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Use of artificial neural networks for transport energy demand modeling

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Abstract

The paper illustrates an artificial neural network (ANN) approach based on supervised neural networks for the transport energy demand forecasting using socio-economic and transport related indicators. The ANN transport energy demand model is developed. The actual forecast is obtained using a feed forward neural network, trained with back propagation algorithm. In order to investigate the influence of socio-economic indicators on the transport energy demand, the ANN is analyzed based on gross national product (GNP), population and the total annual average veh-km along with historical energy data available from 1970 to 2001. Comparing model predictions with energy data in testing period performs the model validation. The projections are made with two scenarios. It is obtained that the ANN reflects the fluctuation in historical data for both dependent and independent variables. The results obtained bear out the suitability of the adopted methodology for the transport energy-forecasting problem.

Keywords: Transport energy demand; Artificial neural networks; GNP

1. Introduction

Energy demand has rapidly been increasing because of developments in the industrial, agricultural, transportation, commercial and housing sectors. The population rise and improved life style are other reasons for the increase in energy demand. The fast growth on the GNP per capita leads to increase a number of vehicle owners and hence to increase in energy demand in transportation sector. This sector takes one of the biggest shares in energy use in Turkey for instance about 23% of total energy consumption (World Energy Council Turkish National Committee (WEC-TNC), 2000).

Transport energy demand and GNP, population and veh-km, in last three decades, are increased 3.7, 8, 1.9 and 7.5 times, respectively, when they are compared with 1970 figures as can be seen in Table 1. Observations showed that the growth rate of Turkish GNP and population rate have been increasing between 4–5% and 0.12–0.18% per annum, respectively, for last three decades. The vehicle ownership is about 10% (National Statistics (NS), 2003).

Turkey expects a very large growth in energy demand in the future as its economy expands, especially for petrol in transportation sector. Because of its limited energy resources, Turkey is greatly dependent on imported oil and gas, which is the most important fuel in Turkey, contributing 43% of TPES (International Energy Agency (IEA), 1999) and imports 63% of its energy needs in 1997.

Ediger and Tatlidil (2002) projected the total energy demand of Turkey using *cyclic pattern approach*. Wohlgemuth (1997) estimated transport energy demand

Abbreviations: ANN, artificial neural networks; GNP, gross national product; WEC-TNC, World Energy Council Turkish National Committee; NS, national statistics; MENR, The Ministry of Energy and Natural Resources; MTOE, million tons of oil equivalents; TPES, total primary energy supply; IEA, International Energy Agency; TS, time series; STSM, structural time series model; SSE, sum of squared error; GDTH, General Directorate of Turkish Highways; veh-km, vehicle-kilometers

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Table 1
The growth of transport energy demand and socio-economic indicators (fixed at 1970 values)

Years	Transport energy demand	GNP	Population	veh-km
1970	1.00	1.00	1.00	1.00
1980	1.63	3.66	1.26	2.37
1990	2.72	8.00	1.59	4.17
1995	3.45	9.03	1.76	5.38
1996	3.67	9.70	1.79	5.79
1997	3.53	10.21	1.81	6.47
1998	3.35	10.82	1.85	6.93
1999	4.15	9.86	1.88	6.93
2000	3.78	10.58	1.92	7.69
2001	3.74	7.72	1.94	7.43

and examined the factors that affect the transport energy sector based on the IEA (1999) approach. The IEA also analyzed the price elasticity between income and transportation demand for the OECD and non-OECD countries. Hunt et al. (2003) investigated the energy demand of the UK in sectoral basis using *time-series* (TS) approach. They used the STSM for energy estimation by considering seasonal effects. The analysis emphasized the empirical relevance of evolving trends and seasonal for energy demand.

There are clear signs that the nature of the trend in energy demand and its corresponding socio-economic and transport related indicators is typically not linear and deterministic but stochastic in form, with its pace and even direction altering over time. Ceylan and Ozturk (2004) and Haldenbilen and Ceylan (2005) estimated the energy demand of Turkey based on genetic algorithm approach. Minimizing the SSE between observed and estimated values carried out in modeling process. The results were compared with the MENR (WEC-TNC, 1997) projections, and energy savings were obtained when the demand on transport sector was controlled. Data from energy systems, being inherently noisy, are good candidate problems to be handled with artificial neural networks (ANN).

The appeal of the ANNs can be explained by the ability of the network to learn complex relationships between input and output patterns that would be difficult to model with conventional algorithms.

ANNs are mathematical tools with a *connected structure* taking the notion of human brain as a functional structure. The recent up-surging research activities in ANNs as well as their numerous successful forecasting applications suggest that it can also be an important candidate for transport energy demand forecasting. Being a flexible modeling tool, neural networks can, in principle, model any type of relationship in the data with high accuracy. Instead of complex rules and mathematical routines, ANNs are able to learn the key information patterns within a multidimensional information domain. In addition, they are fault tolerant and robust. They are also good for tasks involving incomplete data sets, fuzzy or incomplete information and for highly complex and ill-defined problems, where humans usually decide on an intuitional basis (Hobbs et al., 1998; Kalogirou, 1999). Furthermore, although ANNs are inherently nonlinear models, they are capable of modeling linear processes as well (Zhang et al., 1998). The tasks that ANNs cannot handle effectively are those requiring high accuracy and precision, as in logic and arithmetic.

In particular, referring to transport energy demand, many applications show that ANNs are able to learn the properties of forecasted energy that would otherwise require deep and careful analysis to be discovered (Beccali et al., 2004; Haldenbilen and Ceylan, 2005). In the ANN models, historical GNP, population and the veh-km data may represent the network inputs, and forecasted transport energy values represent the outputs. Providing input–output pairs extracted from historical data conduct the network's training. Because neural networks are universal function approximators, it is natural to use them to directly model transport energy demand. The main objective of this paper is to present a new approach for the transport energy prediction using a *feed forward neural network*[1] trained by means of a *k-fold*[2] validation algorithm based on population, GNP and veh-km.

2. Artificial neural network model

ANNs are a class of flexible nonlinear models that can discover patterns adaptively from the data. Theoretically, it has been shown that given an appropriate number of nonlinear processing units, neural networks can learn from experience and can estimate any complex functional relationship. Empirically, numerous successful applications have established their role for pattern recognition and forecasting (Gonzalez and Zamarreno, 2005; Abraham and Nath, 2001; Kalogirou and Bojic, 2000). Although many types of neural network models have been proposed, the most popular one for transport energy demand estimation is the feed forward network model. ANNs are composed of many nodes that operate in parallel and communicate with each other through connecting synapses. The greatest advantage of a neural network is its ability to model complex nonlinear relationship without a priori assumptions of the nature of the relationship like a black box (Karayiannis and Venetsanopoulos, 1993). A multi-layer feed forward neural network, which consists of an input layer, hidden

[1]A type of networks which have no lateral connections between neurons in a given layer and none back to previous layers.

[2]See next section for definition.