Transactions on Quantitative Finance and Beyond

www.tqfb.reapress.com

Trans. Quant. Fin. Bey. Vol. 1, No. 1 (2024) 48–57.

Paper Type: Original Article

Evaluating Hybrid Model of Neural Networks and Genetic Algorithms in the Forecast Energy Consumption in the Transportation Sector

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Citation:

Received: 4 April 2024 *Revised: 20 May 2024* *Accepted:26 June 2024*	Heidari Haratemeh, M. (2024). Evaluating hybrid model of neural networks and genetic algorithms in the forecast energy consumption in the transportation sector. *Transactions on quantitative finance and beyond, 1* (1), 48-57.

Abstract

Energy, besides other factors, production is considered the main factor in growth and economic development, and economics can play beneficial roles in the performance of different sectors. Hence, the country authorities should try to predict anything more precisely regarding energy consumption in the proper planning and guidance of consumption to control the way they desire energy demand and supply parameters. This paper aims to evaluate the hybrid model of artificial neural networks and genetic algorithms in forecasting demand energy to predict energy consumption in the country. A case study is energy consumption in Iran's transportation sector. So, for this review, we use the annual data on energy consumption of transport as a variable output of forecast models and data from the entire country's annual population, GDP, and the number of vehicles as the input variables. Evaluation results showed that the model of Artificial hybrid model of Neural Networks (ANN) and Genetic Algorithm (GA), campared to other models, has the highest accuracy in predicting energy demand in the transportation sector.

Keywords: Energy consumption, Multivariate regression, Artificial neural networks, Genetic algorithm.

1 | Introduction

Economic growth and development are the main objectives of economic policy. Research has shown that many researchers worldwide tend to largely trend toward a rate of economic growth in developing countries. Energy efficiency depends on the level of consumption [1]. The security of energy supply worldwide is a strategic issue facing all governments. Along the axis of the energy supply side management, the lower part of the name comes, which is the demand side of energy. Today, in our country, more efforts are directed

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toward managing the Energy Supply, and Less attention is paid to managing the energy demand. In contrast, managing energy demand and striving towards improved energy efficiency are the most important factors for sustainable industrial development [2].

Given that Iran has rich resources and potential energy, predicted energy consumption can help explain the energy sector policies effectively. Also, since the issue of limiting the consumption of energy, especially petroleum products, is placed at the top of the government's economic policies, and on the other hand, Problems caused by the drop in pressure or a lack of natural gas every so often is problematic and additionally the shortage of energy source, for various sectors of the economy, is causing a problem. Forecasting and modeling energy consumption and its relation to economic growth can be a suitable guide for politicians in the energy sector and the economy [3].

According to statistics and data, the transportation sector is the largest energy consumer and the major consumer of petroleum products. This sector's annual energy consumption reached 12.5 million barrels in 1967 to 273.79 million barrels in 2008 (21.9 times), which shows a 47.24 percent share of the transport sector (Optimizing the fuel consumption organization).

Considering the high growth opportunities to reduce petroleum consumption in the transportation sector, increase efficiency in fuel consumption, and reduce the volume of produced pollutants from fuel utilization in the sector is necessary than accurately forecasting the energy consumption in this sector, energy supply, and demand parameters are controlled properly in this country's crucial economic. In this regard, the present study uses efficiency in hybrid models of neural networks and genetic algorithms as an optimized procedure for forecasting energy consumption in the transport sector.

The paper is structured so that Related research and relevant studies are reviewed after the introduction. After the research paradigm includes introducing an artificial neural network model, ANN-GA, it presented how to assess the models used and the nature of the research.

2 | Artificial Neural Networks-Genetic Algorithm

In the next unit, the results of the data analysis will be described. The results include linear multivariate regression, neural networks, genetic algorithms, and assessment models used in forecasting in this section. Finally, it expressed conclusions and conclusions.

2.1 | History of Research Background

The subject has a cause-and-effect relationship between energy consumption, economic indicators, and population, and it has been well-studied in the energy economics literature. It has been considered in many studies, Using modeling techniques or accumulation or multiple regression analysis to examine the impact of various factors on energy consumption. Also, different methods used to predict energy consumption in some of these studies are briefly reviewed. Ahmadi Gharacheh [4] forecasted the nature of crude oil prices using neural networks for univariable deals. He compared his model with different models, and he concluded that the model was better than the previously proposed models.

Azari et al. [5] utilized artificial neural networks because of their extraordinary ability to emulate the linear mapping of input to output for short-term Forecasting of natural gas consumption in Tehran. A comparison of forecasting results with the actual amount of natural gas suggests that the model's accuracy for daily and monthly gas is about 93% and 99%, respectively.

Poorkazemi and Asadi [6] forecast crude oil price dynamics using artificial neural networks and Auto Regressive Integrated Moving Average (ARIMA) models using econometric methods.

The results suggest that the error is less than the neural network predictions compared with ARIMA. Abrishami and coworkers [7]. They used neural networks GMDH to forecast gasoline prices based on technical analysis rules, including short-term and long-term moving averages. They used them as input to the network during periods of market. In this study, the neural network predictions are compared to the time series, and the error is less and more careful.

Menhaj et al. [8], using a neural network and considering socio-economic indicators, predicted energy demand in the transport sector in the country between 1386 and 1400. They used neural networks in the forward observer to predict and use the propagation algorithm to train the networks. The forecasting result of this method compared with the multiple regression method indicates a significantly lower error, so the absolute error was reduced from 15 % to 6 %.

Sadeghi et al. [9], using an artificial neural network based on price expectations for daily data, notice the modeling and forecasting of crude oil OPEC daily basket price, and the results are compared with the values predicted by the ARIMA model based on measurement criteria as prediction accuracy. The result explains that the used neural network has better predictive power than the ARIMA model.

Zarezadeh et al. [10], by using neural networks and algorithms after the release, forecasted gasoline consumption in Lebanon.

Pao [11]used linear and nonlinear statistical models such as the neural network approach to examine the economic impact of four factors (national income, population, Gross Domestic Product (GDP), and Consumer Price Index) on the electricity consumption in Taiwan and then develop an economic Forecasting Model.

Murat and Ceylan [12], Using a three-layer neural network and algorithm after release, forecasted the energy needed for the transport sector in Turkey. In researching the indicators, GDP, population, and number of vehicles are considered per kilometer as inputs to the neural network.

Ediger and Akar [13] presented a neural network model to predict the consumption of petroleum products in Turkey. In their study, three different models were used in the design and use of standard error, and they selected the model as a suitable model to forecast oil consumption in Turkey.

Yu et al. [14], Also among the findings of these studies, suggests a neural network based on their Regression moving average in the forecasting.

Bianco et al. [15] examined the impact of economic and demographic variables on the annual electricity consumption in Italy and developed a model to predict in the long term. Economic and demographic variables studied include past Power consumption, GDP, GDP per capita, and population.

Pin et al. [16], In a study, they have predicted the crude oil price for the next three days and concluded that a dynamic model with 13 delays is suitable for predicting the short-term spot price of crude oil. Also, accurate prediction is estimated at 78%, 66%, and 53% for the next two or three days.

Geem and Roper [17] suggest a neural network model that includes four independent variables, GDP, population, imports, and exports, which can effectively forecast energy demand in South Korea.

3 | Model and Methodology

As the previous section shows, each study evaluates and predicts energy using special techniques. In this study, we tried to make a combination of genetic algorithms and neural network models to use in modeling and forecasting energy consumption in the transportation sector of Iran by comparing the results with other models (neural networks and regression). The efficiency of this combined model is determined in forecasting.

3.1 | Artificial Neural Network

Work on artificial intelligence began in the 1950s by pioneers in statistics, neuroscience, psychology, and more. In these methods, humans seek to conquer the universe and use the best and most effective natural method. One of the most important areas of Artificial Intelligence is Artificial neural networks, which look for simulation of a little brain human function to dominate the cosmos.

Artificial neural network is a simulation method that inspires the study of brain systems biological neural networks. The high-performance power biological systems are caused by natural parallel neurons planned. An Artificial Neural Network does with distributed simulation of interconnected simple processing units (what the neuron is called). The main role of a biological neuron is the input's operation, which sets its feedback to the extent that it is called the threshold, which it should not exceed, and then it produces an output [18].

One of the most common neural networks is the Multi-Layer Perceptron neural network (*Fig. 1*). Multi-layer Perceptron includes a standard mix of inputs, linear and nonlinear neural units, and the output. The output of all Processing Units of each layer is transferred to all processing units in the next layer. All input layer processing units are linear, but the hidden layers of neurons with tangent sigmoid function can use hyperbolic or any other differentiable nonlinear function. Usually, the training speed, which is the linear output of the layer neuron, is selected.

Against input and output units, hidden units do not make any sense. Hidden units do not have significant interpretation; they are an intermediate result in calculating the output value. Hidden units behave like the output units. For example, they calculate the total coordination of input variables, and then, by using the activation function, which is logistic most of the time, they process the result. The main issue in this network is determining the number of hidden layers and the number of neurons; in this regard, there are many comments. The number of hidden nodes is important because they play significant roles in neural networks with properties of nonlinear configuration.

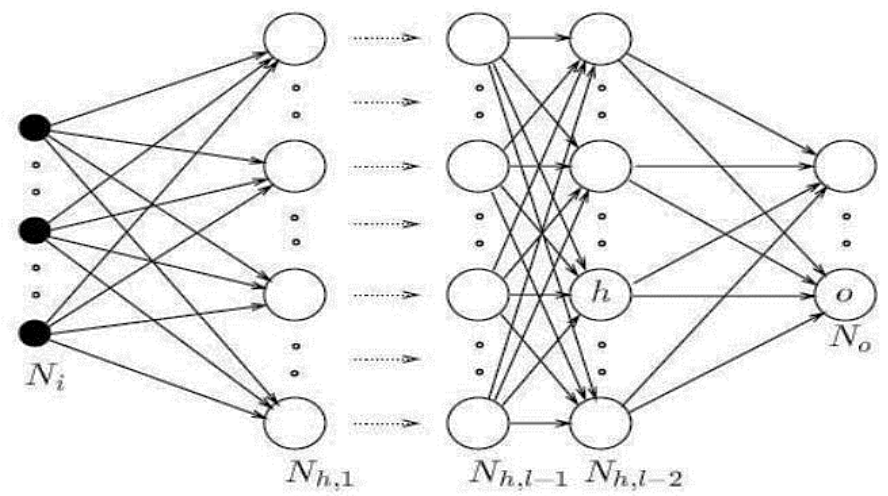

Fig. 1. The structure of a multi-layer perceptron with a hidden layer [19].

Determining the number of input nodes is the most used trial-and-error method. But, the overall number of neurons in the input layer indicates the number of input variables [19]. In this case, it was proved that in neural networks with a hidden layer with a sigmoid function in the intermediate layer and a linear function in the output layer, nearly all functions can be approximated to any degree, provided that there are enough neurons in the hidden layer that is known Universal approximation.

3.2|Artificial hybrid model of Neural Networks and Genetic Algorithm

Genetic algorithms were first proposed by Holend in 1975 and, in later years, were developed by other researchers. Genetic algorithms are part of the evolutionary computation theory, which is growing rapidly as part of artificial intelligence. The main idea of this algorithm lies in the Darwinian theory of evolution. Practically, the Genetic algorithm is one of the optimization matters based on some important concepts of natural selection and genetics. This method is used to optimize the objective function, an initial population of chromosomes (individuals) answering the original question that is assumed to be a new population of chromosomes or a new generation that answers the second question. By repeating this operation and generating a new population from the old population in each stage, and thus reaching successful generations, the population will grow to an optimal solution [20].

This method is called population, as a fixed number, a series of data, and target parameters are generated randomly and tested against this data set. It remains the most appropriate and forms a new generation. This process is repeated for the next generation to meet the convergence criteria.

With these qualities, the combined and developed integrated models of neural networks and genetic algorithms to forecast energy demand are described in the following steps in the transport sector in Iran, as shown in *Fig. 2* [10]. Descriptions of each of the steps are presented in the next section.

Step 1. It specifies the total population in each generation and the maximum number of generations in the first step. At this stage, an initial population is created randomly.

Step 2. The formation of artificial neural networks was determined using gene values in each population.

Step 3. The designed Network is trained using normalized entry data. After the network training, calibration procedures and network training in this step can be done.

Step 4. After forecasting, the mean square error criterion is calculated by designing the network. By calculating the measure, using the objective function in this study is determined to minimize the mean square error.

Step 5. To create the next generation of genetic and evolutionary operators such as mutation and gene combinations, the Roulette wheel for the next generation selection is used in the genetic algorithm. This stage is also used so that some of the best of the current generation is transferred to the next generation.

Step 6. The new population replaces a previous population, creating a new generation. At this stage, the value is added to the number of generations. As the number of generations reaches its maximum value, the above steps are repeated

Fig. 2. Algorithms to forecast energy demand [10].

3.3 | Evaluation Indexes of Models

In this study, for evaluating the performance of the hybrid model of synthetic genetic networks, an artificial neural network and multiple regression parameters and Relative Standard Error (RSE), Mean Error (ME), and Root Mean Square Error (RMSE) can be calculated from the following used equations.

$$\mathrm{RSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_0 - z_p)^2}}{z_{ave}}. \tag{1}$$

$$\mathrm{ME} = \frac{1}{n}\sum(z_0 - z_p). \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_0 - z_p)^2}. \tag{3}$$

That it means,

Z0 = the predicted values.

Z p = observed value.

Z ave = the average values of observations.

n = number of data.

3.4 | Data

Because artificial neural networks are based on data, data preparation is an important step and the key to success in using neural networks. When the amount of data is greater, the hidden structure in the model can be assured to be more approximate. The study includes data from the annual energy consumption in the transport sector as output variables (Y), annual data of the number of cars (x_1), Population (x_2), and GDP (x_3), prediction models were used as input variables for the period 1981 to 2022. In this study, 80% of the data was for learning, and another 20% was used for the test.

4 | Analysis of Results

4.1 | Results of Linear Regression

Using learning data *Eq. (4)*, the regression equation was determined by determining multiple regressions to the parameters studied. This relationship was applied to the test data, and the result of the square root of the error, the RSE, the ME, and the coefficient of determination earned, respectively 6.09, 0.05, 5.11, and 0.993. The regression coefficient of π is smaller than 0.05; also, an analysis of the variance table for the regression was calculated, which significant results imply from the fitted equation. ($p<0.05$) The distribution of the error values was calculated, indicating the regression model's accuracy and the lack of alignment between the input parameters.

$$y = -3.13 - 0.00034\,X1 + 0.00075\,X2,$$
$$y = -0.0826 + 0.290\,X1 + 0.313\,X2 + 0.483\,X3. \tag{4}$$

4.2 | The Results of the Neural Network

In the neural network design, models should be identified, learned, and test sets, normalizing data, the number of hidden layers of the network, number of neurons in each layer, learning algorithms, a conversion function, Function, learning rate, and number of repetitions. There are no systematic methods for determining the cases, and the best network design is obtained based on experience and trial and error. If the raw data enters a network, the large data changes impact the network differently, so some neurons come soon to fire. In contrast, some of the other neurons have not reached the activity threshold, which causes a reduction in the model prediction. One way to normalize the data in the range $[\lambda_1 , \lambda_2]$ is the following equation:

$$x_i = \lambda_1 + (\lambda_2 - \lambda_1)\left(\frac{z_i - z^t_{min}}{z^i_{max} - z^i_{min}}\right). \tag{5}$$

Accordingly, the present study was determined after the test and training datasets, and input data to the network was standardized1 using *Eq. (6)*.

$$y = 0.8 \times \frac{x_i - x_{min}}{x_{max} - x_{min}} + 0.1. \tag{6}$$

X min = the smallest data, and X max = the largest input data set. Using this relation, the input data is between 0.1 and 0.9. In this study, a network with one hidden layer with a sigmoid activation function $f(x) = \frac{1}{1+e^{x}}$ and linear activation function in the output layer determines the number of varied neurons from 2 to 10 and the best number of neurons by trial and error. Also, due to this study's efficiency, simplicity, and speed, Lundberg Markuat used training algorithms.

These features of values RMSE are presented in *Fig. 3*. Consideration will be given to the figure, the minimum amount of RMSE related to the network with nine neurons in the hidden layer. As seen in the figure, the Change in RMSE does not have a clear trend; since the neural network is a black box model, the weights are chosen randomly, and the trend cannot be completely explained. Only the best structure can be obtained by trial and error.

Attention: Normalization is not generally recommended for neural networks but for other techniques. When training data are normalized in the range of zero and one, there is no problem, and the network proves weights by them, but the data usually include trial and error, etc. Given this finding, the neural network is a finder within the network so that the data may be out of range from zero to one. Hence, it is better to have less scope to consider the data obtained valid results using the network.

We can say that the more complex neural network models are trained too and cannot fit right on the new data.

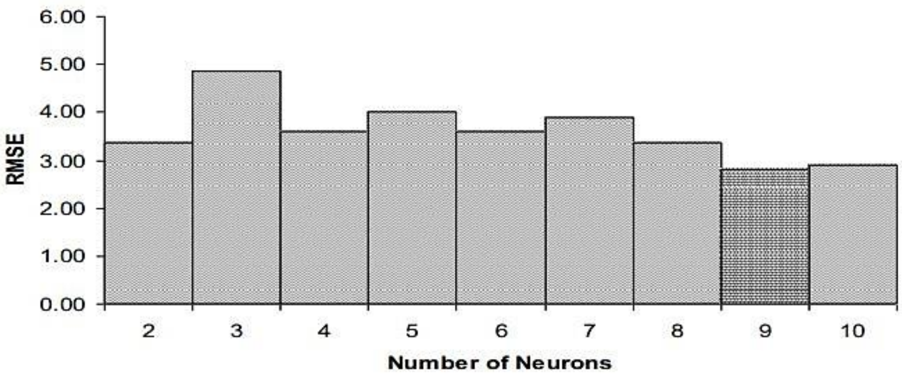

Fig. 3. RMSE values for the different numbers of neurons.

In *Fig. 4*, the best performance has proposed the distribution of test data for a neural network structure. According to this chart, the best-fit line has an angle close to 45 degrees and indicates high accuracy.

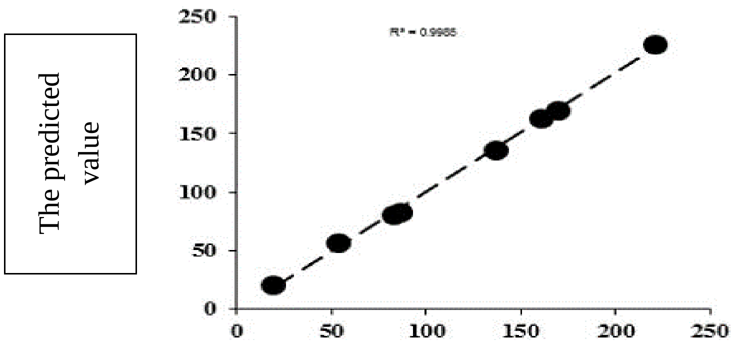

Fig. 4. The distribution of observed and predicted values by using the neural network technique.

4.3 | The Results of the Hybrid Model of Neural Networks and Genetic Algorithms

In the way of the genetic algorithm, randomly and various initial populations influence the phenomenon (as the training data to be learned from) due to the nature of the mechanism of the phenomenon to increase the complexity of the model and will be involved in memory, in this research, the initial population is 50, the maximum generation 100 and it is considered the number 100 Circulation. The error of this method is based on the square root of the error, the RSE, the ME, coefficient for energy demand in Iran's transport sector, and earned respectively 2.54, 0.02, 1.9, and 5.67. In *Fig. 3*, neural networks are given to distribute test data for model genetic algorithms.

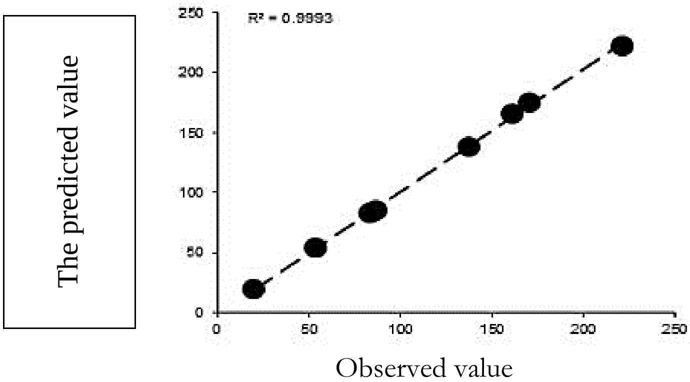

Fig. 4. The distribution of observed and predicted values by using a hybrid genetic-neural network.

4.4 | Evaluation of Various Models in Forecasting

The results of the genetic neural network models, neural networks, and multiple regression to predict energy demand are presented in *Table 1* and *Table 2*. According to these tables, it can be seen that, in general, the best performance in forecasting energy demand of the transport sector is related to the hybrid model of neural networks and genetic algorithms, which in all three assessment criteria (RMSE ، RSE, ME) are better than the neural network and multiple regression.

After the genetic neural network model, artificial neural networks perform better after release than the regression model. The low-value RMSE for most models indicates low errors and high accuracy for the fitted models.

Table 1. Actual values and the predicted energy use by different models.

Year	Actual values	REG	ANN	GA/ANN
1	86.5573	88.2476	82.8009	85.0386
2	82.7947	86.4629	80.7166	82.4529
3	161.1954	157.2355	163.5090	166.1552
4	136.9701	135.9545	136.0993	138.2015
5	19.6856	8.6134	19.8472	19.5090
6	220.8235	212.2304	226.0391	222.4436
7	53.7557	57.1645	57.1284	54.7237

*Reference: research computing

Table 2. Performance of different models in predicting energy consumption.

	REG	ANN	GA/ANN
RMSE	6.09	2.81	2.54
RSE	0.05	0.02	0.02
ME	5.11	2.23	1.90
R^2	0.993	0.998	0.999
RI	0.00	5.63	5.67

*Reference: research computing

Also, it shows that at the level of 5%, there are no significant differences between the models" estimated power consumption. An indicator RI can be used to assess model efficiency in this situation. This statistic shows the reduction of error in the regression model. As it is clear from Table 2 information, the genetic neural network model of forecasting accuracy compared to the multiple linear regression increased at a rate of 5.67 to forecast the energy demand.

5 | Conclusions

Energy is a vital element and important factor for production, and various forms of wood and fossil fuels are at the lowest level of refinement, while nuclear energy is at the highest level of recycling in nature. The increasing dependence on energy communities due to the replacement of machines instead of the workforce has led to the idea that energy, along with other production factors, should be considered an important factor in economic growth and development and play a significant role in the performance of various sectors of the economy. The more accurate the forecast of power consumption would be undeniable. Accordingly, this research evaluates the effectiveness of multiple methods of forecasting the amount of energy consumption in the transport sector of Iran using the genetic neural network model (as the method of choice for this study), ANN, and multivariate regression. Also, the annual energy consumption in the transport sector was considered an output variable, and yearly population data, GDP, and number of vehicles were considered input variables in predictive models.

The results show that the genetic neural network model (the method of choice for this study) accurately forecasts energy demand in the transport sector. After that, the model of artificial neural networks performs better than the basic regression equation. In other words, the artificial neural network performs better in all evaluated parameters than the regression equations.

Funding

The authors declare thatno external funding or support was received for the research.

Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

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