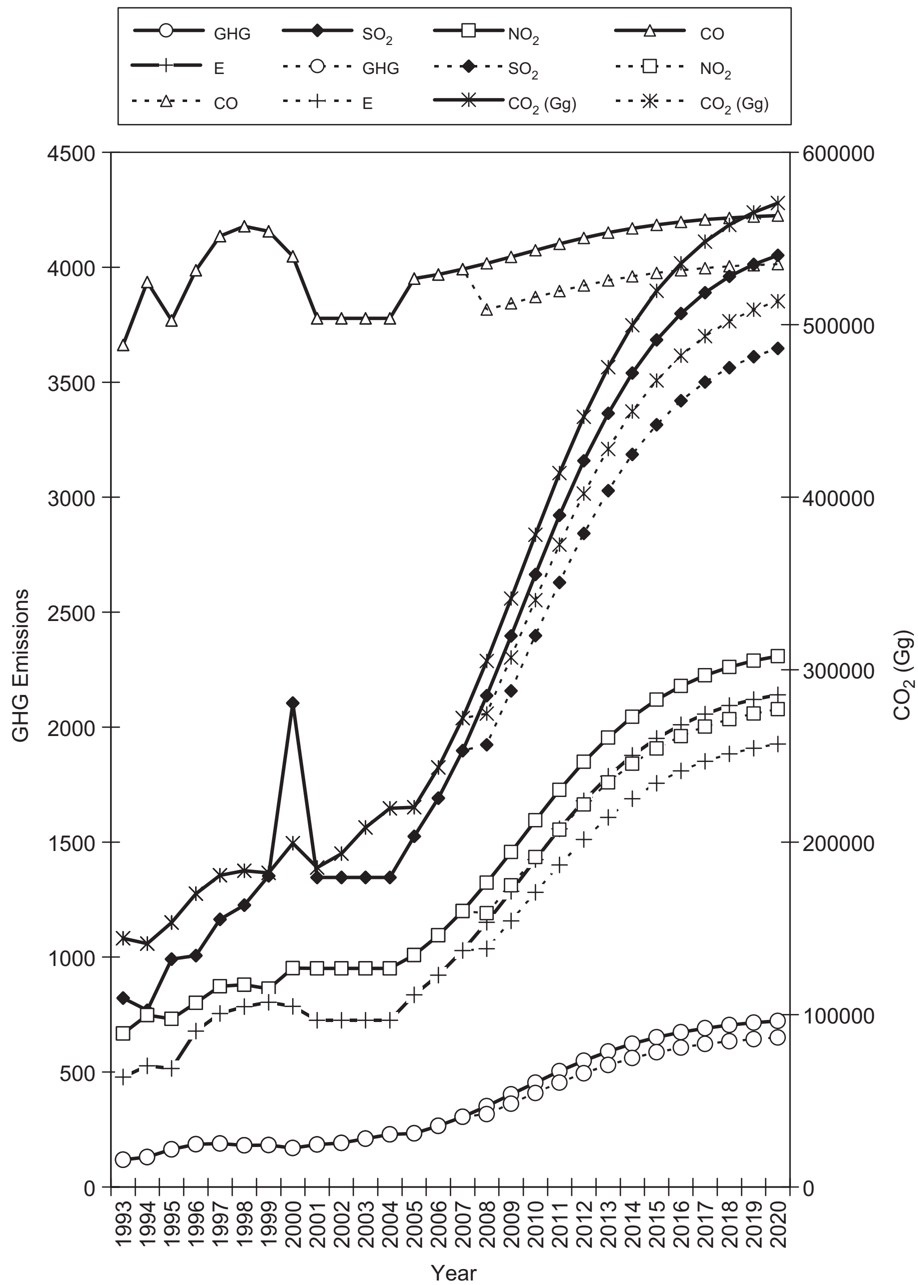


Fig. 16. Estimation of GHG mitigation as fundamental planning criteria.

The results of this study show that planning in usage of energy sources is very important in determining GHG emissions.

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