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A Hierarchical Artificial Neural Network for Gasoline Demand Forecast of Iran

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Abstract

This paper presents a neuro-based approach for annual gasoline demand forecast in Iran by taking into account several socio-economic indicators. To analyze the influence of economic and social indicators on the gasoline demand, gross domestic product (GDP), population and the total number of vehicles are selected. This approach is structured as a hierarchical artificial neural network (ANN) based on supervised multi-layer perceptron (MLP), trained with back-propagation (BP) algorithm. This hierarchical ANN is designed properly. The input variables are GDP, population, total number of vehicles and the gasoline demand in the last one year. The output variable is the gasoline demand. The paper proposes a hierarchical network by which the inputs to the ending level are obtained as outputs of the starting levels. Actual Iranian data between 1967 and 2008 were used to test the hierarchical ANN hence; it illustrated the capability of the approach. Comparison of the model predictions with validation data shows validity of the model. Furthermore, the demand for the period between 2011 and 2030 is estimated. It is noticeable that if there will not be any price shock or efficiency improvement in the transportation sector, the gasoline consumption may achieve a threatening level of about 54 billion liters by 2030 in Iran.

Keywords: ANN; MLP; BP Algorithm; Forecasting; Gasoline Demand.

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Introduction

The transportation sector in many developing countries relies heavily on gasoline for its daily mobility. This reliance is even more acute in the under developing countries due to the lack of efficient public transportation. Gasoline demand forecast becomes an essential function in planning for the future demand to design more efficient transportation systems as well as to control the demand by a proper price mechanism.

During past decades, a variety of technical and statistical methods for energy forecasting have been proposed with varying results. However, no technique or combination of techniques has been consistently successful enough to forecast the energy demand. ANNs one such method being used extensively in forecasting different types of energy demands. Although there are simpler, faster, and easier alternatives, ANNs have been applied to the energy forecasting problem with considerable success. Evidently, an ANN yield more useful insights than a regression based model and that ANNs architecture used to forecast energy demands presents higher accuracy than a traditional polynomial fit method (Nasr et al, 2003: 893–905).

Applications of artificial neural networks for energy forecasting problems have resulted in several research papers (Nasr et al., 2003; Azadeh, 2010:7427–37). Kermanshahi and Iwamiya developed an artificial neural network model to predict the peak electric load in Japan up to 2020 (Kermanshahi & Iwamiya 2002: 789–974). Hsu and Chen collected an empirical data to formulate an artificial neural network model to predict the regional peak load of Taiwan in 2003 (Hsu CC, Chen, 2003:1941–9). Nasr *et al* formulated a neural network approach for the gasoline consumption prediction in Lebanon (Nasr et al, 2003). Murat and Ceylan developed yet another model based on artificial neural network to predict transportation of energy demand in Turkey (Murat & Ceylan, 2006: 3165–72). Azadeh, Ghaderi and Sohrabkhani formulated a neural network model to predict the annual electricity consumption in high energy consuming industrial sectors in Iran (Azadeh et al., 2008:2272-78). Geem and Roper used neural networks to estimate energy demand in South Korea (Geem & Roper, 2009:4049-54). Ekonomou developed a neural network model to predict Greek long-term energy consumption (Ekonomou, 2010:512-17). The same year, Azadeh, Arab and Behfard came up with a model to forecast long-term gasoline demand in the US, Canada, Japan, Kuwait and Iran using artificial neural networks (Azadeh et al., 2010:7427–37).

In this paper, the gasoline demand of Iran is forecasted using MLP trained by BP algorithm considering economic and social indicators for the time span 2011 to 2030. For the estimation, time series data covering period between 1967 and 2008 are used. The remaining parts of the paper are organized as follows. In Section 2, ANNs are introduced. Details of the proposed forecast strategy and numerical results are described in Section 3.A brief review of the paper and future researches are given inSection 4.

Artificial Neural Networks

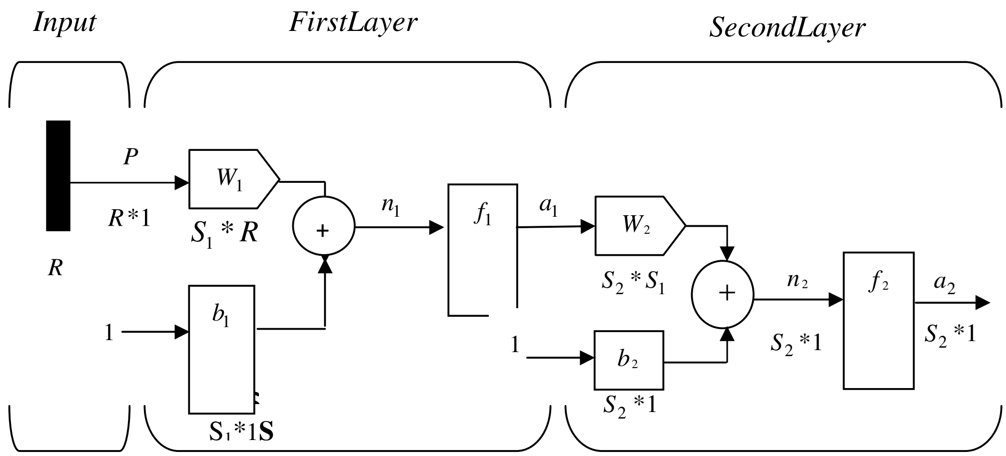
ANNs are computational modeling tools that have recently emerged and found extensive acceptance in many disciplines for modeling complex real-world problems. In an ANN model, a neuron is an elemental processing unit that forms part of a larger network. ANNs consist of an inter-connection of a number of neurons. There are varieties of connections under study; however, only one type of network called the multi-layer perceptron (MLP) will be discussed here. A MLP consists of (i) input variables, (ii) an output layer with nodes representing the dependent variables (i.e. what is being modeled), and (iii) one or more hidden layers containing nodes to help capture the nonlinearity in the data. Using supervised learning, these networks can learn the mapping from one data space to other using examples. In MLPs, the data are feed-forward into the network without feedback. These networks are so versatile and can be used for forecasting. Fig. 1 shows a typical two layer feed-forward model.

In this figure, R is the number of inputs, p is the vector of inputs, S_1 is the number of hidden nodes, S_2 is the number of output, therefore the construction is defined as follow:

$$R - S_1 - S_2 \tag{1}$$

f_1 and f_2 are transfer functions such as the sigmoid function: $f(x) = \frac{1}{1+\exp(-x)}$ and the linear function: $f(x) = x$, W_1 is a matrix of weights from the inputs to the hidden nodes, W_2 is a matrix of weights from the hidden nodes to the output nodes. The vector b_1 and b_2 are the weights of arcs leading from the bias terms, which have values always equal to 1. n_1 and n_2 are vectors of net input and a_1 and a_2 are vectors of actual output.

To build a model for forecasting, the network is processed through three stages: (1) The training stage where the network is trained to predict future data based on past and present data. (2) The test stage where the network is tested to stop training or to keep in training. (3) The evaluation stage where the network ceases training and is used to forecast future data and to calculate different measures of error (Kermanshahi & Iwamiya 2002: 789–974).



$$a_1 = f_1(W_1 p + b_1) \qquad a_2 = f_2(W_2 a_1 + b_2)$$

Fig 1 A Two-layer MLP Network [Menhaj, 2005]

The most popular learning rule of MLPs is the error BP algorithm. BP learning is a kind of supervised learning introduced by Werbos and later developed by Rumelhart and McClelland [Azadeh et al., 2008]. At the beginning of the learning stage, all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input, target pattern pairs. Each input–output pair is obtained by offline processing of historical data. These pairs are used to adjust the weights in the network to minimize the sum squared error (SSE), which measures the difference between the real and the target values over all output neurons and all learning patterns. After computing SSE, the back-propagation step computes the corrections to be applied to the weights. With input, target pairs: $\{(P_1,T_1),(P_2,T_2),\ldots,(P_Q,T_Q)\}$, the BP algorithm can be written as (Menhaj, 2005):

1. Forward path: The first step is to propagate the input forward through the network:

$$\begin{aligned} &a_{(0)} = P(k) \\ &a_{l+1}(k) = F_{l+1}(W_{l+1}(k)a_l + b_{l+1}(k)) \quad l = 0,1,\ldots,L-1 \\ &a(k) = a_L(k) \end{aligned} \tag{2}$$

where L is the number of layers of a neural network.

2. Backward path: The next step is to propagate the sensitivities backward through the network:

$$\begin{aligned} &\delta_L(k) = -2\dot{F}_L(n)e(k) \\ &\delta_l(k) = \dot{F}_l(n_l)(W_{l+1})^T \delta_{l+1}, l = L-1,\ldots,1 \\ &e(k) = T(k) - a(k) \end{aligned} \tag{3}$$

3. Weights adjustment: Finally, the weights and biases are updated using the approximate

steepest descent rule:

$$W_l(k+1) = W_l(k) - \alpha\delta_l(k)(a_{l-1}(k))^T$$
$$b_l(k+1) = b_l(k) - \alpha\delta_l(k), l = 1,2,...,L \tag{4}$$

4. Stop: when the sum squared error dips below a particular error threshold or the chosen maximum number of epochs is reached then stops.

It should be mentioned that some constraints would appear when ANN models are applied to socio-economic systems. In such cases, it would be necessary to adjust the ANN model by force in order to prepare the feasible outputs forecasts.

Hierarchical ANN Model Development and Application

In Iran, a sharp growth in the gasoline consumption started during 1970s. This was due to the first oil price shock as well as the positive foreign exchange. The 1.2bn liters consumption in 1970 jumped to 5.7bn by 1979. Even the rationing of gasoline during the Iraq-Iran war between 1980 and 1988 could not cause gasoline consumption to decrease. After the war, gasoline consumption increased and reached to a level of 8.2bn liters in 1990. Gasoline rationing vanished in 1992. As a result, gasoline consumption jumped sharply. In 1994, the gasoline price doubled although, it was expected that the price hike would led to fall in the gasoline consumption. One reason was the increasing number of vehicles. In fact, consumption increased to about 1.6 milliard liters in 2000. The average growth rate of gasoline consumption was 6.44% per year during 2001 to 2007. Then gasoline consumption was 24.5% milliard liters in 2008.

In this section gasoline demand in Iran from 2011 to 2030 is forecasted regarding socio-economic and transport related indicators using a hierarchical ANN model. The structure of the designed hierarchical ANN is given in Fig. 2. The main ANN (4) takes population, GDP, the total number of vehicles and the gasoline demand in the last year as inputs and produces the gasoline demand. The inputs to the ending level are obtained as outputs of the starting levels. Population, GDP and the total number of vehicles are forecasted using ANNs. Table1 summarizes the ANNs inputs and output. The general strategy of the hierarchical ANN model is given in Fig. 3.

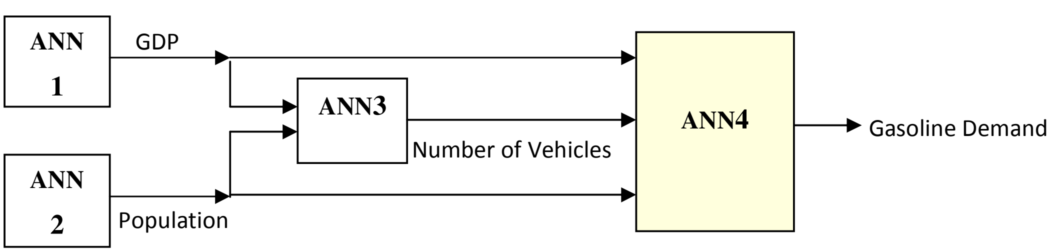


Fig 2 Structure of Designed Hierarchical ANN

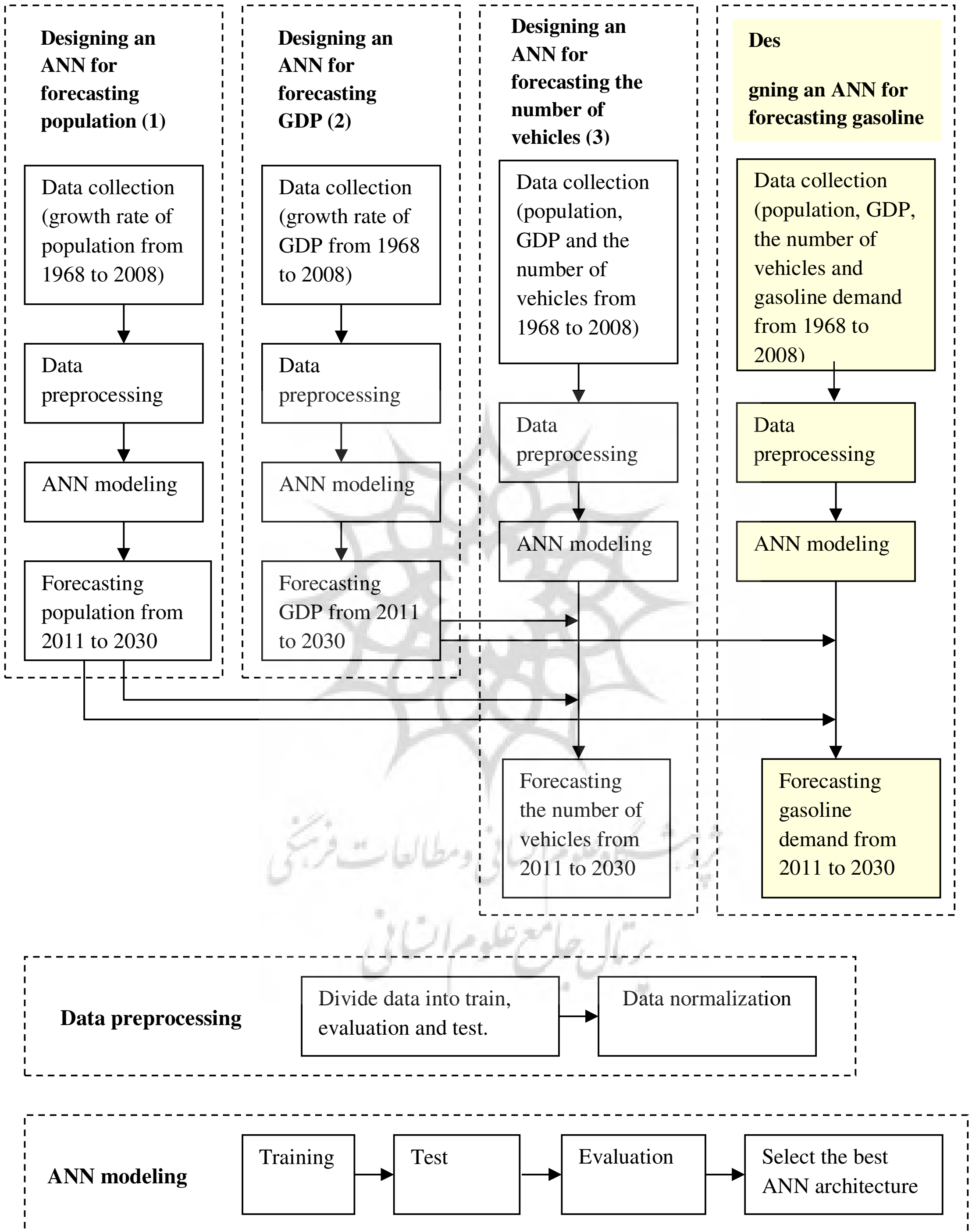


Fig 3 Strategy of the Hierarchical ANN model

Table 1 ANNs Inputs and Output

ANN	Inputs	Output
1	1- Growth rate of population in the last year 2- Growth rate of population in the last two years	Population
2	1- Growth rate of GDP in the last year 2- Growth rate of GDP in the last two years	GDP
3	1- Population 2- GDP 3- Total number of vehicles in the last year	Total number of vehicles
4	1- Population 2- GDP 3- Total number of vehicles 4- Gasoline demand in the last year	Gasoline demand

Data related with gasoline modeling are collected from different sources. GDP and population are collected from Iran Ministry of Energy. The total number of vehicles is collected from Ministry of Industries and Mines. The gasoline consumption is collected from National Iranian Oil products Distribution Company. Data are given in Table 2.

Table 2 Population, GDP, Total Number of Vehicles and the Gasoline Demand in Iran

Years (t)	Population (10^6)	GDP (10^{12} R)	Number of Vehicles (10^3)	Gasoline Demand (10^9 liters)	Years (t)	Population (10^6)	GDP (10^{12} R)	Number of Vehicles (10^6)	Gasoline Demand (10^9 liters)
1967	26.49	88.26	NA	0.85	1988	51.89	180.82	54.0	7.11
1968	27.21	99.00	21.0	0.94	1989	53.17	191.50	41.4	7.66
1969	27.95	111.61	59.4	1.07	1990	54.48	218.54	64.1	8.28
1970	28.70	122.59	86.2	1.23	1991	55.84	245.04	131.3	8.97
1971	29.48	139.28	104.4	1.41	1992	56.96	254.82	201.8	9.81
1972	30.28	162.56	132.4	1.60	1993	58.11	258.60	184.6	10.73
1973	31.11	174.67	163.9	1.99	1994	59.29	259.88	135.3	11.42
1974	31.95	196.58	224.3	2.47	1995	59.15	267.53	155.7	11.45
1975	32.82	206.11	352.1	3.11	1996	60.06	283.81	209.7	12.02
1976	33.71	242.33	449.9	3.92	1997	60.94	291.77	288.0	12.77
1977	35.03	236.65	493.7	4.62	1998	61.83	300.14	365.2	13.76
1978	36.39	219.19	460.1	5.03	1999	62.74	304.94	429.5	14.29
1979	37.81	209.92	294.0	5.69	2000	63.66	320.07	518.8	15.53
1980	39.29	178.15	187.5	4.80	2001	64.53	330.57	658.9	16.72
1981	40.83	170.28	204.6	4.43	2002	65.54	355.55	891.3	18.44
1982	42.42	191.67	210.2	4.54	2003	66.99	379.84	1253.0	20.54
1983	44.08	212.88	277.5	5.94	2004	67.48	398.23	1602.2	22.14
1984	45.72	208.52	351.5	6.61	2005	68.47	419.71	1840.5	24.46
1985	47.54	212.69	262.0	7.20	2006	70.50	467.93	2048.7	26.89
1986	49.45	193.24	132.6	6.76	2007	71.53	499.07	2193.9	23.52
1987	50.65	191.31	75.0	7.03	2008	72.58	501.00	2375.9	24.48

The study spans the time period from 1968 to 2008. This period is used to train, evaluate and test the ANN models. The mode sampling is based on a 33 year training set i.e. 1968 to 2000, while the test stage covers the period from 2001 to 2005. Also, the evaluation stage covers the period between 2006 and 2008.

All data are normalized before to be applied to each ANN. Normalization (scaling) of data within a uniform range (e.g., 0–1) is essential (i) to prevent larger numbers from overriding smaller ones, and (ii) to prevent premature saturation of hidden nodes, which impedes the learning process. This is especially true when actual input data take large values. There is no one standard procedure for normalizing inputs and outputs. One way is to scale input and output variables (z_i) in interval $[\lambda_1, \lambda_2]$ corresponding to the range of the transfer function (Basheer &Hajmeer, 2000:3-31):

$$x_i = \lambda_1 + (\lambda_2 - \lambda_1)\left(\frac{z_i - z_i^{\min}}{z_i^{\max} - z_i^{\min}}\right) \quad (5)$$

where x_i is the normalized value of z_i , and $z_i^{\max}$ and $z_i^{\min}$ are the maximum and minimum values of z_i in the database, respectively.

A computer program, written in MATLAB programming language, is used for estimating population, GDP, the total number of vehicles and the gasoline demand. The implementation procedure for ANNs is as follows:

1.Divide the available data into training, test and validation set
2. Select architecture and training parameters
3. Train the model using the training set
4. Test the model using the test set
5.Repeat steps 2 through 4 using different architectures and training parameters
6.Select the best network architecture from the training and test set
7.Assess this final network architecture using the evaluation set

Several MLP networks were generated and tested. The transfer function for the first layer was sigmoid and for the second layer was linear. The BP algorithm was used to adjust the learning procedure. For forecasting the gasoline demand the MLP network with 4–5–1 construction based on definition (1) had the best output with estimated 2.71% average absolute error percentage (AAEP) on the validation data. The AAEP is calculated with the following equation:

$$AAEP = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{a(t) - T(t)}{T(t)}\right| \quad (6)$$

where $a(t)$ is the estimated gasoline demand and $T(t)$ is the actual value of gasoline demand.

For forecasting population and GDP the MLP network with 2–3–1 and 2-4-1 construction had the best output with estimated 0.02% and 2.34% AAEP on the validation data.

As mentioned in Section 2, for the existing socio-economic model of the total number of vehicles a constraint on the total maximum is applied. Regarding restrictions on some parameters like roads status, parking places, number of vehicles per household, environmental protections; an upper bound of 6% is considered on the maximum rate of the total number of vehicles. This constraint which forces on the output of ANN3 is derived from some experts' opinion in this regard.

$$a(t+1) \leq a(t) * 1.06 \quad (7)$$

MLP network with 3-4-1 construction had the best output with estimated 3.33% AAEP on the test data.

The estimation of population, GDP and the total number of vehicles are given in Fig. 4, 5 and 6. These graphs show the actual data versus the ANN results. Population will reach to a level of about 101 million, GDP is about 1300 trillion Rials and the total number of vehicles is about 12 million in 2030.

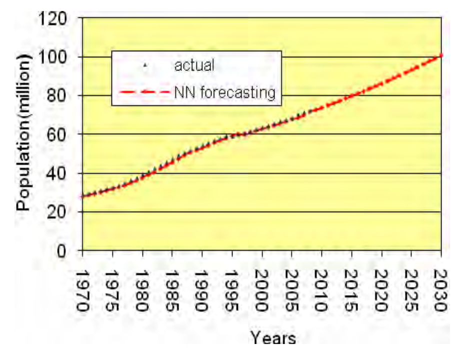


Fig 4 Estimated Population

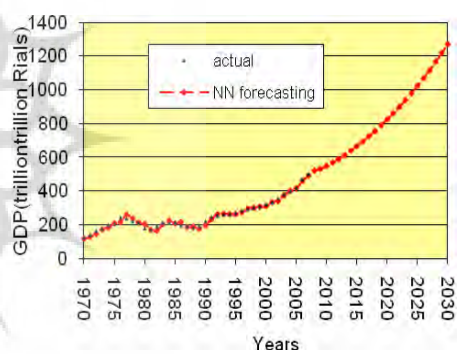


Fig 5 Estimated GDP

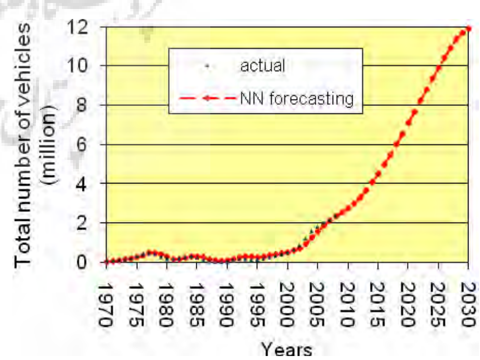


Fig 6 Estimated the Total Number of Vehicles

After selecting the best architecture ANNs, the estimated population, GDP and the total number of vehicles from 2011 to 2030 were passed to the network and the gasoline demand for these years was forecasted. The estimated gasoline demand from 2011 to 2030 can be seen in Table 3. The gasoline demand will reach to a level of about 54 milliard liters in 2030.

Table 3 Forecasted Gasoline Demand

Years	Gasoline Demand (10^9 L)	Years	Gasoline Demand (10^9 L)
2011	26.55	2021	43.02
2012	27.94	2022	44.65
2013	29.43	2023	46.20
2014	31.01	2024	47.69
2015	32.66	2025	49.04
2016	34.36	2026	50.30
2017	36.09	2027	51.45
2018	37.85	2028	52.51
2019	39.60	2029	53.35
2020	41.33	2030	53.98

Conclusion

This paper focused on forecasting the annual gasoline demand regarding socio-economic and transport related indicators using a hierarchical artificial neural networks. An ANN was designed to take population, GDP, the total number of vehicles and the gasoline demand in the last year as inputs and produce the gasoline demand. Population, GDP and the total number of vehicles were forecasted using ANNs. Actual data from 1967 to 2008 were used and the gasoline demand of Iran from 2011 to 2030 was forecasted. This paper considered four standard variables as inputs to the main ANN for forecasting of the gasoline demand. Other input variables like the average energy usage of the vehicles, the price of energy, technological developments, etc., may be identified and inserted in to the model. Also, a future study may incorporate integration of a genetic algorithm (GA) and an ANN to foresee whether the estimated error is further decreased.

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یک مدل شبکه عصبی مصنوعی سلسله مراتبی برای پیش‌بینی تقاضای بنزین در ایران

عالیه کاظمی[1]، محمدرضا مهرگان[2]، حامد شکوری گنجوی[3]، محمدباقر منهاج[4]، عزت‌اله اصغری‌زاده[5]، محمدرضا تقی زاده[6]

تاریخ دریافت: ۸۸/۲/۱۲ تاریخ پذیرش:۹۰/۱/۲۸

این مقاله با استفاده از شبکه‌های عصبی و با در نظرگرفتن شاخص‌های اقتصادی و اجتماعی، تقاضای بنزین در ایران را پیش‌بینی کرده است. برای بررسی تأثیر شاخص‌های اقتصادی و اجتماعی بر تقاضای بنزین، تولید ناخالص ملی، جمعیت و تعداد خودرو مورد توجه قرار گرفته‌اند. با استفاده از شبکه‌های عصبی سلسله‌مراتبی پرسپترون چندلایه که با الگوریتم پس‌انتشارخطا آموزش داده شده‌اند، پیش‌بینی انجام شده است. متغیرهای ورودی، تولید ناخالص ملی، جمعیت، تعداد خودرو و تقاضای بنزین در سال قبل و متغیر خروجی تقاضای بنزین می‌باشد. این مقاله یک شبکه سلسله مراتبی را پیشنهاد داده است که ورودی‌های لایه آخر، خروجی‌های لایه‌های اولیه هستند. داده‌های سال‌های ۱۹٦۷ تا ۲۰۰۸ برای آموزش شبکه عصبی سلسله مراتبی استفاده شده. مقایسه مقادیر پیش‌بینی مدل با داده‌های اعتبار، اعتبار مدل را نشان می‌دهد. علاوه بر این تقاضای بنزین طی سال‌های ۲۰۱۱ تا ۲۰۳۰ نیز پیش‌بینی شده است. قابل ذکر است در صورت عدم اتخاذ سیاست قیمتی مناسب و بهبود بخش حمل و نقل، مصرف بنزین به سطح بحرانی ٥٤ میلیارد لیتر در سال ۲۰۳۰ خواهد رسید.

واژگان کلیدی: شبکه‌های عصبی مصنوعی، پرسپترون چندلای، الگوریتم پس انتشار خطا، پیش بینی، تقاضای بنزین.

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۱. دانشجوی دکترای مدیریت تحقیق در عملیات دانشکده مدیریت دانشگاه تهران

۲. دانشیار گروه مدیریت صنعتی دانشگاه تهران

۳. دانشیار گروه مهندسی صنایع دانشگاه تهران

٤. استاد گروه مهندسی برق و الکترونیک دانشگاه امیرکبیر

٥. دانشیار گروه مدیریت صنعتی دانشگاه تهران

٦. دانشجوی دکتری مدیریت تولید و عملیات دانشگاه تهران