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Forecasting Energy Price and Consumption for Iranian Industrial Sectors Using ANN and ANFIS

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Abstract

Forecasting energy price and consumption is essential in making effective managerial decisions and plans. While there are many sophisticated mathematical methods developed so far to forecast, some nature-based intelligent algorithms with desired characteristics have been developed recently. The main objective of this research is short term forecasting of energy price and consumption in Iranian industrial sector using artificial intelligence including an Adaptive Neuro-Fuzzy Inference System (ANFIS) and an Artificial Neural Networks (ANN). The dataset contains monthly price and consumption of gas oil, petrol, and liquid petroleum gas in the period between March 1996 and March 2010. Based on dataset, energy price and consumption for 2011 and 2012 are forecasted. The results obtained utilizing the two methods show that while both are appropriate tools to forecast price and consumption, most of the time ANFIS has lower error than ANN in terms of the mean squared error criterion.

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1. Introduction

Due to industrial development and the change of life style because of modernism, energy sources have become of great importance. Consequently, modeling and forecasting of energy issues such as price and consumption plays an important role in industries, economic, marketing, engineering planning, and decisions-making (Baumgartner and Midttun 1987).

Although there are many sophisticated mathematical methods of forecasting such as time-series modeling available in the literature, the use of artificial intelligence models has been emphasized recently, among which artificial neural network (ANN), the well-known task-approximation method in predicting and system modeling, plays an important role (Kamruzzaman and Saker 2003). Besides, the fuzzy logic approach based on which fuzzy rules that use linguistic expressions are possible to formulate, can be applied in a wide range of problems including data analysis, forecasting, and decision-making. This study involves ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) tools for short-term forecasting of energy prices and consumptions for Iranian industrial sector along with a comparative study on their performances.

Since industrial sector is one of the sectors that consume most of the available energy, prediction of energy consumptions and price is valuable to policy-makers of this sector. It is worth noting while there are other types of energy such as solid fuel, electricity, natural gas, fuel oil, and kerosene used in the industrial sector, due to unavailability or limited availability of monthly data, only three of them are considered to be forecast in this paper. The dataset includes monthly data of gas oil, petrol, and liquid petroleum gas from March 1996 to March 2010.

The remainder of the paper is structured as follows. In the next section, the related literature is reviewed. Section 3 contains the proposed ANN and ANFIS methodologies. The results of implementing the methodologies come in Section 4. Section 5 contains performance evaluation, where the mean squared errors of both procedures are compared. We conclude the paper in Section 6, where some recommendations for future research are given.

2. Literature Review

A review of several studies in the literature reveals that there has been a rapid and increasing use of artificial intelligence in forecasting field. Some of these research works in chronological order are:

Hipert et al. (2001) reviewed and evaluated a collection of papers that reported the application of artificial neural networks to short time load forecasting, where a great number of them show successful implementation and useful results in the forecasting field. Ahmari Nejad et al. (2005) investigated electricity price forecasting methods in the energy market. An interesting idea in this paper was to analyze the electricity price environment in two parts; energy demand and customers' behavior in the energy market. The forecasting tool in this research was ANN with a multi-layer perceptron architecture. The available number of data was 1036, where 836 pieces of data were used to train the network and the rest were used for testing. The results showed good performances of the employed ANN in electricity price forecasting.

Moshiri and Foroutan (2005) compared the performances of ANN with the ones of the non-linear GARCH and linear ARIMA models. The purpose of this work was to obtain better results of daily oil price forecasting. This study showed ANN to be the best with the least error.

To forecast gold price, Sarafraz and Afsar (2005) utilized regression and ANFIS methods using 520 inputs, 50% for training, 25% for test data, and the other 25% was for evaluation. The results of this study indicated that while 93% of gold price tolerance was predictable by the regression method, this figure was 99.23% in the ANFIS method.

Sinaie et al. (2005) tried to forecast Tehran stock index using ANN and ARIMA models. The compared results in this study showed that the ANN with back-propagation training algorithm has better performances than ARIMA in terms of forecasting error. Besides, Azar and Afsar (2006) took a hybrid neural network and fuzzy logic model based on theoretical arguments in Takagy-Sugeno model (ANFIS) to forecast stock price. In this paper, the proposed method was compared to ARIMA. They showed that the fuzzy neural network system procedure could forecast better than the ARIMA method. The fuzzy neural network system had also a unique rapid convergence and high precision to predict stock price, based on this research. In this research, the daily stock price data of five years were selected. The experimental results showed that the combination of artificial neural networks and fuzzy logic were successful and led to a significant reduction in forecast error.

Catalao et al. (2007) discussed that producers and consumers require short-term price forecasting to derive their bidding strategies to the electricity market, where accurate forecasting tools are required for producers to maximize their profits and for consumers to maximize their utilities. A three-layered feed-forward ANN, trained by the Levenberg-Marquardt algorithm, was used in this research for forecasting the next 168 hour electricity prices. The neural network toolbox of MATLAB[1] was selected due to its flexibility and simplicity. Historical data for the year 2002 from the mainland Spain market, namely previous electricity prices, were the main inputs to train the artificial neural network proposed in this paper. The authors compared the performance of the ARIMA model with the one of the ANN and showed superiority of the latter.

Farjam Nia et al. (2007) employed ARIMA and ANN in order to forecast daily price of crude oil based on the data between 1983 till 2005, where a sensitivity analysis was performed to detect input shares in oil price trends. The results indicated the ANN model had superior features compared to the ARIMA model in predicting the daily price of oil.

Mandal et al. (2007) explored a technique in ANN model based on similar days (SD) method in order to forecast day-ahead electricity price in the PJM market. In this paper, the authors mainly described day-ahead price forecasting in the environment of competitive electricity market where price forecasting aimed at providing estimates of electricity prices for the upcoming several days. In this study, a multi-layer feed-forward neural network was proposed for forecasting next-day 24-h electricity prices. The network model was composed of one input layer, one hidden layer, and one output layer. The network was trained using data available in the past 45 days from the day before the forecast day, and past 45 days before and after the forecast day in the previous year. The training algorithm for the proposed neural network used in this paper was the well-known error back-propagation training algorithm. The test results obtained through the simulation demonstrate that the proposed algorithm was robust, efficient, and accurate, where it produced better results for any day of the week.

Haidar et al. (2008) presented a short-term forecasting model for crude oil prices based on a three layer feed-forward neural networks with back-propagation algorithm. The network structure was selected after systematic rigors tests involved large number of experiments on the crude oil data. In addition, two groups of inputs were tested, crude oil futures data, and market data that includes S&P500, gold price, Dollar index and heating oil price. The results showed that with adequate network design and appropriate selection of the training inputs, feed-forward networks were capable of forecasting noisy time series with high accuracy.

ZaraaNejad and Hamid (2009) forecast Iran’s inflation rate using neural networks in MATLAB work space. In this study, three training algorithms were examined, Conjugate Gradient, Quasi-Newton, and Levenberg-Marquard. Time series data were gathered from 1959 to 2007. The training algorithms were compared and the Levenberg-Marquard training algorithm was selected the best because of its least forecast error.

Mirbagheri (2010) tried to forecast Iranian GDP growth using fuzzy logic and neuro-fuzzy methods. In this research, the Takagi–Sugeno fuzzy inference system (ANFIS) was used to design the fuzzy neural network. The predicted average annual GDP growth in the period of 2002-2006 showed to be 5.92% and 6.46% based on the neural-fuzzy and fuzzy-logic, respectively. Employing some comparison criteria, they showed that neural-fuzzy predicts better than fuzzy-logic, recommending neural-fuzzy to forecast annual GDP growth.

Bilgehan (2011) investigated the ability of ANFIS and ANN models to predict successfully the buckling of slender prismatic columns with a single non-propagating open edge crack subjected to axial loads. Statistical tools that were employed to evaluate the performances of these methods showed that the ANFIS tool with Gaussian membership function had better performance than the multilayer feed forward ANN with a learning back-propagation algorithm.

Sadeghi et al. (2011) compared the performances of an ANN with those of an ARIMA model in short term forecasting of OPEC crude oil price. The results showed the neural network model with back-propagation training algorithm had significantly better ability to forecast daily crude oil price. They concluded that the artificial neural network approach was much less time consuming than the ARIMA technique. They also concluded that the ANN, which was previously applied with success for load and electricity price forecasting, was quite capable to approximate nonlinear functions corresponding to OPEC crude oil price, where it was able to solve problems in which the input-output relationship is neither well defined nor easily computable (because artificial neural networks are data-driven.) The numerical results presented in this paper confirmed the considerable value of the proposed artificial neural network approach in forecasting short-term OPEC crude oil price, taking into account the results previously reported in the technical literature by the ARIMA technique.

Esmaeili et al. (2012) studied the application of ANN and ANFIS models to forecast the back-break in an open pit blasting and compared them with the traditional statistical model of multiple regressions. The performance measures were the root mean square error, correlation coefficient (R^2), and mean absolute percentage error. Results showed that the ANFIS exhibited the highest performance.

Abdulshahed et al. (2013) employed ANFIS, ANN with back-propagation algorithm (ANN_BP), and ANN with particle swarm optimization technique (ANN-PSO) to forecast thermal error compensation on CNC machine tools. According to the results, the ANFIS model was superior in terms of forecasting ability. The results also indicated ANN-BP to have a good level of forecasting accuracy. Moreover, in all the methods used in this paper, the accuracy of the results generated by the ANFIS model was better than that generated by the ANN model.

Latif et al. (2013) compared the performance of ANFIS with the one of ANN in seasonal forecasting of power demand. The data was gathered based on annual electricity demand in Bangladesh for the last five years. The results indicated that ANFIS was the better method to forecast in terms of different error measures.

In summary, there are various methods available in the literatures that have been proposed to forecast different indices. The results of surveying these techniques reveal that artificial intelligent algorithms have appropriate applications in forecasting price, load, demand, and the like. Generally, artificial intelligence helps human with its features including high accuracy, understanding, quick responding, and solving ability of complex models. Moreover, it seems that artificial intelligence, especially ANN and ANFIS play significant roles in different fields of forecasting. Thus, in this research ANN and ANFIS with some special characteristics are utilized in this research to forecast energy price and consumption in Iranian industrial sector.

3. Materials and Methods

As mentioned, the methodologies used in this paper to forecast future consumption of three types of energy sources (gas oil, petrol, and liquid petroleum gas) and their prices are neural networks and adaptive neuro-fuzzy inference system. Moreover, according to studies and past investigations in forecasting tools software, the MATLAB software can analyze the data using neural networks and neuro-fuzzy System. This software has specific toolboxes for these methods and its work place is the best environment for neural networks and neuro-fuzzy methods. In this research, MATLAB 7.10 is used for the forecasting process.

The dataset represents monthly energy data from March 1996 to March 2010. Energy data includes gas oil, petrol, and liquid petroleum gas price and consumption information. Because of some unusual changes in economic after fall 2010 in Iran, the trend of data in this year is different from the past data trend. Thus, the work is divided into three parts of forecasting in order to achieve better results. The parts are composed of price and consumption forecasting of 2009, 2010, and 2011-2012, separately.

The price data of petrol, gas oil and liquid petroleum gas have been gathered from the National Iranian Oil Refining & Distribution Company web site (www.niordc.ir/.) Moreover, the consumption data are collected from several balance sheets of energy, ministry of energy, power and energy affairs.

Since economists differentiate between the nominal and the real gross domestic product (GDP) that are based on the current and the fixed prices, where the fixed price is preferable (Mankiw 2012), in order to obtain better results, the data of energy prices is selected in fixed form based on year 2004 as the base year. Moreover, the collected raw data on the consumption and on the price are pre-processed as

$$\begin{aligned}\text{Consumption} = & \left(\text{Monthly consumption in purposed year}\right) \\ & \times\left(\text{Number of day in the purposed month, 30 or 31 days}\right) \\ & \times\left(\text{Percentage of industrial sector share of energy consumption}\right)\end{aligned} \tag{1}$$

$$\begin{aligned}\text{Price} = & \left(\text{Monthly consumption in purposed year}\right) \\ & \times\left(\text{Number of day in the purposed month; 30 or 31 days}\right) \\ & \times\left(\text{Percentage of industrial sector share of energy consumption}\right) \\ & \times\left(\text{Fixed price of purposed year}\right)\end{aligned} \tag{2}$$

In the next section, the neural network tool is first described.

3.1 Artificial Neural Network Models

As stated by Faucett (1994), "Artificial neural networks have been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions that:

l. Information processing happens at many simple elements named neurons

2. Signals are passed between neurons over connection links

3. Each connection link has a related weight, which, in a typical neural network, multiplies the signal transmitted.

4. Each neuron applies an activity task to its net input (sum of weighted input signals) to choose its output signal."

In general, the learning process in neural networks may be classified as follows:

- Learning with a supervisor: The teacher compares the output of network with the target or expected data in order to decrease the difference between the forecast output and real one. The supervised learning is categorized into three types as:

o Error Correction Learning: Network tries to minimize the error, the difference between the forecast data and the target (Kartalopoulos 1996).

- o Reinforcement Learning: This method is slower than the one mentioned above. In this learning type, the network only gives good or bad output and it is rewarded if the output is correct and it is punished if the output is not correct (Nauck et al. 1997).
- o Stochastic Learning: This kind of learning selects weights randomly, making changes in the value that follows a probability distribution and evaluates its effect from the expected goal.

- Learning without a supervisor: This type of learning that does not have target output, does not receive information from the environment. Unsupervised learning is mostly used for neural networks whose work is pattern recognition and clustering. Generally, the two kinds of unsupervised learning are:

- o Hebbian Learning: The synaptic contact strength between two nodes is modified according to the correlated activity degree between input and output.
- o Competitive Learning: In this method, several neurons that are at the output layer compete with each other to generate the closest forecast output to the expected one when an input is applied. When one neuron achieves the goal, all others fail to reach the goal. This type of un-supervised learning suites to find data cluster. (Kartalopoulos 1996).

Based on their layers, neural networks are classified into two types as:

- Feed-Forward: This kind of neural network is mostly used in diverse network's applications. It contains inputs, outputs, and hidden layers. The signal from input feeds the next layer, output, in a single direction. This process continues until the signal travels through all the layers to the output. Feed-forward networks include the following categories:

- oPerceptron: This kind of network can be categorized into single-layer perceptron and multi-layer perceptron. While the single-layer Perceptron is used for linear and simple problems, the multi-layer Perceptron is used for non-linear and complex problems. Comparing the single-layer Perceptron with multi-layer perceptron, the multi-layer has the advantage of solving problems. In addition to theoretical documents, the most important model that has been used in over 90% of all neural networks applications is the multi-layer perceptron trained by the back-propagation learning algorithms (Nack et al. 1997).

A multi-layer Perceptron has an input layer of source nodes and an output layer of neurons; these two layers link the network to the outside world. In addition to these two layers, the multi-layer perceptron usually has one or more layers of hidden neurons, these neurons are not directly accessible. The hidden neurons take important characteristics contained in the input information (Sandberg et al. 2001). Multi-layer Perceptron (MLP) networks are layered feed-forward networks typically trained with back-propagation (Aris and Mohamad 2008). MLP with back-propagation are used for supervised learning to minimize the error in its prediction on the training data set. The back-propagation indicates a backward propagation of an error through the network (Nauck et al. 1997).

- Radial basis function (RBF): Another important neural network is the RBF network. It is also a multi-layer feed-forward neural network that uses different transfer function than MLP. The inspiration idea for RBF network creation comes from traditional statics. It is a linear combination of radial basis functions. This network consists of an input layer, a hidden layer, and one output layer. The connection between the input and the hidden layer is not weighted. Its applications are mainly in function approximation, time series forecasting, and controlling (Nack et al. 1997). A comparison between MLP and RBF networks is illustrated in Table 1.

Table 1. Comparison between Perceptron and RBF Network

Network	Features
Perceptron	• Has one or more hidden layer • Based on sigmoid function • Has application in over 90% of all ANNs functions • Most popular network in researches • Multi-layer feed-forward • Has weighted connection between all layers • Learning algorithm is back-propagation
RBF	• Has only one hidden layer • Based on Gaussian function • Requires more hidden neurons • Has application in forecasting, controlling and function approximation • Multi-layer feed-forward • Has not weighted connection between input layer and hidden layer • Learning algorithm is back-propagation

- Feed-Back: In feed-back networks portion of the output returns to the input to modify its characteristics. This network is divided into the following types:
  - Adaptive resonance theory: It is a two-layered, feedback network type. There is a circuit between the input and output layers for comparing the inputs to a threshold that indicates whether a new class pattern should be created for an input pattern.
  - Hopfield networks: They are weighted networks, each link from one neuron to another having the same weight in both directions. Hopfield networks have applications in the field of simulated annealing, or the process used to improve the characteristics of crystals or metals (chemical engineering fields). Feed-back networks are often used in optimization and control systems (Picton 2000).

As discussed above, while there are several networks with different and diverse applications, based on the goal and by considering the available research works and applications, a feed-forward network is selected in this paper. Besides, according to the above mentioned networks characteristics, the goal of this research, and literature review, Perceptron is selected in this work. Moreover, using a faster learning algorithm such as Quasi-Newton, Conjugate Gradient, and Levenberg-Marquardt is suggested to improve the performances of Perceptron networks with the back-propagation learning algorithm. Although there are many variations of the back-propagation algorithm, the most important algorithms are the simple back-propagation and Momentum. Table 2 shows the features of back-propagation learning algorithms and the faster algorithms, based on which the Levenberg-Marquardt is selected to be the training algorithm for the Perceptron network of this research.

Table 2. Learning Algorithms Based on Back-Propagation Features

Learning Algorithms	Features
Simple Back-Propagation	• Adjusts the weights in the steepest descent direction (negative of the gradient)
Back-Propagation with Momentum	• Responding of local gradient and also error surface • Faster than simple gradient descent(BP) • Slow for many practical applications back-propagation
Quasi-Newton	• Often converges faster than conjugate gradient methods • It is complex and expensive for the feed-forward neural networks
Conjugate Gradient	• Faster convergence than steepest descent directions • Higher learning rates than simple back-propagation

Learning Algorithms	Features
Levenberg-Marquardt	• Fastest convergence than above methods • Higher accuracy than above methods • Obtain lower squared error than any of the other algorithms • Normally, it is training algorithm for small and medium size networks

Transfer functions play a significant role in ANN. This function indicates how the activation value is output to the rest of the networks. Among several types of transfer function, the Sigmoid and the Tangent function (Tan-Sig) is widely used for hidden layers and the linear transfer function is used for the output layer. The linear transfer function is employed in back-propagation networks. When linear output neurons are used, the network outputs can take on any value because, if the sigmoid transfer function is used for output neurons, the outputs are limited to small range (Nauck et al. 1997).

A trial and error procedure is usually used to determine the numbers of nodes in layers. In this experimental method, there is an attempt to minimize the mean squared error (MSE) of the Network. In this research, the number of input layer nodes is selected based on a trial and error method that tests between 4 and 15 neurons in one type of energy in 2009 as a sample. This method gives 12 nodes in the input layer as the one with the least MSE. Table 3 shows the details.

Neural networks usually consists of one input layer, one or more hidden, and one output layer, where most researchers employed only one hidden layer for forecasting purposes (Nack et al. 1997). Thus, in this research one hidden layer is used. Further, the number of output nodes is related to the problem at hand. There are two classes for an output node choice:

Table 3. MSE Value for Different Input Layer's Nodes

Number of Nodes	MSE for Petrol Cost forecasting in 2009	MSE for Petrol Consumption Forecasting in 2009
4	3.6567e+015	3.4231e+010
5	2.1569e+016	1.8287e+011
6	1.9621e+016	3.8231e+010
10	3.3679e+015	2.5101e+010
12	2.0376e+015	1.3251e+010
15	2.8784e+015	2.0126e+010

- One-Step-Ahead: In this class, one output node is used.
- Multi-Step-Ahead: In this type, more than one node is used in the output layer

Where most of the time, the one-step-ahead type is used for the output layer empirically (Zhang et al. 1998). This is the case chosen for the current research as well.

In order to determine the number of nodes in the hidden layer, a trial and error procedure based on network MSE is usually utilized. This method, with detailed results shown in Table 4, yields 10 nodes in the hidden layer. Note that the Petrol consumption data in 2009 is used for this experiment.

Table 4. MSE Value for Different Hidden Layer's Nodes

Number of Nodes	MSE for Petrol Consumption Forecasting in 2009
5	2.1279e+010
8	2.3298e+010
10	1.3251e+010
15	2.4051e+010
20	1.9975e+010

In short, the multi-layer Perceptron network of this research consists of 12 nodes in one input layer, 10 nodes in one hidden layer, and 1 node in one output layer with 500 epochs of training in which the Levenberg-Marquardt BP training algorithm is used.

3.2. Neuro-Fuzzy Models

Among the number of acceptable methods to apply some types of learning algorithms to a fuzzy system, combining neural networks and fuzzy systems is very popular. There are several different types of combination of neural networks and fuzzy systems explained as follows:

- Fuzzy Neural Networks: Fuzzy methods are employed to improve the capabilities of learning or the performance of a neural network using fuzzy rules to change the learning rate or by creating a network that works with fuzzy inputs.
- Concurrent "Neural/Fuzzy Systems": In this model, a neural network and a fuzzy system have the same task. Usually the neural network pre-processes the inputs to, or post-processes the outputs from the fuzzy system.
- Cooperative Neuro-Fuzzy Models: A neural network is employed to determine the fuzzy parameters. After the learning phase, the fuzzy system works without the neural network. These models are simple type of neuro-fuzzy systems. It has a wide application in commercial fuzzy development tools.
- Hybrid Neuro-Fuzzy Models: Modern neuro-fuzzy tools are hybrid neuro-fuzzy models. A neural network and a fuzzy system are combined into one structure. ANFIS is classified in this class (Nack et al. 1997).

Jang's ANFIS model is one of the first hybrid neuro-fuzzy systems for function approximation. It shows a Sugeno-type fuzzy system in special five-layer feed-forward network architecture (Nauck et al. 1997). This model is used in this research as well. The learning process of the Jang ANFIS model composes of the following steps:

I. Propagate all models from the training set and determine the consequent factors by iterative least squared error. The antecedent parameters stay fixed.
II. Propagate all models again and update the antecedent factors by BP algorithm.
III. If the error is decreased in four consecutive steps, then increase the learning rate by 10%. If the error is subject to consecutive

combinations of increase and reduction, then decrease the learning net by 10%.

IV. Stop if the error is small enough otherwise continue.

Generally, the ANFIS system includes five functional blocks as:

- A rule base as a fuzzy if-then rule
- A dataset that defines the membership function of the fuzzy sets employed in the fuzzy rules
- A decision-making unit with inference operations on the rules
- A fuzzification inference that transforms the crisp inputs into degrees of match with linguistic values
- A defuzzification inference that transforms the results into a crisp output

A fuzzy inference system employing fuzzy if-then rules can model the qualitative features of human information and reasoning processes without employing precise quantitative analyses (Shing and Jang 1993).

In the ANFIS structure, the shape of the membership function is essential. A ***membership function*** (MF) is a curve that indicates how the input space is mapped to a membership value between 0 and 1. The simplest MFs are designed using straight lines. Of these, the simplest is the ***triangular*** membership function with the function name ‘trimf’. The ***trapezoidal*** membership function, ‘trapmf’, has a flat top. These membership functions have simplicity. The Gaussian distribution and a combination of two Gaussian shapes are used for two membership functions. The two functions are named ‘gaussmf’ and ‘gauss2mf’. The ***generalized bell*** membership function has the function name ‘gbellmf’. It has one more parameter than the Gaussian membership function (three parameters), thus this kind of MF can approach a non-fuzzy set if the free parameter is tuned. Gaussian and bell membership functions are the most common MFs to determine fuzzy sets. The advantage of these MFs is that they are smooth and nonzero at all points and because of this advantage several researchers have used these functions for prediction tasks. Moreover, the gbellmf in ANFIS function achieves higher prediction accuracy than triangular membership function. The Gaussian membership functions and the bell membership functions are unable to specify asymmetric membership functions. Thus, the gbellmf or the generalized bell membership function is programmed in the ANFIS structure of this research to play the role of the membership function. (See MATLAB help) .

In short, the ANFIS or the Sugeno-type fuzzy system of this paper has a five-layer feed-forward network with the combination of back-propagation and least squared learning algorithms as the default training which is designed for the prediction model. The input variables of the ANFIS framework to forecast the energy price and consumption are similar to the input database of the ANN method. Moreover, the numbers of training and testing data are similar to the ones in the ANN method. Like the neural network model, the ANFIS model in this research has 12 inputs and 1 output using weighted average (called *Wtaver* in MATLAB programming code for defuzzification). Besides, this ANFIS model contains:

- Number of Epoch: 200
- Number of Nodes: 67
- Number of Rules: 2
- Number of Linear Parameters: 26
- Number of Non-Linear Parameters: 48
- Number of Membership Function: 3
- Membership function Type: ‘gbellmf’ or generalized bell membership function

4. Results

In the following two subsections, the forecasts of energy price and consumption for Iranian industrial sector are given for the ANN and the ANFIS approaches, separately.

4.1. ANN Results

In the proposed ANN method, the dataset for the year 2010 includes 180 data points and the dataset for the year 2009 composed of 168 data points, where 60% of the dataset is used for network training and the rest is used for the network testing. The forecast values of the gas oil consumptions along with real consumptions for the year 2009-2012 are given in Figures 1(a&b)-2(a&b), respectively, where the last 12 values are shown in Table 5-6. Based on the results shown, the proposed ANN works well to forecast gas oil consumption in different years. Moreover, the forecast values of the gas oil price along with their real prices are shown in Tables 7-8 and Figures 3(a&b)-4(a&b), where good forecasts are provided. Similar tables and figures (not shown here) that were derived for Petrol and Liquid Petroleum Gas show that ANN is a good approach to forecast energy price and consumption in Iranian industrial sector.

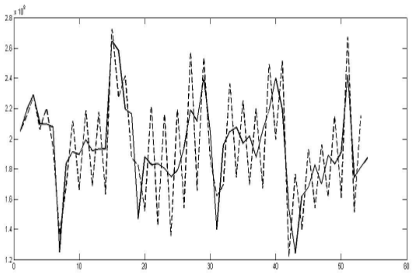

Figure 1-a. Plot of 57 Real and ANN-Forecasted Gas Oil Consumptions for 2009

Full Line= Real Dotted Line= Forecasts

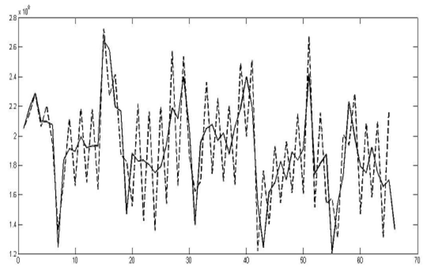

Figure 1-b. Plot of 69 Real and ANN-Forecasted Gas Oil Consumption for 2010

Full Line= Real Dotted Line= Forecasts

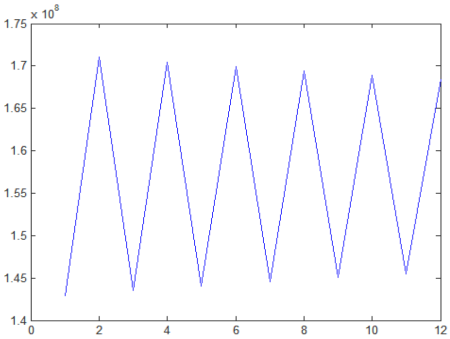

Figure 2-a. Plot of ANN-Forecasted Gas Oil Consumption for 2011

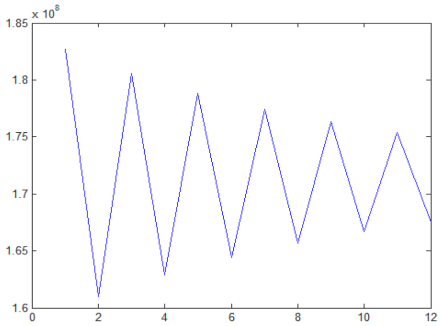

Figure 2-b. Plot of ANN-Forecasted Gas Oil Consumption for 2012

Table 5. The Last 12 Real and ANN Forecast Gas Oil Consumption Data for 2009 & 2010

Month	Forecasted data 2009	Real data 2009	Forecasted data 2010	Real data 2010
March	138510000	216782070	132810000	198636220
April	156320000	249397790	152030000	228914540
May	159770000	252209490	163540000	244314720
June	169490000	264018630	194760000	292081380
July	165730000	257551720	180820000	272504880
August	176740000	272172560	169810000	256321640
September	173630000	267474300	168300000	252600000
October	177380000	272916300	178490000	267503400
November	206980000	320261700	169350000	252600000
December	168790000	261216000	164430000	242496000
January	175880000	267474300	167490000	244769400
February	182280000	272100000	143380000	207889800

Table 6. ANN Forecast Gas Oil Consumption for 2011 & 2012

Month	Forecasted data 2011	Forecasted data 2012
March	142970000	182710000
April	171100000	160960000
May	143550000	180560000
June	170480000	162870000
July	144090000	178840000
August	169920000	164400000
September	144590000	177460000
October	169390000	165650000
November	145060000	176330000
December	168910000	166660000
January	145490000	175410000
February	168460000	167490000

Table 7. The Last 12 Real and ANN Forecast Gas Oil Price for 2009 & 2010

Month	Forecasted data 2009	Real data 2009	Forecasted data 2010	Real data 2010
March	11348000000	17559347670	25907000000	130503996540
April	13495000000	20201220990	23655000000	150396852780
May	14153000000	20428968690	22393000000	160514771040
June	15238000000	21385509030	22217000000	191897466660
July	15106000000	20861689320	20914000000	179035706160
August	16222000000	22045977360	20031000000	168403317480
September	16104000000	21665418300	19550000000	165958200000
October	16581000000	22106220300	19509000000	175749733800
November	19666000000	25941197700	18848000000	165958200000
December	16060000000	21158496000	18304000000	159319872000
January	16890000000	21665418300	18048000000	160813495800
February	17908000000	22040100000	16261000000	136583598600

Table 8. ANN Forecast Gas Oil Price for 2011 & 2012

Month	Forecasted data 2011	Forecasted data 2012
March	18352000000	16303000000
April	17835000000	17752000000
May	18344000000	16321000000
June	17393000000	17734000000
July	18336000000	16339000000
August	17401000000	17716000000
September	18328000000	16356000000
October	17408000000	17698000000
November	18320000000	16373000000
December	17416000000	17682000000
January	18313000000	16389000000
February	17423000000	17665000000

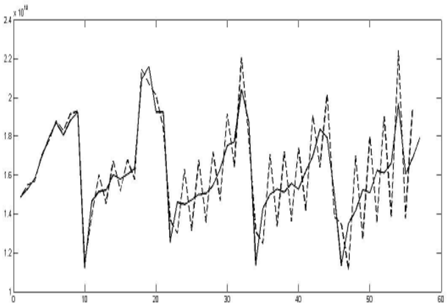

Figure 3-a. Plot of 57 Real and ANN-Forecasted Gas Oil Price for 2009
Full Line= Real Dotted Line= Forecasts

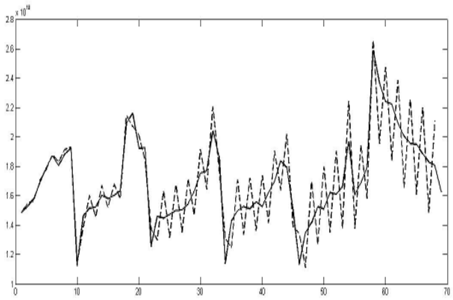

Figure 3-b. Plot of 69 Real and ANN-Forecasted Gas Oil Price for 2010
Full Line= Real Dotted Line= Forecasts

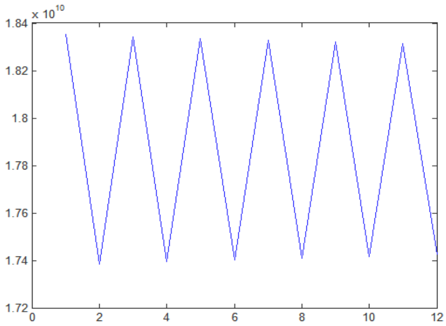

Figure 4-a. Plot of ANN-Forecasted Gas Oil Price for 2011

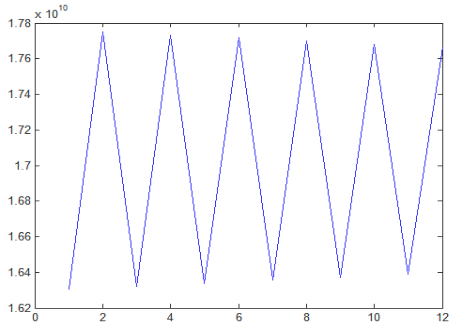

Figure 4-b. Plot of ANN-Forecasted Gas Oil Price for 2012

4.2. ANFIS Results

Similar to the proposed ANN approach, the forecast values of the gas oil consumptions along with real consumptions for the year 2009-2012 are given in Table 9-10 and Figures 5(a&b)-6(a&b) as well. Based on the results shown, the proposed ANFIS approach also works well to forecast gas oil consumption in different years. Further, the forecast values of the gas oil price along with their real prices are shown in Tables 11-12 and Figures 7(a&b)-8(a&b), where good forecasts are provided. Similar tables and figures (not shown here) that were derived for Petrol and Liquid Petroleum Gas show that ANFIS is also a good approach to forecast energy price and consumption in Iranian industrial sector. The performance evaluation and comparison of the two forecasting methods are made in Section 5 based on the mean squared error (MSE) criterion.

Table 9. The Last 12 Real and ANFIS Forecast Gas Oil Consumption for 2009 & 2010

Month	Forecasted data 2009	Real data 2009	Forecasted data 2010	Real data 2010
March	124190000	216782070	120660000	198636220
April	162080000	249397790	153900000	228914540
May	168000000	252209490	173030000	244314720
June	182710000	264018630	222970000	292081380
July	170120000	257551720	198820000	272504880
August	188950000	272172560	179260000	256321640
September	183340000	267474300	174840000	252600000
October	190840000	272916300	192180000	267503400
November	241820000	320261700	175000000	252600000
December	174160000	261216000	165540000	242496000
January	181300000	267474300	169970000	244769400
February	187360000	272100000	136870000	207889800

Table 10. ANFIS Forecast Gas Oil Consumption for 2011 & 2012

Month	Forecasted data 2011	Forecasted data 2012
March	136870000	179710000
April	175690000	161210000
May	136870000	179710000
June	175690000	161210000
July	136870000	179710000
August	175690000	161210000
September	136870000	179710000
October	175690000	161210000
November	136870000	179710000
December	175690000	161210000
January	136870000	179710000
February	175690000	161210000

Table 11. The Last 12 Real and ANFIS Forecast Gas Oil Price for 2009 & 2010

Month	Forecasted data 2009	Real data 2009	Forecasted data 2010	Real data 2010
March	11006000000	17559347670	34957000000	130503996540.00
April	14108000000	20201220990	30907000000	150396852780.00
May	14410000000	20428968690	28633000000	160514771040.00
June	15824000000	21385509030	28295000000	191897466660.00
July	14789000000	20861689320	25997000000	179035706160.00
August	16746000000	22045977360	24468000000	168403317480.00
September	16477000000	21665418300	23654000000	165958200000.00
October	17370000000	22106220300	23577000000	175749733800.00
November	22779000000	25941197700	22524000000	165958200000.00
December	16230000000	21158496000	21720000000	159319872000.00
January	17165000000	21665418300	21403000000	160813495800.00
February	17977000000	22040100000	19491000000	136583598600.00

Table 12. Forecast Gas Oil Price for 2011 & 2012

Month	Forecasted data 2011	Forecasted data 2012
March	19491000000	16519000000
April	21123000000	16403000000
May	19491000000	*16519000000*
June	21123000000	16403000000
July	19491000000	16519000000
August	21123000000	16403000000
September	19491000000	16519000000
October	21123000000	16403000000
November	19491000000	16519000000
December	21123000000	16403000000
January	19491000000	16519000000
February	21123000000	16403000000

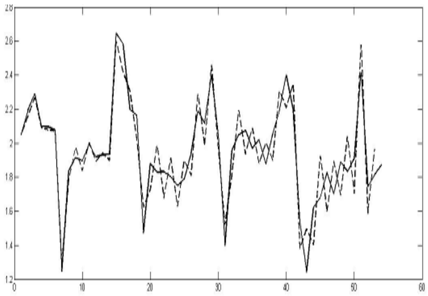

Figure 5-a. Plot of 57 Real and ANFIS-Forecasted Gas Oil Consumption for 2009
Full Line= Real Dotted Line= Forecasts

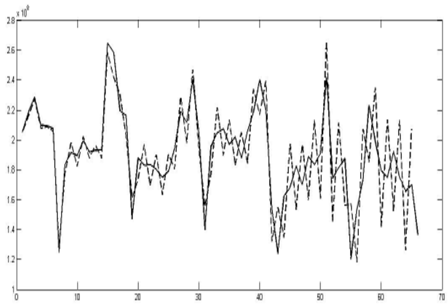

Figure 5-b. Plot of 69 Real and ANFIS-Forecasted Gas Oil Consumption for 2010
Full Line = Real Dotted Line = Forecasts

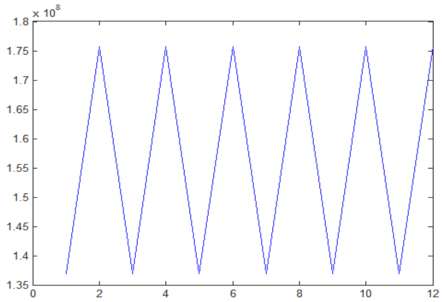

Figure 6-a. Plot of ANFIS-Forecasted Gas Oil Consumption for 2011

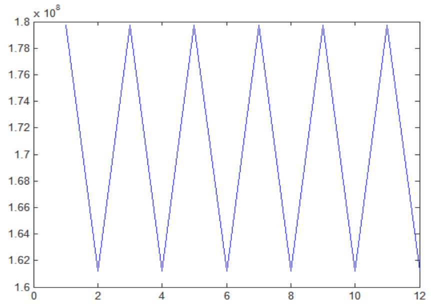

Figure 6-b. Plot of ANFIS-Forecasted Gas Oil Consumption for 2012

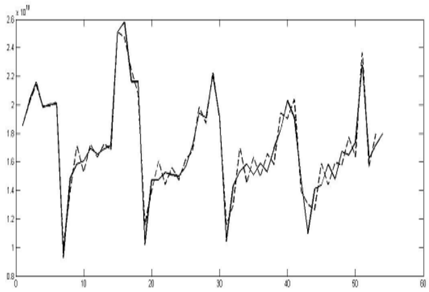

Figure 7-a. Plot of 57 Real and ANFIS-Forecasted Gas Oil Price for 2009
Full Line= Real Dotted Line= Forecasts

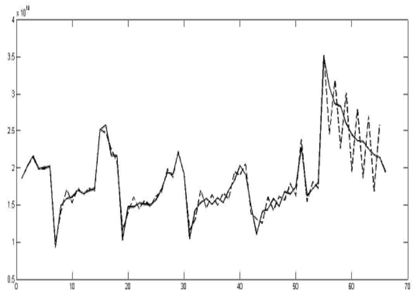

Figure 7-b. Plot of 69 Real and ANFIS-Forecasted Gas Oil Price for 2010
Full Line= Real Dotted Line= Forecasts

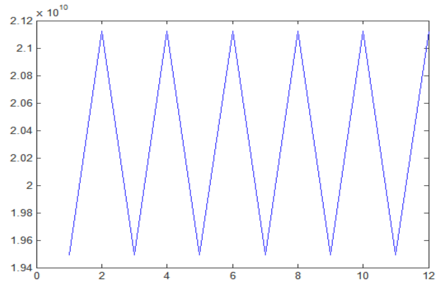

Figure 8-a. Plot of ANFIS-Forecasted Gas Oil Price for 2011

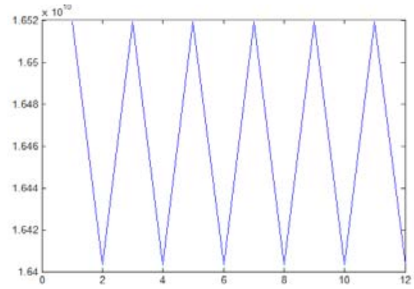

Figure 8-b. Plot of ANFIS-Forecasted Gas Oil Price for 2012

5. ANN & ANFIS Performance Evaluation and Comparison

In this section, the mean squared error (MSE) of a forecast is used as a measure to evaluate and compare the performances of the proposed methodologies, where the error or residual (e_i) is defined the difference between the real and the forecast data and MSE is obtained by

$$MSE = \frac{\sum_{i=1}^{n} e_i^2}{n} \quad (3)$$

As previously discussed, high accuracy of the forecasting methods is desired and lower MSE represents better performance of a forecasting procedure (Wheelwright and Makridakis 1985).

Based on available data on the price and consumption of gas oil, petrol, and liquid petroleum gas in 2009 and 2010 and the forecast results obtained by the proposed ANN and ANFIS methods in these years, MSE as well as the error percentage of both methods are obtained and are summarized in Tables 13-16. The results in Tables 13-16 show that while both methods are quite capable of forecasting energy price and consumption due to their low MSE and error percentages, the ANFIS method has lower error than ANN in most of the cases.

Table 13. MSE for ANN and ANFIS, 2009

Type of Energy Data/Method	ANN	ANFIS
Petrol Consumption	1.40E+10	1.05E+10
Petrol Price	7.33E+14	7.63E+14
Liquid Petroleum Gas Consumption	7.52E+11	2.51E+10
Liquid Petroleum Gas Price	1.89E+15	2.88E+14
Gas Oil Consumption	6.82E+14	5.73E+14
Gas Oil Price	1.27E+18	2.77E+18

Table 14. Percentage Errors for ANN and ANFIS, 2009

Type of Energy Data/Method	ANN	ANFIS
Petrol Consumption	0.0009	0.0006
Petrol Price	0.0005	0.0002
Liquid Petroleum Gas Consumption	0.0012	0.0003
Liquid Petroleum Gas Price	0.0039	0.0004
Gas Oil Consumption	0.0407	0.0211
Gas Oil Price	0.0154	0.0116

Table 15. MSE for ANN and ANFIS, 2010

Type of Energy Data/Method	ANN	ANFIS
Petrol Consumption	1.06E+10	9.63E+09
Petrol Price	3.68E+15	1.47E+15
Liquid Petroleum Gas Consumption	5.32E+10	3.43E+10
Liquid Petroleum Gas Price	5.52E+14	7.96E+14
Gas Oil Consumption	3.98E+11	7.67E+14
Gas Oil Price	6.77E+14	3.95E+18

Table 16. Percentage Errors for ANN and ANFIS

Type of Energy Data/Method	ANN	ANFIS
Petrol Consumption	0.0006	0.0005
Petrol Price	0.0052	0.0004
Liquid Petroleum Gas Consumption	0.0064	0.0005
Liquid Petroleum Gas Price	0.0009	0.0009
Gas Oil Consumption	0.003	0.0295
Gas Oil Price	0.0537	0.0144

6. Conclusions and Future Works

This research concentrated on forecasting of energy price and consumption of Iranian industrial sector based on Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference System. Considering that energy plays a significant role in managing and governing a country, providing an optimal model and more accurate than classical existing methods for forecasting monthly energy prices and consumptions of Gas Oil, Petrol, and Liquid Petroleum Gas was the main objective of this research. Moreover, a comparison between ANN and ANFIS performance in prediction was another objective.

Due to some abrupt changes in Iranian economic after fall 2010, the trend of data in this year was different from the past data trend. Thus, the work was divided into three parts in order to achieve better result. The parts included price and consumption forecasting of 2009, 2010, and 2011-2012, separately. The database encompassed the monthly energy price and consumption from March 1996 to February 2010, where they were collected from two different sources. The models were developed based on real data in MATLAB software environment using Neural Networks and Adaptive Neural Fuzzy Inference System (ANFIS) toolboxes.

A comparison between the two forecasting methods revealed that while both methods were quite capable of forecasting due to their low mean squared errors, the ANFIS procedure had better performance than the ANN method. This conclusion is consistent with the ones made in previous researches.

Some recommendations for future research are:

I. Artificial intelligence can be very useful to forecast other important industrial and commercial factors and indices.

II. Research works similar to this study are recommended for other countries as well.

III. A comparative investigation of forecasting Iranian industrial and commercial indices with the ones of other countries may be another useful research.

IV. Considering artificial intelligence features, more studies and investigations in this field could be fruitful in many parts of engineering activities.

7. Acknowledgment

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Endnote

1. Learning MATLAB, Student Version (Version 6), by Math Works INC. 2001. Available: http://www.mathwork.com/

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