Journal of Research in Business, Economics and Management (JRBEM)
ISSN: 2395-2210

SCITECH
RESEARCH ORGANISATION

Volume 10, Issue 3
March 3, 2018

Journal of Research in Business, Economics and Management
www.scitecresearch.com

A New Planning to Forecasting Fuel Consumption in Iran Transportation Using a Hybrid Algorithm and Artificial Neural Network

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Abstract

Forecasting fuel demand is one of the preconditions for energy planning and management. Fossil fuels, a major part of which is consumed in transportation, are one of the most important energies. Therefore, forecasting fuel demand in transportation is of particular importance. An MLP perceptron neural network has been proposed in this study, which is trained using a Hybrid algorithm. The hybrid algorithm is based on an imperialist competitive algorithm (ICA), in which the specifications of simulated annealing (SA) algorithm have been used. To perform the forecasting, the effective parameters on road transportation including the amounts of ton kilometer of transported goods, person kilometer of passengers, the average age of cargo fleet, and the average age of passenger fleet were identified. The results of the investigation indicate the effective performance of the proposed algorithm in ANN training.

Keywords: Artificial Neural Network; Hybrid algorithm, Imperialist Competitive Algorithm; Forecasting; Simulated annealing.

1. Introduction

Given its dual role in the country's energy supply and foreign exchange income, energy sector is considered as the development infrastructure and has always had a fundamental part in the economic and social sections (Moradi Nasab, Amin-Naseri, Behbahani, & Nakhai Kamal Abadi, 2016; Nasab & Amin-Naseri, 2016) Energy is of great significance with regards to road transportation, which is responsible for 25% of Iran's energy consumption and is the largest consumer of oil products compared to residential, commercial, industrial, and agricultural sectors. Transportation will result in lots of energy loss if it is not performed by correct and rational planning. Different technical and statistical methods have been developed for forecasting energy consumption and plans in the past few decades yielding various results (Elyasi, Jafarzadeh, & Khoshalhan, 2012; Hasani, Jafarzadeh, & Khoshalhan, 2013; Sojoudi & Saeedi, 2017).

However, no technique or combinations of techniques have been successful enough for forecasting energy demand. On the other hand, neural networks have been widely used for forecasting different types of energy demand. Neural networks have been remarkably successful in energy forecasting (Kazemi, 2011). Some evidences indicate much better performance of neural networks compared with regression based models. The architecture of neural networks for forecasting energy demand has a higher precision in comparison with traditional polynomial methods (Nasr, Badr, & Joun, 2003). Therefore, neural network method has been used in this work for forecasting energy consumption in the road transportation considering its higher accuracy.

One of the important factors in the performance of neural networks is their training. There are different methods for neural network training. A Hybrid algorithm has been used for network training in this work to improve the performance of neural network and forecast energy consumption in the transportation section. In fact, there are three strategic, tactical and operational levels in planning (Jafarzadeh, Gholami, & Bashirzadeh, 2014; Simchi-Levi, Kaminsky, & Simchi-Levi, 2004). Forecasting energy consumption is done on a monthly basis (tactical level) here. One of the first measures in energy planning is energy forecasting. Energy forecasting has been performed on an yearly basis (strategic level) in all literature reports ((Azadeh, Ghaderi, & Sohrabkhani, 2008; Ekonomou, 2010; Geem, 2011; Joghataie & Dizaji, 2010; Kazemi, 2011; Kermanshahi & Iwamiya, 2002; Limanond, Jomnonkwao, & Srikaew, 2011; Murat & Ceylan, 2006; Nasr et al., 2003; Nizami & Al-Garni, 1995; Sözen & Arcaklioglu, 2007);). Energy forecasting is performed on a monthly basis in this work considering the importance of energy planning in the medium-term (tactical) level and the requirement of energy forecasting.

Here, the artificial neural network are used for energy consumption forecasting. In neural network the aim is to find a set of weights in which the error measure is minimized. Determination of the weights is the optimal problem and the search space is high dimensional and multimodal which is usually polluted by noises and missing data. According to this fact, neural network training needs powerful optimization technique (Askarzadeh & Rezazadeh, 2013; Jafarzadeh, Moradinasab, & Gerami, 2017; Joghataie & Dizaji, 2009; Zeyghami, Bode-Oke, & Dong, 2017, Lashgari, 2017) and metahuristic algorithms are good tools for this purpose.

Eventually, in this paper a Hybrid metaheuristic method has been proposed for training of the proposed neural network algorithm. In order to evaluate the performance of this method, the results obtained using this method have been compared with those of network training using imperialist competitive algorithm (ICA), invasive weed optimization algorithm (IWO) and MATLAB multi-layer perceptron default network. A short review of the prior art follows in section 2. The proposed model including model parameters, multi-layer perceptron network, network training and metaheuristic Hybrid algorithm are explained in details in section 3. The results obtained using the model is finally presented in section 4.

2. Literature Review

Literature survey indicates that artificial neural network (ANN) has been used in different areas; especially energy (Azadeh et al., 2008; Ekonomou, 2010; Geem, 2011; Kalogirou & Bojic, 2000; Kazemi, 2011; Kermanshahi & Iwamiya, 2002; Limanond et al., 2011; Murat & Ceylan, 2006; Nasr et al., 2003; Nizami & Al-Garni, 1995; Sözen & Arcaklioglu, 2007). Some sample forecasting problems are shown here.

Hazim (1989) has developed a computer simulation model for forecasting gasoline and gasoil consumption by public transportation vehicles(Bode-Oke, Zeyghami, & Dong, 2017; Zeyghami & Dong, 2015; Sojoudi, 2017).

Kermanshai and Iwamiya (2002) have developed an artificial neural network for forecasting the peak electrical load in Japan. Two neural networks including three layer back propagation and recurrent neural network have been used in this investigation. Ten parameters were considered as network inputs for forecasting the peak electrical load and the forecasting was ultimately performed using the network by 2020 (Kermanshahi & Iwamiya, 2002).

Nasr et al. (2003) have proposed a neural network model for forecasting gasoline consumption in Lebanon. Four neural network models based on gasoline consumption in the past, gasoline consumption time series and price were proposed in this study. The models were then evaluated based on performance criteria (Nasr et al., 2003).

Morat and Ceylan (2006) proposed a model on the basis of neural network for forecasting energy demand and transportation in Turkey. This model was based on supervised neural network approach and the corresponding economic, social and transportation indexes as inputs. The neural network model in this work is a feedforward model with a propagation training algorithm. The indexes considered in this model included population, growth national product (GNP) and transportation indexes (Murat & Ceylan, 2006).

Sozen and Arcakliglu (2007) have proposed a neural network model for forecasting energy consumption in Turkey.They used three different models for network training in their study. Based on their investigation, neural network model is an appropriate model to estimate the net energy consumption using population and economic indexes (Elyasi et al., 2012; Sözen & Arcaklioglu, 2007).

Azadeh et al. (2008) have proposed a neural network model for forecasting annual electricity consumption in highly consuming Iranian industrial sectors. Such industries as chemical, base metals, inorganic and non-metals are highly energy consuming. It was shown that regression models are not very precise given fluctuations in energy consumption. Thus, a multi-layer perceptron neural network was used for forecasting in this work and ultimately a model based on neural network and ANOVA was developed for forecasting long term electricity consumption in high energy consuming industries (Azadeh et al., 2008).

Ekonomov (2010) used a multi-layer perceptron neural network for forecasting long term electricity consumption in Greece and compared it with the regression method. The results indicated the effectiveness of multi-layer perceptron neural network model (Ekonomou, 2010).

Limanound et al. (2011) have used a feedforward neural network model for forecasting energy consumption in the next 20 years in Thailand and forecasted energy consumption during the period of 2010-2030. The various inputs considered in this study were population, number of vehicles and gross national product (Limanond et al., 2011).

Geem et al. (2011) have used a neural network model for forecasting energy consumption in transportation in Korea. The input variables considered in this investigation were net national product, population, petroleum price, number of vehicles and number of trips. Neural network model was selected here as the more efficient method (Geem, 2011).

Kazemi et al. (2011) have used a neural network model for forecasting energy demand based on social and economic indexes. They have used a supervised, multi-layer neural network and BP algorithm for training in this investigation (Abedzadeh, Mazinani, Moradinasab, & Roghanian, 2013; Kazemi, 2011). Abual-Foul (2012)have proposed a model for forecasting energy consumption in one of the Middle Eastern countries based on the annual data. An artificial neural network using four artificial variables including gross national product, population, imports and exports has been used for this purpose (AbuAl-Foul, 2012).

Behrang et al. (2011) proposed the bees algorithm (BA) technique to estimate total energy demand in Iran. Their model estimates energy demand based on population, gross domestic product, import and export data by two forms (exponential and linear) model. They compared the obtained results of BA-DEM models with particle swarm optimization and genetic algorithm demand estimation models to show the accuracy of the BA. Finally their model forecasts energy demand up to year 2030 (Behrang, Assareh, Assari, & Ghanbarzadeh, 2011).

Baskan et al. (2012) proposes a heuristic algorithm based on ant colony optimization for estimating the transport energy demand (TED) based on gross domestic product, population, and vehicle-km. they uses three forms of the improved ant colony for improving estimating capabilities of TED model (Baskan, Haldenbilen, Ceylan, & Ceylan, 2012).

Bastani (2012) has used possible techniques and evaluation models for forecasting production of greenhouse gases and fuel consumption under uncertainty conditions in the USA. This work shows the possible distribution of the emission of greenhouse gases and fuel consumption up to 2050. The parameters, which are the main causes for variations in the production of greenhouse gases and fuel consumption, have been identified and ranked via analysis of uncertainty. The parameters include the kilometers traveled per year and vehicle sales (Bastani, Heywood, & Hope, 2012).

Ozdemir G et al. (2016) developed a hybrid genetic algorithm-simulated annealing (GA-SA) algorithm based on linear regression to forecast natural gas demand of Turkey. They consider gross national product, population, and growth rate as independent variables and forecast the amount of natural gas consumption for years between 2001 and 2009 (Ozdemir, Aydemir, Olgun, & Mulbay, 2016; Zeyghami, Babu, & Dong, 2016, Soltani, 2017) .

3. Proposed Model

In order to make a forecasting model for energy consumption in road transportation in medium term time, the effective parameters must first be identified. The data corresponding to the identified variables have been taken within 84 months (7 years on a monthly basis) and the forecasting model for energy consumption in road transportation has been developed accordingly.

3.1 Model Variables

The model proposed in this work is a forecasting model for energy consumption in road transportation in medium term time for tactical (monthly) planning in this area. Given the importance of specific transportation parameters and monthly energy forecasting, these parameters have been considered as the main parameters. The specific transportation parameters can be categorized into two groups. The first group of parameters is those, which are affected by several factors and must be forecasted based on them. The second group is generally affected by the country's general policies as well as transportation policies. The first group includes two parameters: person-kilometer of passengers and ton kilometer of transported goods. The second group includes two parameters: average age of cargo fleet and average age of passenger fleet. In order to forecast the first group parameters, the effective factors must first be identified. Transportation is divided into passenger and cargo sections. Thus, these two sectors are considered independently with regards to forecasting person kilometer of passengers and ton kilometer of goods transported. In the passenger sector, the factors influencing person kilometer of passengers and ton kilometer of goods transported are the number of trips and passenger companies and the person kilometer of passengers transported default factor is forecasted based on these factors. In the cargo sector, the factors influencing ton kilometer of goods transported are the amounts of goods transported, the number of trips and cargo companies. The ton kilometer of goods transported default factor is forecasted based on these factors. The second group of parameters are determined by the general policies of the country. Therefore, there are three forecasting models. Figure 1 shows each parameter forecasted and the corresponding effective factors. Figure A shows the main model, which is the energy consumption forecasting and figures B and C show person kilometer of passengers and ton kilometer of goods transported, respectively.

The predictable agent: consumed energy in transportation

Determined by forecasting models
- ✓ The number of people transported per kilometer
- ✓ The amount of load carried per kilometer

Determined by the general policies of the country
- ✓ The average age of cargo fleet
- ✓ The average age of passenger fleet

The amount of load carried per kilometer
- ✓ The amount of carried load
- ✓ The number of travels in cargo fleet
- ✓ The number of cargo fleet company

The number of people transported per kilometer
- ✓ The number of passenger
- ✓ The number of travels per passenger

Fig 1: The Factors Forecasted and the Effective Parameters

3.2 Multi-Layer Perceptron Neural Network (MLP)

Multi-layer perceptron neural network is one of the most successful models in forecasting. In general, multi-layer perceptron neural network is composed of an inlet, an outlet and several hidden layers. In neural networks, hidden layer or layers ar added to solve resolvable non-linear problems and increase the strength of the network in identification of the algorithms and functions. The number of hidden layers and neurons in each layer of these networks are found by trial and error method; that is, comparison of different network structures in terms of precision of the f al model. X = (x1,…,xn) vector is the input signal and z scalar is the output signal of the network. The effect of x on z is determined by w = (w11, w12,…..,wij) vector. The net input to the neuron is shown by net and is defined using the following equation:

Sentence b in this equation is called the bias sentence. Following the entrance of net into the neuron, the actuation function acts with the transfer function, F, to give z output signal via equation z = f(net). The transfer function chosen and used in the hidden layers is a function of hyperbolic tangent, shown in equation 2.

The average root mean square error (RMSE) criterion has been used here to compare the models, as shown in equation 3.

Zm scalar is the output signal of the model and is an actual value.

70% of the data is used for training, 15% is used for testing and the remaining 15% is used for validation. A Hybrid algorithm has been used for network training and the results have been compared with those of other three models.

3.3 Authors Neural Network Training by Hybrid Algorithm

A new algorithm known as hybrid algorithm is presented here based on ICA and SA algorithms. ICA algorithm constitutes the basic structure of this algorithm and the specifications of SA algorithm are used for the displacement of the positions of the colony and imperialist in each decade. The concept of neighborhood in SA algorithm is also used in the proposed algorithm. To define the proposed hybrid algorithm, ICA and SA algorithms are briefly gone over. The proposed algorithm will then be dealt with in details.

3.3.1. Imperialist Competitive Algorithm

Atashpaz-Gargari and Lucas introduced imperialist competitive algorithm (ICA) in 2007. This algorithm is inspired by a social/political process known as imperialist competition. Similar to other evolutionary optimization methods, ICA starts out with a number of initial populations. Each element of the population is called a country in this algorithm. The countries are divided into imperialists and colonies. The best countries (countries with minimum expense of minimization and maximum objective function in maximization problems) are selected as imperialists and other countries form the colonies. Each imperialist conquers and controls a number of non-imperialist countries depending on its power. The power of an imperialist is calculated using an objective function. An imperialist and its colonies make up an empire. The power of an empire is the sum of the imperialist's power and a percentage of the medium power of its colonies. The colonial policy of assimilation and competition forms the main core of this algorithm. The colonial competition between the early empires starts out such that the colonies of each empire move toward their imperialist and the imperialists also try to increase the number of their colonies. Therefore, weaker colonies fall during the competition, ultimately leaving one empire. ICA is applicable in many optimization problems.

3.3.2. SA Algorithm

SA is a local search technique developed by Kirkpatrick. SA approach is a modified version of a local search started with the generation of a primary response. A new response is generated in the vicinity of the existing one in each step (temperature). The new response is accepted if its expense is less than or the same as that of the present response. Otherwise the new response is accepted with a possibility. This possibility depends on the difference between the present and new responses as well as the current temperature. Temperature is a high value moving towards a value near zero. In other words, it decreases periodically as an array. Therefore, wrong responses are accepted in the beginning of SA algorithm and SA moves the responses to reach the best response.

3.3.3. Hybrid Algorithm

The framework of hybrid algorithm is as follows. It must be pointed out that the common parts of this algorithm and ICA algorithm will not be repeated here. This section includes creation of new emperors, movement of colonies towards empires (homogenization), total empire cost, colonial competition and elimination of the weakest empire.

3.3.4. Updating the Colonies of an Empire

A number of neighbors are generated for each empire based on the SA neighborhood definition in this section. In other words, a number of neighbors form in the vicinity of each empire by one of the substitution, succession and reverse policies. The number of neighborhoods for each empire is equal to the number of colonies. Thus, empires with few colonies generate few neighborhoods and vice versa. Following generation of neighborhoods empires, the population of colonies and neighborhoods in the empire merge and the best of them are selected as the number of colonies and are assigned as updated colonies to the corresponding empire.

3.3.5. Revolution

Two situations are selected in each imperialist's array in each repetition. These situations are substituted with each other and the resulting array then replaces the imperialist's weakest colony. The process is repeated as a percentage of the total number of situations in each array for each imperialist. This percentage is shown by parameter "Prct-Imp-R". In addition, some of the colonies are selected and then two situations from the colony's array are randomly selected and switched. The process is repeated as a percentage of the total number of situations in each array. This percentage is shown by parameter "Prct-Col-R". A percentage of colonies are selected in each empire for the homogenization process. This percentage is shown by P-R. This process in the ICA algorithm has been reported by (Jafarzadeh, Moradinasab, & Elyasi, 2017; Nazanin Moradinasab, Shafaei, Rabiee, & Ramezani, 2013; Shafaei, Moradinasab, & Rabiee, 2011; Shafaei, Rabiee, & Mazinani, 2012).

3.3.6. Temporary Switching of the Position of Colony and Imperialist

SA algorithm is used for temporary switching of the position of colony and imperialist, as shown below. The best colony of each imperialist ingeneration is selected. The difference between the objective function of each imperialist and the best colony ($\Delta = c_{bestcolony} - c_{imperialist}$) is then calculated. The positions of the imperialist and colony are switched in the minimization problem if $\Delta \prec 0$. Following the switching, the algorithm is continued with the imperialist in the new position. If $\Delta \succ 0$, the positions of the imperialist and colony are switched with a probability calculated by $\exp(-\Delta / T)$. T is the control parameter here and is called temperature. Temperature is relatively high in the first generation, but gradually decreases. If $\Delta = 0$, the costs of the best imperialist and colony are equal. Therefore, the neighborhoods of the best colonies are constantly checked and the second colony is selected if its cost is not the same as that of the first colony. If the costs are the same, the next colonies are checked. The selected neighborhood is then used for calculation of Δ'. Given that $\Delta' \succ 0$, the positions of the imperialist and colony are switched with a probability calculated by $\exp(-\Delta' / T)$. The initial and final temperatures are represented by parameters "To" and "Tf ", respectively.

3.3.7. World War

World war will occur after a number of repetitions represented by parameter "I-GW". New countries are then generated by size of the population which is shown by parameter "PopSize". The population of new countries then merges with the original population and is sorted in increasing order based on cost function. Finally, the population sorted and the number of them with size of "PopSize" is selected as the final population and the algorithm continues with this population. This process is repeated and the number of the repetition is shown by parameter "N-GW" times. The Hybrid algorithm pseudocode algorithm is shown in Figure 2:

Fig 2: Hybrid Algorithm Pseudocode Algorithm

1. Value Initialization
   1.1. Parameters tuning
   1.2. Generate the initial countries (randomly in the number of *PopSize*)
2. Evaluate Fitness Function for each countries
3. Establish the initial Empire (in the number of *N-Emp*)
   3.1. Select the Imperialists
   3.2. Align other countries to each Imperialist
4. Assimilate the colonies (in the number of *P-Asimlt*)
5. Update the colonies
   5.1. Generate the neighborhoods for each Imperialist
   5.2. Merge the neighborhoods and colonies
   5.3. Establish the new colonies
6. Revolution (P-R is the parameter which is shown the percentage of the revolution in each iteration)
7. Calculate $\Delta = c_{bestcolony} - c_{imperialist}$
   7.1. If $\Delta \prec 0$ (in minimization)
      Exchange the position of the Imperialist and colony
   7.2. If $\Delta \succ 0$
      Exchange the position of the Imperialist and colony with probability of $\exp(-\Delta / T)$
   7.3. Else
      Calculate Δ'
      Exchange the position of the Imperialist and given colony with probability of $\exp(-\Delta' / T)$
8. Calculate $TC_n = \cos t(imperialist_n) + \xi mean\{\cos t(colonies \text{ of empire}_n)\}$ (ξ is parameter between 0 and 1)
9. Imperialistic competition
10. Eliminate the weak empire
11. World ware
12. Stop if the condition satisfied (the maximum number of the iteration is shown by parameter Max-It

3.4 Numerical Results

A completely connected, multi-layer perceptron neural network with a hidden layer and an output layer has been considered for forecasting energy consumption in the transportation sector. Network inputs include cargo fleet average age, passenger fleet average age, ton kilometer of goods transported and person kilometer of passengers transported. The first two inputs; that is, cargo fleet average age and passenger fleet average age are a function of the country's policies. However, the ton kilometer of goods transported and person kilometer of passengers transported must be forecasted. Two separate neural networks have been used for forecasting these two inputs.

A metaheuristic hybrid algorithm, described in details in previous sections, has been used for network training in this research. This method is compared with the default neural network MATLAB R2012b and neural networks trained by ICA and IWO. The best method is finally chosen for perceptron MLP network training. The structure of one response for one problem with two inputs and three neurons in the hidden layer and an output with weights of

Wij= (W11, W12, W21, W22, W13, W23) in the proposed algorithm is shown in Figure 3. The numbers with initial weights are randomly generated.

Fig 3: The Structure of One Response for One Problem With Two Inputs and Three Neurons in the Hidden Layer					
W_{11}	W_{12}	W_{13}	W_{21}	W_{22}	W_{23}
-1.2	1.34	1.9	-0.78	-0.97	1.7

The appropriate adjustment of parameters has been performed for better performance of the proposed algorithm. To do this, the optimal value of each parameter is obtained by varying that parameter while keeping the others constant.

Table 1. Parameter Adjustment Values and Execution Result

Parameter Adjustment Values				
Algorithms	**Parameters**	**Values**	**Parameters**	**Values**
Hybrid algorithm	PopSize	100	Pr-Imp-R	0.2
	Max-It	500	Pr- Col -R	0.1
	N-Emp	6	P-R	0.3
	P-Asimlt	0.3	I-GW	200
	ξ	0.03	N-GW	2
	T_0	10	T_f	0.1

Execution Results				
Method	**Average_RMSE**	**Stdev_ RMSE**	**Min_ RMSE**	**Max_ RMSE**
ICA	738.6446	95.31637	562.932	871.8777
Hybrid algorithm	595.8531	90.89332	447.4525	725.8837
IWO	644.5034	57.52952	557.6867	811.0888
ANN	790.0626	86.15386	647.4966	956.6697

The optimal values of the parameters for experimental simulation were determined after several simulations. Having adjusted the parameters, the problem is solved using a neural network with the proposed hybrid algorithm and three other algorithms including ICA, IWO and the default neural network MATLAB R2012b. All four neural networks are executed 20 times in Matlab R2012b modeling software. The results of the execution are shown in Table 1. The results are evaluated on the basis of the root mean square error of validation measurement criterion.

The criteria considered for comparison of training methods include the average root mean square error (Average RSME), standard deviation root mean square error (Stdev. RSME), minimum root mean square error (min-RMSE) and maximum root mean square error (max-RSME). Table 1 shows that the hybrid algorithm has the smallest root mean square error and lowest standard deviation root mean square error compared with other methods. In addition, this algorithm has the smallest numerical value on the basis of min-RMSE and max-RSME criteria. This indicates the more efficiency of this algorithm. The next best training methods are IWO, ICA algorithm and ANN, respectively. Given its greater efficiency, the hybrid algorithm was selected for network training in this research.

The best weights are selected for forecasting from the executions of the two layer perceptron neural network with four neurons in the hidden layer using hybrid algorithm training method.

As previously indicated, in order to forecast the energy consumption, four parameters including ton kilometer of goods transported, person kilometer of passengers transported, cargo fleet average age, and passenger fleet average age are used. Therefore, the main network, which is forecasting energy consumption, must be modelled by the two layer perceptron neural network using hybrid algorithm training method. The corresponding data for the network are the monthly data, which are categorized into training (70%), test (15%) and validation data (15%) groups. The input data for each year are used for forecasting energy consumption during the same year. Thus, the first step in this investigation is the determination of ton kilometer of goods transported, person kilometer of passengers transported, cargo fleet average age, and passenger fleet average age. Therefore, the neural network trained using the hybrid algorithm is used for forecasting ton kilometer of goods transported. The three inputs of this network are the number of fleet companies, the number of fleets and the quantity of fleet transported.

Monthly data for 2000-2005 periods have been used for forecasting the ton kilometer of goods transported. The default data are randomly categorized into training (70%), test (15%) and validation data (15%) groups. Since it is desirable to design a network, which can forecast the ton kilometer of goods transported in the next three years using the data from a given month, the outputs for each month are placed for the inputs of the same month for the next three years for network design.

For example, the output data for April of 2002 are placed for the inputs for April of 2000. Ultimately, using the inputs for the months of 2000, the ton kilometer of goods transported in the year 2002 are forecasted and thus the ton kilometer of goods transported during 2015 are forecasted using the data for 2012. Given that the objective of this research is forecasting energy consumption in the 2016-2018 period (36 months), the data for 2000-2012 period are used for forecasting 2016-2018 period after network training. The MLP perceptron neural network is now ready for forecasting the ton kilometer of goods transported. Thus, the monthly input data for the years 2013-2015 can be used for forecasting the ton kilometer of goods transported during the months of 2016-2018 period. The results of forecasting the ton kilometer of goods transported are shown in Table 2.

Afterwards, the person kilometer of passengers transported is forecasted by the two layer perceptron neural network and the data during the years 2000-2012 using hybrid algorithm, similarly to forecasting the ton kilometer of goods transported. The forecasting results for the months of 2016-2018 range are shown in Table 2.

Table 2: The Result of Forecasting

The Results of Forecasting the Amount of Load Carried Per Kilometer (Ton)

Year	Month	The amount of load carried per kilometer (ton)	Year	Month	The amount of load carried per kilometer (ton)
2016	April	13871.37	2017	October	15843.2
	May	15591.67		November	15853.92
	June	15370.7		December	15549.67
	July	15375.07		October	15622.37
	August	15399.12		November	15084.05
	September	15390.21		December	15498.67
	October	15485.99	2018	April	14873.61
	November	15395.64		May	16268.85
	December	15007.72		June	16225.19
2017	January	15083.38		July	15898.05

	February	15087.36		August	15889.14
	March	19806.83		September	15883.13
	April	14675.83		October	15903.49
	May	15939.13		November	15531.74
	June	15952.99		December	15475.74
	July	15648.49		October	15782.95
	August	15774.55		November	15395.52
	September	15695.32		December	15853.04
The results of forecasting the person kilometer of passengers transported					
Year	**Month**	**The number of people transported per kilometer**	**Year**	**Month**	**The number of people transported per kilometer**
2016	April	4495.503	2017	October	4832.105
	May	4204.293		November	4785.323
	June	4501.736		December	5028.667
	July	4369.164		October	5904.295
	August	4305.356		November	6026.592
	September	5744.243		December	5107.394
	October	4329.899	2018	April	5217.959
	November	4455.429		May	4383.322
	December	4595.622		June	4570.192
2017	January	5394.419		July	4617.474
	February	5210.174		August	5918.428
	March	4749.69		September	4736.524
	April	4931.868		October	4854.126
	May	4426.547		November	4861.048
	June	4731.511		December	5231.926
	July	5123.52		October	5101.036
	August	5759.477		November	5223.373
	September	5604.084		December	4975.959

In order to forecast energy consumption in the transportation sector on a monthly basis in the 2016-2018 range, two parameters, namely ton kilometer of goods transported and person kilometer of passengers transported were forecasted during the months of 2016-2018 range. The other two parameters; that is, cargo fleet and passenger fleet average age were functions of the government policy. Therefore, with regards to the government policies, two possible scenarios for forecasting these parameters are considered.

A: Scenario 1:

With regards to cargo fleet and passenger fleet average age, the government will not take add new fleet to the system or renovate the aging fleet. Thus, the fleet average age (cargo or passenger) will be calculated in the range of 2016-2018, without the addition of new fleet. The energy consumption in the transportation sector will then be forecasted by two layer perceptron neural network using hybrid algorithm training.

B:Scenario 2:

During its objectives in the fourth and fifth economic development plan in the transportation sector, which is achieving an average age of 10 years in both cargo and passenger fleets, the government will carry out renovation of the aging fleet. The energy consumption in the transportation sector in the 2016-2018 periods will then be forecasted by two layer perceptron neural network using hybrid algorithm training considering the new data.

Table 3: Results of Energy Consumption Forecast with Regards to the Two Scenarios

Year	Month	Energy consumption in the first scenario (millions of barrel)	Energy consumption in the second scenario (millions of barrel)
2016	April	20.38454	20.38577
	May	19.73528	19.72082
	June	19.98491	19.96354
	July	19.87383	19.84659
	August	19.82324	19.78912
	September	21.88697	21.7533
	October	19.82923	19.77686
	November	19.93738	19.87691
	December	20.14436	20.08982
2017	January	21.33331	21.19686
	February	20.99007	20.86647
	March	20.0381	19.59224
	April	20.6709	20.58788
	May	19.87501	19.72082
	June	20.12314	19.92411
	July	20.67608	20.43154
	August	21.87468	21.38325

	September	21.57907	21.13415
	October	20.28626	20.01078
	November	20.24778	19.95863
	December	20.6205	20.30141
2018	January	22.43396	21.66544
	February	22.95338	22.13884
	March	20.80307	20.3951
	April	21.17919	20.8159
	May	19.99676	19.5983
	June	20.15424	19.69211
	July	20.2217	19.77266
	August	22.70198	21.45132
	September	20.39132	19.85152
	October	20.55736	19.93732
	November	20.61613	20.04006
	December	21.28081	20.49716
	January	21.03724	20.20289
	February	21.35366	20.50273
	March	20.91135	20.03467
Average		**20.7363**	**20.35852**
Stdve		**0.843038**	**0.680908**

Table 3 shows the results of energy consumption forecast with regards to both scenarios. The results indicate that energy consumption will decrease considerably by carrying out the renovation plan.

3.5 Conclusion

The monthly amounts of energy consumption during the period of 2016-2018 were forecasted in this research. In order to do this, the effective factors were first identified and forecasted afterwards. The two parameters affecting energy consumption including ton kilometer of goods transported and person kilometer of passengers transported were forecasted using two neural networks. Two different scenarios were considered for the other two parameters affecting energy consumption, namely cargo fleet average age and passenger fleet average age, both of which are dependent on the government policies. MLP perceptron neural network, trained by the proposed hybrid algorithm, was used here for forecasting. The efficiency of the proposed algorithm was evaluated by comparison with other methods. Based on the results obtained, the proposed hybrid algorithm was selected as an appropriate model for network training. Finally, MLP perceptron neural networks were trained using this training method and energy consumption was forecasted. In order to forecast regarding the average fleet (cargo and passenger) age, two different scenarios resulting from two different government policies were analyzed. These policies are: a) not renovating the fleet and b) renovating the fleet to reach an average age of 20 years. The results of the execution of the model indicate reduction of energy consumption in the case of renovating of the fleet. Further research may be carried out concerning the evaluation and forecasting the whole country's energy consumption and/or using new metaheuristic methods or a combination of them for network training.

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