Journal of AI and Data Mining
Vol 5, No 1, 2017, 79-88

DOI: 10.22044/jadm.2016.782

Artificial neural networks, genetic algorithm and response surface methods: The energy consumption of food and beverage industries in Iran

B. Hosseinzadeh Samani*, H. Houri Jafari[2] and H. Zareiforoush[3]

1. Dept. of Mechanics of Biosystems Engineering, Faculty of Agriculture, Shahrekored University, Shahrekord, Iran.
2 .International Institute of Energy Studies, Tehran, Iran.
3. Dept. of Mechanization Engineering, Faculty of Agricultural Sciences, University of Guilan, , Rasht, Iran.

Received 16 March 2016; Accepted 10 October 2016
**Corresponding author: b.hosseinzadehsamani@gmail.com (B. Hosseinzadeh Samani).*

Abstract

The energy consumption in food and beverage industries in Iran was investigated. The energy consumption in this sector was modeled using artificial neural network (ANN), response surface methodology (RSM) and genetic algorithm (GA). First, the input data to the model were calculated according to the statistical source, balance-sheets and the method proposed in this paper. It can be seen that diesel and liquefied petroleum gas have respectively the highest and lowest shares of energy consumption compared with the other types of carriers. For each of the evaluated energy carriers (diesel, kerosene, fuel oil, natural gas, electricity, liquefied petroleum gas and gasoline), the best fitting model was selected after taking the average of runs of the developed models. At last, the developed models, representing the energy consumption of food and beverage industries by each energy carrier, were put into a finalized model using Simulink toolbox of Matlab software. The results indicated that consumption of natural gas is being increased in Iranian food and beverage industries, while in the case of fuel oil and liquefied petroleum gas a decreasing trend was estimated.

Keywords: *Artificial Neural Network, Energy, Food Industry, Modeling.*

1. Introduction

In all of the societies, in order to plan to supply the required energy for the different consuming sectors, it is necessary to predict the demand properly according to the type of energy carriers. In this regard, one of the issues that has become more important nowadays is energy security. This aspect is usually defined as reliable and adequate energy supply at affordable prices. For many decades, energy security has been of the most important objectives of public policy. It has been sometimes discussed with other important goals such as economic development and environmental protection, and at times, it has been a competitor for these goals. This issue is more important than the global economy, because energy is one of the key factors for all of the economic projects.

Development of prediction models along with organizing appropriate tariff structure is important stages in macro programming for achieving sustainable energy supply, economic development and social welfare. Nowadays, in addition to traditional economic view to the energy sector, the social, political, security and environmental considerations have raised the importance of studies in this sector. The study of demands for energy and energy carriers can be carried out based on various models. Considering the importance of models in prediction and evaluation of energy demand in different countries, and also the importance of surveying the demands in economic development and optimization of energy distribution in different sub-sectors, the study of the different models and selection of the best method for modeling is one of the essential parts of each management systems [1].

Energy is one of the most important production inputs in each country and plays an important role in the world economic interactions. For this reason, many of international institutes around the world try to model the energy demand and supply system and also predict their relation for the future years [2].
The first edition of OPEC World Energy Model (OWEM) was rendered to OPEC secretariat in 1981 (about 33 years ago). This model was constructed in University of South California (USC). The initial complexities associated with this model caused several problems for scientific evaluation and gathering the required statistics. Therefore, this model was reconsidered by the OPEC secretariat in 1984 [3].
The MESSAGE model, an alternative model for energy supply systems, is an optimizing model that is utilized for medium-term and long-term planning, energy policies analysis, and scenarios development. This model has been formed from the energy systems program (IIASA) in 70s. The MESSAGE model finds optimal energy flow from first resources to final demands, which are mathematically reasonable, and offers a combination of possible supply choices with least cost capable of complying energy demands. The feasibility of achievement to choices is guaranteed by matching the energy flow with model limitations regarding to initial extraction of energy, energy conversion and transportation, as well as final consumption technologies. These energy flows are determined in turn according to limitations that are existed on gradual creation of new capacities, substitution of energy carriers, and restoration of energy resources [4-6].
Soft computing is an innovative method for development of intelligent systems attracted increasing interest by the scientific communities during the past few decades. It has been stated that utilization of the machine vision and artificial intelligence can result in increased quality of the product, abolish inconsistent manual evaluation, and reduce dependence on available manpower [7].
Review of the literature indicated that ANN has been successfully used in different branches of medicine [8], mathematics [9], engineering, [7] etc. ANNs have also been applied for energy prediction and estimation purposes in different sectors of demand and supply [10-18].
The wide application of ANNs in these areas is the method’s ability to help researchers in designing and developing predictive models for estimating importance indices with high accuracy and reliability [18].
An artificial neural network model was developed to relate the electric energy consumption in the Eastern Province of Saudi Arabia to the weather data (temperature and humidity), global solar radiation and population [10].
Azadeh et al., (2008) showed the advantage of the ANN approach through analysis of variance (ANOVA). Furthermore, the ANN forecast is compared with actual data and the conventional regression model through ANOVA to show its superiority [16].
Ekonomou and Oikonomou (2008) described an artificial neural network method for the forecasting of the daily Hellenic electricity demand load. Actual input and output data collected from the Hellenic power network were used in the training, validation and testing process [19].
Szoplik (2015) was presented the results of forecasting of the gas demand obtained with the use of artificial neural networks. Design and training of MLP (multilayer perceptron model) was carried out using data describing the actual natural gas consumption in Szczecin (Poland). In the model, calendar (month, day of month, day of week, hour) and weather (temperature) factors, which have a pronounced effect on gas consumption by individual consumers and small industry, were considered [18].
The objective of this research was to combine artificial neural networks, response surface methodology and Genetic algorithm as novel approaches for modeling the energy demand in different sectors of food and beverage industries of Iran in dissociation of energy carriers.

2. Material and methods

2.1. Source of study

The first stage in development of the prediction model was to assemble and calculation of input variables. For this purpose, six sources were utilized:

- Hydrocarbure balance sheet of the Ministry of Petroleum of Iran
- Energy Balance Sheet of the Ministry of Energy of Iran
- Economic statistics and national accounts system, Central Bank of the Islamic Republic of Iran
- Output and data table works sheets provided by the Statistical Center of Iran (2001)

- Output and data table based on the supplied energy reported by Electricity and Energy Deputy Ministry of Energy of Iran
- The census prepared by Statistical Center of Iran for industrial workshops with 10 employees and more

In order to obtain the share of each subsector in dissociation of carriers, Iran economy consumption table was used in dissociation of market and non-market purchasers. The information in dissociation of market producers and consumers was extracted from the table in terms of purchaser price. Then, the share of each activity was calculated by the following equations:

$$a_j = \frac{c_{ij}}{A_i} \quad (1)$$

$$A_i = \sum_{j=1} c_{ij} \quad (2)$$

where c_i is share of each sector of energy carrier, a_{ij} is purchaser price of each energy carrier subsector, A_i is total purchase price of each energy carrier subsector.

The other source used in this study was results of census performed by Statistical Center of Iran in the case of industrial workshops with 10 or more than 10 labors. Since the reports on total energy consumption values in the case of industrial sector was not consistent with the corresponding reported values by hydrocarbure balance sheet, only the share of each subsector of industrial applications in total energy consumption of industry was considered as evaluation criterion. At last, the share of each activity was obtained by averaging the three values (reports of census performed in industrial workshops with 10 employees and more, the output and data table of 2001 and 2006). These cause to use the three data for estimating the final share of each activity of energy carriers. In some carriers, the variation range of data is wide which cause the averaging method to be not sufficient and another condition is required for data monitoring. For solving this problem, the standard deviation of the three data was calculated. The differences between the three values were obtained separately from the average value. By comparing the differences with the standard deviation, the data that might be larger than standard deviation was considered as outlier data and was deleted from the table.

Finally, the share of food and beverage industries from energy carriers was determined. Then, according to the hydrocarbure balance sheet of ministry of petroleum and the consumption share of the mentioned industries from energy carriers, the amount of energy consumption of each activity was determined. It is necessary to mention that since the three resources were evaluated in three different times. This is because the difference between the shares for energy carriers was negligible in the case of the three evaluated resources, it can be deduced that the industries share of energy consumption was approximately constant over the time. Consequently, in this paper, the time series of energy consumption were estimated assuming a constant share for the mentioned industries over the years.

2.2. Artificial neural network (ANN)

In this study, a multi-layer perceptron (MPL) in which all of the neurons were connected to each other was utilized. This model is widely used in nonlinear modeling due to its simplicity and high accuracy [20]. Different transfer functions such as sigmoid (logsig), logarithm (tansig), linear (purelin) and supervised learning algorithms, as well as Feed Forward Back Propagation (FFBP) networks such as Levenberg–Marquardt (trainlm) and “trainnscg” algorithms were used and their corresponding results were compared together (Figure 1). The input values to the ANN were firstly normalized and then divided randomly into three groups, namely, train (70 %), validation (15 %) and test (15 %).

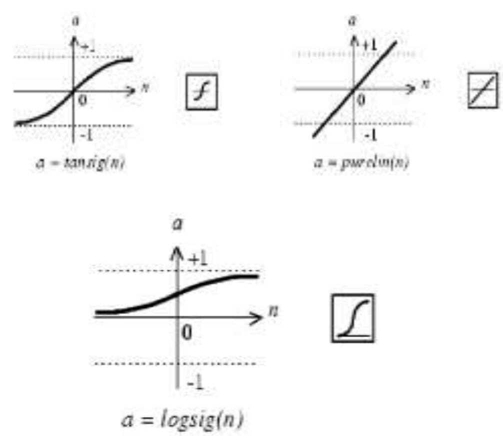


Figure 1. Transfer functions.

The required code for ANN simulation was developed in MATLAB software version R2013a.The best topology for the ANNs was determined based on two criteria including coefficient of determination (R^2) and Mean Squared Error (MSE). The best fitting for estimation of energy consumption for food and beverage industries is one that has largest R^2 and smallest MSE. The R^2 and MSE values were calculated using the following equations:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n} \left(a_i - p_i \right)^2}{\sum_{i=1}^{n} \left(p_i \right)^2} \right]^{\frac{1}{2}} \quad (3)$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (a_i - p_i)^2 \quad (4)$$

where, a_i is the actual value, p_i the output value and n the number of data values.

The ANNs modelling was carried out separately for seven energy carries, namely, diesel, kerosene, fuel oil, natural gas, electricity, liquefied petroleum gas and gasoline. The input variable to the model was a year of evaluation, whilst the output variable was the amount of energy consumption in million barrels of crude oil. The model data was between the years 1998 and 2010 and due to lack of training data, the model was run 20 times. Next, the mean values of R^2 and MSE for the 20 run times were reported. The results of modeling for the evaluated industries were obtained separately for each energy carrier and the results were eventually related together using the Simulink toolbox of MATLAB software. It should be noted that the modeling was implemented using the time series of artificial neural networks with the time delay of 2 years. Eight data were used for training stage and four data were utilized for validation and test processes. Among the source of variations in ANNs optimization, the number of neurons in hidden layers and transfer functions can be mentioned.

2.3. Response surface method

Response surface methodology (RSM) has an important application in the design, development and formulation of new products, as well as in the improvement of existing product design. It defines the effect of the independent variables, alone or in combination, on processes. In addition, to analyze the effects of the independent variables, this experimental methodology generates a mathematical model which describes the chemical or biochemical processes [20-22]. In order to obtain the optimum value for a variable, (5) is used:

$$\left[Y_i = \beta_0 + \sum \beta_i X_i + \sum \beta_{ij} X_i X_j + \sum \beta_{ij} X_i^2 + \varepsilon \right] \quad (5)$$

where, β_0, β_j, β_{ij}, β_{jj} are regression coefficients for intercept, linear, interaction and quadratic coefficients, respectively, while X_i and X_j are coded independent variables and ε is the error. In the present study, Box-Behnken design with 3 central points was used. The coded values of the experiment independent variables for artificial neural networks parameters are given in table 1.

Table1. The range of artificial neural networks parameters

Parameter	Down	Up
X1: Number of neurons	1	15
X2: Momentum coefficient	0.05	0.95
X3: Learning rate	0.05	0.95

The variables presented in table 1 were assessed separately for each of the transfer functions (Tansig, Logsig) and the best transfer functions as well as the optimum values for the variables in table 1 were selected for the ANN.

2.4. Optimization using Genetic Algorithm

Genetic Algorithms (GAs) are adaptive heuristic search algorithms premised on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural systems necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem [21]. In this research, GA was used for optimization of ANN parameters. Data analysis is responsible to obtain regression model from experimental data, so that these models were used for goal functions. Solving the problem needed to adjust some parameters to reach the best answers. Some adjustment parameters in cloud of initial range, fitness scaling, selection function, Elicit count, crossover fraction, Mutation function, and migration.

3. Results and discussions

3.1. Share of energy carriers in food and beverage industries

The share of consumption for different energy carriers in food and beverage industries is shown in figure 2. Diesel (17.33 %) and liquefied petroleum gas (3.01 %) has respectively the highest and lowest shares of energy consumption compared with the other types of carriers.

The share of each activity in consumption of energy carriers is given in table 2. As shown in the first subsector (labeled as A in the table), the highest, and lowest shares belong to kerosene and electricity, respectively. In the second subsector (shown with label B), diesel has the highest share, whilst the lowest share is related to fuel oil. The highest and lowest shares belong to electricity and fuel oil, respectively, in the third subsector (labeled as C in the table). Liquefied petroleum gas and kerosene has respectively the highest and lowest shares of consumption in the fourth and fifth subsectors (labels D and E in the table). Finally, the highest and lowest shares in the Sugar subsector (labeled as F in the table) belong to natural gas and liquefied petroleum gas, respectively.

The amount of energy consumption in the food and beverage industries over a period of 13 years is shown in figure 3.

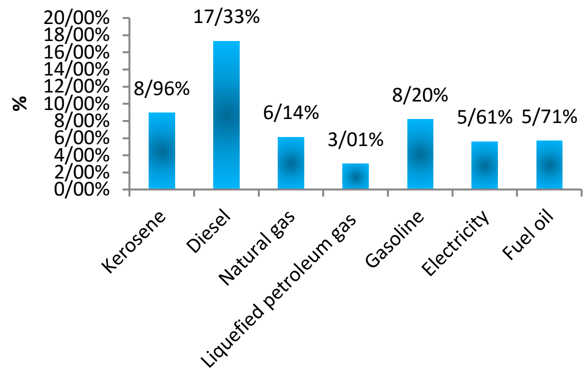


Figure 2. The consumption share of energy carriers in food and beverage industries of Iran.

The highest energy consumption belongs to natural gas. The increased utilization of natural gas in 2008 onwards can be related to the government policies to increase the use of natural gas instead of other energy carriers such as petrol and diesel.

Table 2. Percentage share of energy carriers in food and beverage industries of Iran.

Label	Industry	ISIC	kerosene	diesel	natural gas	liquefied petroleum gas	gasoline	electricity	fuel oil
A	Production, processing and preservation of meat, fish, fruit, vegetables, oils and fats	151	42	33	24.5	28	27	23.5	23
B	Manufacture of dairy products	152	3	26	11	8	15	20	1
C	Manufacture of grain mill products, starches and starch products, and prepared animal feeds	153	14	8	4	7	11	16	2
D	Manufacture of other food products except sugar	154	9	18	15	43	22	16	11
E	Manufacture of beverages	155	1	8	3	11	5	10	2
F	Sugar	156	31	7	43	3	11	14	42

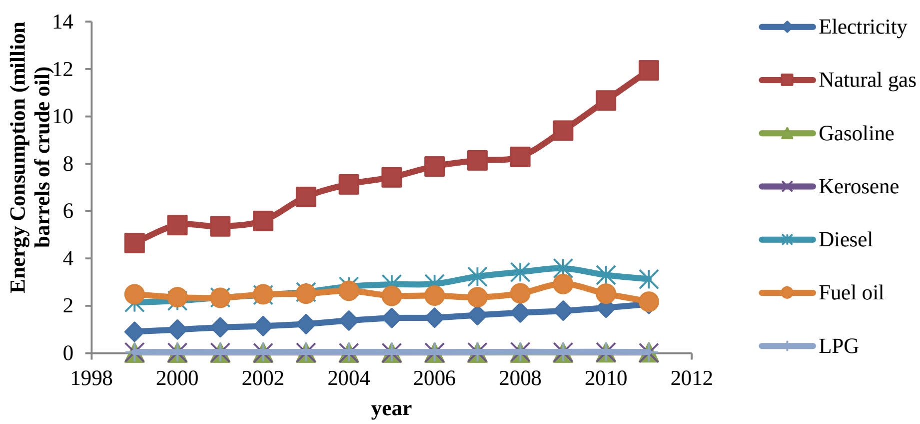


Figure 3. The amount of energy consumption over a period of 13 years in the food and beverage industries of Iran.

The rise of added value of the food and beverage industries over a period of 13 years can be observed in figure 4 showing that the added value in 2011 is almost doubled compared to 1999. It can also be seen that the variations trend is linear (R^2= 0.96). Increase in the added value is due to the inflation in the country. To maintain the purchasing power, the profit from the sale of products has been increased.

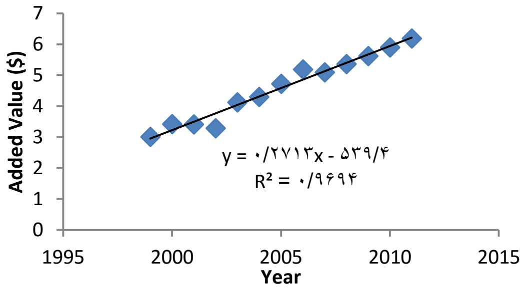


Figure 4. Variations of added value in the food and beverage industries over a period of 13 years.

The amount of energy consumption in the food and beverage industries has been increased linearly between 1999 and 2011 (Figure 5), so that the energy consumption has been increased 9.1-fold within 13 years. The increase in energy consumption during the 13 years can be justified with increasing of increasing the population in the society. Besides, some factories have become obsolete and this in turn is in the fluencies of the energy consumption. However, it should be noted that variations in energy intensity has not followed a clear trend. In more recent years, due to the increase in the price of energy carriers, the energy intensity has been decreased.

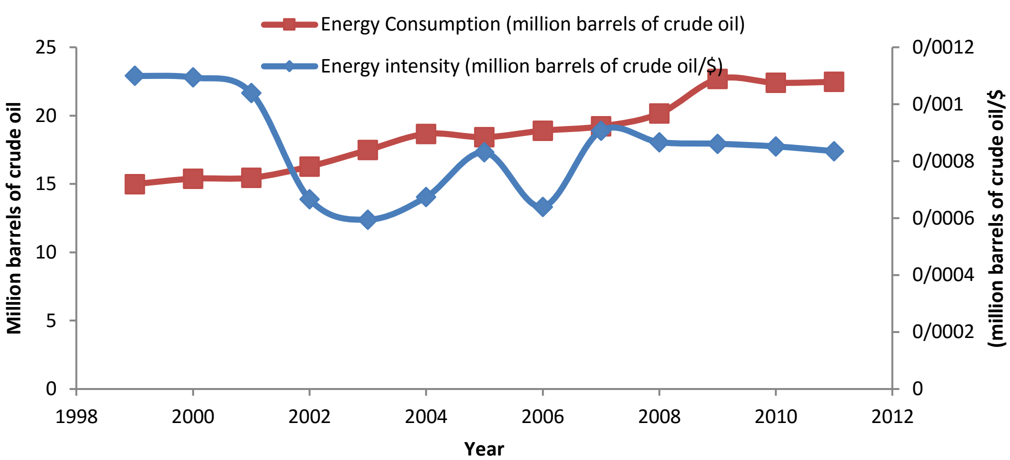


Figure 5. The values of energy consumption and energy intensity in the food and beverage industries of Iran over a period of 13 years.

As shown in figure 6, the relation between the energy consumption and added value can be expressed with a linear equation (R^2= 0.967). This figure indicates the lack of technology in the food and beverage industries during the mentioned period which necessitated more energy consumption to reach to higher profits. The desired condition is obtained by decreased value of energy intensity in the industries. In such a condition, less energy is consumed to obtain the unit of money.

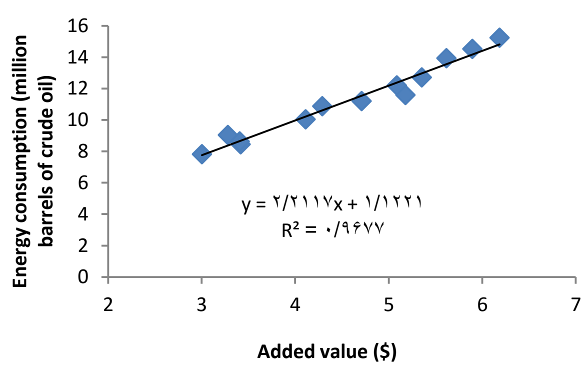


Figure 6. Variations of the energy consumption versus the added value.

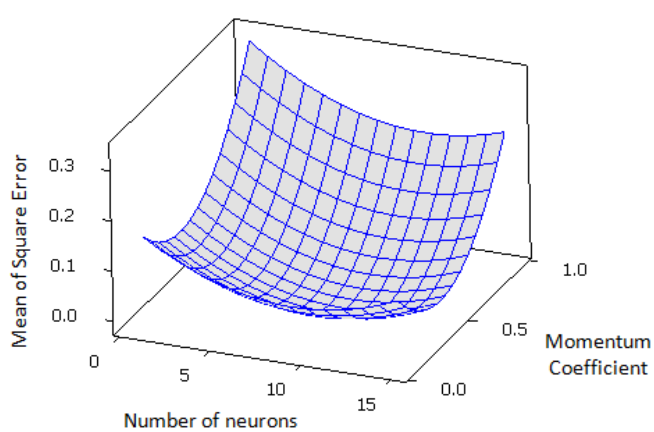
3.2. Results and discussion of modeling

The regression equations representing the relation existed between number of neurons (N), coefficient of momentum (M) and learning rate (L) with MSE are shown in table 3. Considering the values obtained for coefficient of determination and standard errors, it can be concluded that the fitted models have an appropriate accuracy for estimation of MSE.

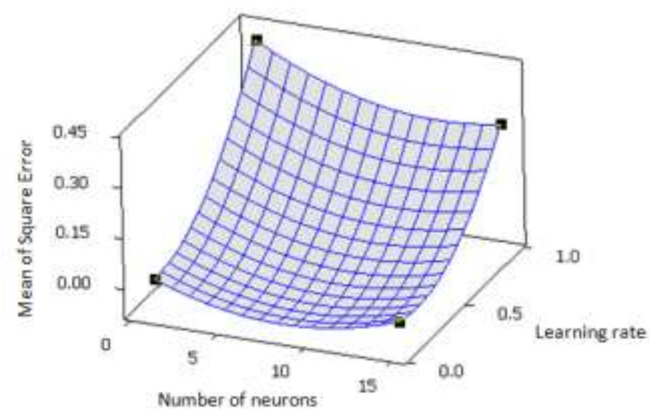
For example, the variations of MSE versus the number of neurons; the coefficient of momentum and learning rate for the created network for natural gas are illustrated in figure 7. As shown in figure 7a, with increasing the number of neurons and coefficient of momentum respectively from 1 to 10 and from to 0.05 to 0.4, MSE decreased, while further increase in the values of parameters caused the MSE to increase. It can also be seen that MSE increased with increasing the learning rate (Figure 7b and Figure 7c). Therefore, lower values of learning rate are desired, although this increases the processing time. The higher processing time can be neglected due to the small size of ANN and limited number of input and output variables.

Table 3. The regression equations representing the relation existed between number of neurons (N), coefficient of momentum (M) and learning rate (L) with MSE.

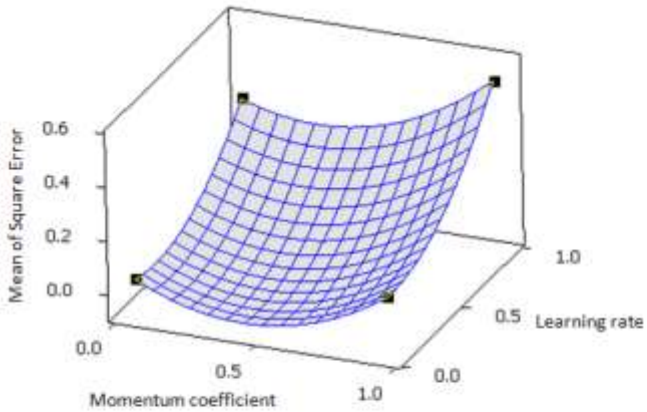
Equation	R^2	Standard Error
MSE=0.144836-0.020687*N-0.020687*M+0.126939*L+0.001382*N^2+ 0.633926*M^2+0.501846*L^2-0.004161*N*M-0.009303*N*L+0.147488*M*L	**0.97**	**0.0096**
MSE=0.138469-0.016859*N-0.548822*M-0.131677*L+ 0.001162*N^2+0.681081*M^2+0.545531*L^2-0.004284*N*M-0.009802*N*L+ 0.108040*M*L	**0.98**	**0.0089**
MSE=0.194838-0.016195*N-0.585970*M-0.175425*L+ 0.001219*N^2+0.738508*M^2+0.675127*L^2-0.005960*N*M-0.013994*N*L+ 0.172704*M*L	**0.98**	**0.0090**
MSE=0.269564-0.019342*N-0.738899*M-0.239700*L+ 0.001497*N^2+0.931518*M^2+0.882122*L^2-0.008109*N*M-0.018684*N*L+ 0.243311*M*L	**0.95**	**0.0099**
MSE=0.36562-0.02444*N-0.96240*M-0.32434*L+ 0.00192*N^2+1.21304*M^2+1.16785*L^2- 0.01095*N*M-0.02498*N*L+ 0.33341*M*L	**0.93**	**0.0101**
MSE=0.49162-0.03174*N-1.27122*M-0.43703*L+ 0.00252*N^2+1.60202*M^2+1.55566*L^2- 0.01474*N*M-0.03344*N*L+ 0.45205*M*L	**0.98**	**0.0068**
MSE=0.65860-0.04182*N-1.69106*M-0.58769*L+ 0.00333*N^2+2.13088*M^2+2.07893*L^2- 0.01981*N*M-0.04481*N*L+ 0.60988*M*L	**0.99**	**0.0054**



(a)



(b)



(c)

Figure 6.Variations of MSE versus the number of neurons, coefficient of momentum and learning rate for the created network for natural gas

In order to determine the optimized points, two methods including GA and RSM were used. The goal functions were selected in the form shown in table 4-6 with the purpose of MSE minimization.

Table 4. Optimized number of neurons for the created networks.

Energy Carrier	RSM	GA	Selected
GAS Oil	8.51	8.89	9
Kerosene	10.31	10.53	10
Fuel Oil	8.56	8.1	8
Liquid Gas	9.23	9.31	9
Electrical	11.03	11.21	11
Gasoline	8.87	8.46	9
Natural Gas	10.12	10.02	10

Table 5. Optimized coefficient of momentum for the created networks.

Energy Carrier	RSM	GA	Selected
GAS Oil	0.32	0.36	0.32
Kerosene	0.41	0.38	0.38
Fuel Oil	0.35	0.41	0.41
Liquid Gas	0.37	0.39	0.39
Electrical	0.43	0.42	0.43
Gasoline	0.29	0.32	0.32
Natural Gas	0.48	0.44	0.48

Table 6. Optimized learning ratios for the created networks.

Energy Carrier	RSM	GA	Selected
GAS Oil	0.08	0.10	0.08
Kerosene	0.13	0.09	0.13
Fuel Oil	0.10	0.10	0.10
Liquid Gas	0.11	0.10	0.10
Electrical	0.08	0.08	0.08
Gasoline	0.10	0.11	0.11
Natural Gas	0.16	0.13	0.13

For all of the energy carriers, two-layer networks were used with “tansig” and “purelin” transfer functions in the first and second layers, respectively. The mean values of R^2 and MSE obtained from the ANNs for different energy carriers are shown in table 7.

Table 7. Mean values of R^2 and MSE obtained from the ANNs for different energy carriers

Energy carrier	R^2	MSE
Diesel	0.96	0.031
Kerosene	0.97	0.027
Fuel Oil	0.97	0.022
Natural Gas	0.96	0.010
Electricity	0.97	0.037
Gasoline	0.97	0.028
Liquefied Gas	0.96	0.032

Other researchers have developed ANNs and the energy consumption of industrial sectors has been performed with high accuracy [23].

Results show the estimation and prediction trend of ANNs on energy consumption for each energy carrier, which is considerable. The model error and accuracy in all the train, validation, and test points are calculable. The final model was obtained by the combination of ANN models using Simulink method.

The values estimated by ANNs for energy consumption in food and beverage industries are given in table 8. Analysis of data in this table indicates that the consumption of natural gas in Iran is increasing day by day, while in the case of fuel oil and liquefied petroleum gas, energy consumption is going to be decreased. Table 8 shows that it is estimated that the consumption of fuel oil and liquefied petroleum gas in 2024 will reach 0.7923 and 0.0293 million barrels of crude oil, respectively. The reason for this estimation is vast reserves of natural gas in Iran which convinces the managers and policy makers to use this energy carrier more than the other carriers.

The literature indicate that it has been found that the forecasting methods based on artificial neural network models surpass the traditional models of time series and regression models in terms of the performance of the forecasts. The operation of the artificial neural network is modeled on the action of the human nervous system. Thus forecasting of gas demand without the knowledge of the specific relationships between variables and without knowledge on their impact on the forecasted value is possible. In addition, ANN models can be used in any situation (for short-term, long-term forecasting, for trend series, series characterized by daily or seasonal variability). However, it can be assumed that hybrid models more and more often used in the forecasting, combining various techniques of artificial intelligence, e.g.: artificial neural network models, genetic algorithm or fuzzy logic will enable the development of forecasts with higher performance than artificial neural network models [18].

Table 8. Estimated values of energy consumption (million barrels of crude oil) by ANN for the food and beverage industry.

	Energy carrier						
Year	Electricity	Natural Gas	Gasoline	Kerosene	Diesel	Fuel Oil	Liquefied Gas
1998	0.908546	3.402522	0.016562	0.057462	2.34227	1.058027	0.033628
1999	0.992671	3.952765	0.013249	0.026897	2.419904	1.005296	0.036047
2000	1.088012	3.913687	0.014353	0.026897	2.567598	0.994604	0.039918
2001	1.144096	4.088417	0.015458	0.019562	2.683102	1.057055	0.039918
2002	1.233829	4.82417	0.012145	0.024452	2.827008	1.070178	0.041611
2003	1.379645	5.215853	0.014353	0.019562	3.076952	1.119993	0.044514
2004	1.486203	5.43056	0.014905	0.017116	3.173521	1.032755	0.043547
2005	1.503028	5.767444	0.016562	0.035455	3.198136	1.035428	0.039676
2006	1.609585	5.951607	0.011593	0.044014	3.537074	1.004324	0.040885
2007	1.711504	6.063901	0.01601	0.068466	3.743467	1.074795	0.03895
2008	1.792385	6.872421	0.018218	0.052572	3.913882	1.245381	0.045724
2009	1.923651	7.800872	0.025394	0.044014	3.609028	1.069935	0.048627
2010	2.080684	8.73067	0.023738	0.014671	3.419677	0.928994	0.033144
2015	2.291	12.2729	0.021.3	0.0101	3.455	0.8768	0.0318
2020	2.297	12.3342	0.0191	0.0073	3.467	0.8181	0.0306
2024	2.341	12.3821	0.0187	0.0051	3.4995	0.7923	0.0293

4. Conclusion

The developed ANNs had an acceptable accuracy in estimation and prediction of the amount of energy consumption in food and beverage industry. For the seven evaluated energy carriers, two-layer networks with “tansig” and “purelin” transfer functions in the first and second layers, respectively, gave the encouraging results. For each of the designed networks, the optimum values for number of neurons, momentum and learning ratio were obtained using GA and RSM method. Analysis of data indicated that consumption of natural gas is being increased in Iranian food and beverage industries, while in the case of fuel oil and liquefied petroleum gas a decreasing trend was estimated.

Acknowledgement

The authors would like to acknowledge the funds provided by International Institute of Energy of Iran and Shahrekord University to carry out this research works.

References

[1] Debnath, K. B., Mourshed, M. & Chew S. P. K. (2015). Modelling and forecasting energy demand in rural households of Bangladesh. Energy Procedia, vol. 75, pp. 2731-2737.

[2] Aliakbarisani, S. (2016). At what valuation of sustainability can we abandon fossil fuels? A

comprehensive multistage decision support model for electricity planning. Energy, vol. 107, pp. 60-77.

[3] Barnett, J. (2008). The worst of friends: OPEC and G-77 in the climate regime. Global Environmental Politics, vol. 8, no. 4, pp. 1-8.

[4] Messner, S. & Schrattenholzer, L. (2000). MESSAGE–MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. Energy, vol. 25, no. 3, pp. 267-282.

[5] Ekonomou, L. (2010). Greek long-term energy consumption prediction using artificial neural networks. Energy, vol. 35, no. 2, pp. 512-517.

[6] Gonzalez-Salazar, M. A., et al. (2016). A general modeling framework to evaluate energy, economy, land-use and GHG emissions nexus for bioenergy exploitation. Applied Energy, pp. 223-249.

[7] Pierre, S., Said, H. & Probst, W. G. (2001). An artificial neural network approach for routing in distributed computer networks. Engineering Applications of Artificial Intelligence, vol. 14, no. 1, pp. 51-60.

[8] Lisboa, P. J. & Taktak, A. F. (2006). The use of artificial neural networks in decision support in cancer: a systematic review. Neural networks, vol. 19, no. 4, pp. 408-415.

[9] Hernandez, G. & Salinas, L. (2004). Large scale simulations of a neural network model for the graph bisection problem on geometrically connected graphs. Electronic Notes in Discrete Mathematics, vol. 18, pp. 151-156.

[10] Javeed Nizami, S. & Al-Garni, A. Z. (1995). Forecasting electric energy consumption using neural networks. Energy policy, vol. 23, no.12, pp. 1097-1104.

[11] Islam, S. M., Al-Alawi, S. M. & Ellithy, K. A. (1995). Forecasting monthly electric load and energy for a fast growing utility using an artificial neural network. Electric Power Systems Research, vol. 34, no. 1, pp. 1-9.

[12] Nasr, G., Badr, E. & Joun, C. (2003). Backpropagation neural networks for modeling gasoline consumption. Energy Conversion and Management, vol. 44, no. 6, pp. 893-905.

[13] Murat, Y. S. & Ceylan, H. (2006). Use of artificial neural networks for transport energy demand modeling. Energy policy, vol. 34, no. 17, pp. 3165-3172.

[14] Azadeh, A., Ghaderi, S. & Sohrabkhani, S. (2007). Forecasting electrical consumption by integration of neural network, time series and ANOVA. Applied Mathematics and Computation, vol. 186, no. 2, pp. 1753-1761.

[15] Sözen, A. & Arcaklioglu, E. (2007). Prediction of net energy consumption based on economic indicators (GNP and GDP) in Turkey. Energy policy, vol. 35, no. 10, pp. 4981-4992.

[16] Azadeh, A., Ghaderi, S. & Sohrabkhani, S. (2008). Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors. Energy Conversion and Management, vol. 49, no. 8, pp. 2272-2278.

[17] Geem, Z. W. (2011). Transport energy demand modeling of South Korea using artificial neural network. Energy policy, vol. 39, no. 8, pp. 4644-4650.

[18] Szoplik, J. (2015) Forecasting of natural gas consumption with artificial neural networks. Energy, vol. 85, pp. 208-220.

[19] Asghari, M. & Nematzadeh, H. (2016). Predicting air pollution in Tehran: Genetic algorithm and back propagation neural network. Journal of AI and Data Mining, vol. 4, no. 1, pp. 49-54.

[20] Ekonomou, L. & Oikonomou, D. (2008). Application and comparison of several artificial neural networks for forecasting the Hellenic daily electricity demand load. In Proceedings of the 7th WSEAS International Conference on Artificial intelligence, knowledge engineering and data bases. World Scientific and Engineering Academy and Society (WSEAS).

[21] Harvey, R. L. (1994). Neural network principles. Prentice-Hall, Inc.

[22] Huang, Y., et al. (2010). Development of soft computing and applications in agricultural and biological engineering. Computers and Electronics in Agriculture, vol. 71, no. 2, pp. 107-127.

[23] Fayyazi, E., et al. (2015). An ultrasound-assisted system for the optimization of biodiesel production from chicken fat oil using a genetic algorithm and response surface methodology. Ultrasonics sonochemistry, vol. 26, pp. 312-320.

[24] Sözen, A. (2009). Future projection of the energy dependency of Turkey using artificial neural network. Energy policy, vol. 37, no. 11, pp. 4827-4833.

نشریه هوش مصنوعی و داده کاوی

روش‌های شبکه‌های عصبی مصنوعی، الگوریتم ژنتیک و منحنی سطح پاسخ: مصرف انرژی در صنایع غذایی و آشامیدنی ایران

بهرام حسین زاده سامانی[۱،*]، حامد حوری جعفری[۲] و حماد ذرعی فروش[۳]

[۱] مهندسی مکانیک بیوسیستم، دانشگاه شهرکرد، شهرکرد، ایران.

[۲] موسسه مطالعات بین الملل انرژی، تهران، ایران.

[۳] مهندسی مکانیزاسیون کشاورزی، دانشگاه گیلان، رشت، ایران.

ارسال ۲۰۱۶/۰۳/۱۶؛ پذیرش ۲۰۱۶/۱۰/۱۰

چکیده:

با توجه به اهمیت صنایع غذایی در هر کشور، در این پژوهش مدلسازی میزان انرژی مصرفی این بخش از صنعت مورد مطالعه قرار گرفت. در این مقاله مدلسازی انرژی توسط روش شبکه‌های عصبی مصنوعی، منحنی سطح پاسخ و الگوریتم ژنتیک انجام پذیرفت. در اولین گام با توجه به آمارنامه‌ها، ترازنامه‌ها و روش پیشنهادی در این مقاله داده‌های ورودی مدل محاسبه گشت. برای هرکدام از حامل‌های انرژی (گازوئیل، نفت سفید، نفت کوره، گاز طبیعی، برق، بنزین و گاز مایع) با میانگین‌گیری از ۲۰ بار اجرای برنامه برای هر مشخصه شبکه، بهترین شبکه عصبی انتخاب شد. در انتها با محیط سیمولینک MATLAB هفت شبکه اجرا شده در قالب مدل نهایی تهیه شد. تحلیل داده‌ها نشان می‌دهد روز به روز در این صنعت مصرف گاز طبیعی روبه افزایش است ولی میزان مصرف نفت کوره و گاز مایع رو به کاهش است.

کلمات کلیدی: مدلسازی انرژی، انرژی مصرفی، صنایع غذایی و آشامیدنی، شبکه عصبی.