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Analysis Of The Influence Of Holidays On Short Term Natural Gas Consumption in Iran Based on Artificial Neural Network

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Abstract

In this paper, levels of gas consumption in domestic sector are estimated by using artificial neural networks (ANN) model. This article aims to study the effect of holidays on energy consumption. To this end we have defined models with different structures. For assessing the accuracy of the models the MAPE (Mean Absolute Percentage Error) has been used which comparison of these numbers for training sets show that proposed model has the least error. Also consumption estimations using this model for test sets compared to real data display the efficiency of the mentioned model according to ANN for gas consumption in Iran.

Keywords
Short-term consumption, natural gas, household, artificial neural network

1. Introduction
Energy is one of the key determinates for economic growth [1]. The growth in energy consumption is intrinsically linked to the growth in the economy [2]. When the economic structure changes, it can also have a bearing on energy supply and demand situation [1].

Natural gas is less polluting than other fuel and it is the best fuel in residential sector for heating space, cooking and water heating. Also in Iran, natural gas is fourteen times cheaper than electricity. This caused 34 times increase within 1975 to 2002 in Iran, the consumption of natural gas has increased and the consumption of other fuel has increased three times. On the other hand, high subsidies of energy makes natural gas in Iran among one of the cheapest in the world (Figure1) and low prices of energy represent an effective incentive for inefficient consumption.

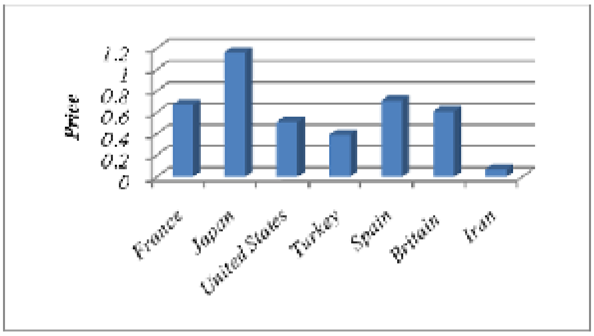

Figure 1 - Natural gas prices for houshold sector at 2006 year- [3]
(U.S. dollars per cubic meter)

The share of gas in Iran's energy basket is over 60% and table1 shows over 64% of consumption of natural gas is in domestic household and commercial sector.

Table 1- Percentage of natural gas consumption

Consumption type	2001	2002	2003	2004	2005
Residential/commercial	65	63.8	62.7	62.1	65.6
Petrochemical fuel	5.7	6.6	6.5	6.1	5.4
Industry	18.1	18.8	18.1	19.5	21.3
Transport	0.01	0.02	0.2	0.5	0.8
Petrochemical feed	7.9	7.5	6.6	6.3	6.9
Acidic gases	3.2	3.3	5.9	5.5	-
Total	100	100	100	100	100

Gas consumption has increased over 10% annually in the past decade [4]. According to the increasing demand of natural gas, demand function estimation is really essential. After a sudden decrease in temperature in June 2008 and subsequently increase in demand, we witnessed low pressure and gas cut in some parts of country. Iran, the country having the second largest gas reserves in the world was not able to meet the domestic need; this issue was not due to inadequate production however it was mainly caused by failing to forecast the demand. It recognizes that this estimation is essential and allows us to adopt an effective energy consumption policy for the future.

There are lots of studies about energy all over the world. A.E.Akinlo has considered the casual relationship between energy consumption and economic growth of eleven countries in sub-Saharan Africa and has used the autoregressive distributed lag (ARDL) bounds test [5]. Nicas M.Christodoulakis has forecasted energy consumption and has assessed the quantitative effects on energy consumption and co_2 emissions [6]. Shaligram Poklarel has used static long-linear Gobb-Douglas function to develop econometric models for energy consumption in Nepal [1]. F. Gerard Adams has built an econometric model of the Chinese energy economy based on the energy balance and uses that model to forecast to 2020 Chinese energy consumption and imports [7].

Primoz Potocnik has accomplished the forecasting of future gas consumption in Slovenia by using some risk models [8]. Dejan Ivezic has forecasted short-term natural gas consumption of Belgrade and has used multilayer artificial neural network models. Qualities of proposed networks were tested with real data for specific urban consumption area [9]. Jakub Siemek has estimated natural gas consumption in 2002-2050 in Poland based on the logistic-Curve interpretation [10]. Ondrej Konar has used a statistical model for natural gas consumption estimation of individual residential and small commercial customers. This model is a nonlinear regression model with individual customer effect, typical time-dynamics part and the temperature correction [11]. R. Gutierrez has examined the possibilities of using a SGIDP as a stochastic growth model of natural gas consumption in Spain, and compared their result with those obtained by stochastic logistic innovation modeling and using a stochastic lognormal growth model based on the non-innovation diffusion process [12].

In this study we forecast Iran's short-term natural gas consumption using the ANN model. Research has shown, holidays can enormously affect energy consumption [9]. The United State has 9 national holidays; Italy, France and Turkey have 12, Japan 14, Australia and Indian seven. Iran has 27 national holidays; this in addition to Fridays means that Iran is among the countries with so many holidays. Therefore, the number of holidays is a fundamental factor in Iran's natural gas consumption which we consider the effects in this paper.

2. Methodology

Different methods are implemented to analyze energy systems. Estimation models, basically based on extrapolation of trends in historical data are used for long, middle or short-term effect analysis of performance. Recently intelligent tools based on Artificial Intelligence (AI) technology are becoming more and more popular for solving complicated problems in different sectors. Artificial neural networks (ANN), one of the two main branches of AI, are used in modeling and estimating energy engineering systems.

The ANNs are suitable for tasks involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems where humans usually decide on an intuitional basis. ANNs learn by example, and able to deal with linear and non-linear problems [13]. The disadvantage is that because the network finds out how to solve the problem itself and its operation can be unpredictable [14].

ANNs consist of an inter-connection of a number of neurons. There are many varieties of connections under study, however, here; we will discuss only one type of network, which is called the multi-layer perceptron (MLP). In this network, the data flows forward to the output continuously without any feedback. Fig. 2 shows a typical multi-layer feed forward model.

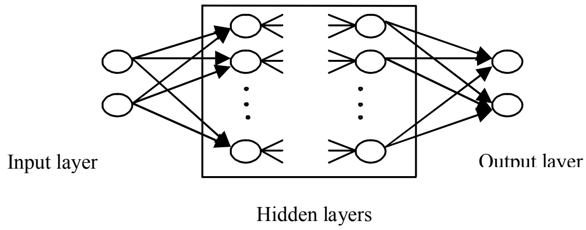

Figure2- A model of multilayer neural-

Input layer of neural networks is the first layer in the network which has the input information. The number of input nodes is dependent on input parameters. Hidden or middle layers are the layers which are placed between input and output layers in the network and are used to process the data received from input nodes by nonlinear transfer functions. The outcome is estimation of the future amount. The model can be written as:

$$y_t = \alpha 0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j} \right) + et \qquad (1)$$

Where m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function, such as the logistic function : $f(x) = \frac{1}{1+e^{-x}}$; $\left\{ x_j, j = 0,\ldots,n \right\}$ is a vector of weights from the hidden to the output nodes and $\{\beta_{ij}$, $i = 1, 2, \ldots, m$; $j = 0, 1, \ldots, n\}$ are weights from the input to the hidden nodes. α_0 and β_{oj} are the weights of arcs leading from the bias terms, which have values always equal to 1. Note that Eq. (1) indicates a linear transfer function employed for the output node as desired for forecasting problems.

There are 3 steps in solving a neural network problem: 1) training 2) generalization 3) implementation [15,16]

A training set is a group of matched input and output patterns used for training the networks, usually by suitable adaptation of the synaptic weights. The outputs are the dependent variables that the network produces for the corresponding input. It is important that all the information the network needs to learn is supplied to the network as a data set. When each pattern is read, the network uses the input data to produce an output, which is then compared with the training pattern, i.e., the correct or desired output [13]. One complete presentation of the entire training set is called on epoch. The learning process is usually performed on an epoch-by-epoch basis until the weights stabilize and the sum of squared errors converges to some minimum value. Generalization or testing evaluates the network's ability to extract a feasible solution when the inputs are previously unknown to the network and have not been used to train the network. We determine how closely the actual output of the network matches the desired output in new situations [9].

The forecasting model for energy consumption should be provided and applied to data validation in order to obtain an estimation forecasting error. The set of influential parameters that are expected to have an influence on the forecasting should be collected. The forecasting model is predominantly based on observation of consumption in previous day, weather conditions, day of week, and so on. The comparison of past gas consumption shows that in Iran the consumption of natural gas has been dependent on the purpose of holiday. Therefore, we have identified some celebrated holidays such as Norouz, Fitr Eid…etc, which they are celebrated in Iran, with 1 also there are some other holidays such as martyrdom anniversary of Imams which are not celebrated. Those holidays were distinguished with 0. In this study, using Matlab a computer program has been designed for the ANN model algorithm.

3. Result and Discussion

The consumption of natural gas in household is considered, in this study. The consumption of natural gas in winter is enormously higher than summer. This shows temperature is one of the most important components in consumption, it means in residential sector a greater part of natural gas is used for heating purposes. We cannot assess minimum and maximum temperature for Iran. Tehran is the capital of Iran and also the biggest consumer. Therefore we have considered the natural gas consumption of Tehran, as a case study.

In natural gas network systems such information is not important for system operation because network itself has some abilities to find relationship between variables. This paper examines the casual relationship between natural gas consumption and different variables for Iran. To this end, we have written some models with different inputs. We can evaluate the effects of each input separately. The model structures are shown in table 2:

Table2-Structure models

Model	Inputs
1	Day of week, max and min temperature, last year consumption
2	Day of week, max and min temperature, last year consumption, holiday
3	Day of week, max and min temperature, last year consumption, humidity
4	Day of week, max and min temperature, holiday, humidity, last year

Considering the models in subject matter literature, most models use the variables such as day of the week, temperature, the consumption level the day or the year before. Hence the model 1 is based on reference models. Considering the length of pipelines in Iran and the fact that 42 hours is required to transfer the gas from refinery to Tehran, the consumption level of the day before is of no usage in this model. However the aim of this project is to assess the new holiday and atmospheric moisture variables which are separately embedded in model 2 and 3. Also model 4 evaluates both variables simultaneously.

We used the data from 21/3/2007 to 19/2/2008 as a training set. Information about weather condition covered by Islamic Republic of Iran Meteorological organization [17] and daily consumption figures were also available [18]. For data pre-process and in order to ease the network learning, the intended data are normalized which indicate that the input and output data are in the (0,1) interval. Program efficiency for every model is evaluated by training sets. To this end, the average percentage of relative percentage error simulated data after the process of network learning is calculated via the below mentioned relation.

$$E = 1 / N \sum_{i=1}^{N} \frac{| Y - Y_{actual} |}{Y_{actual}} * 100\% \tag{2}$$

We selected a three-layered feed forward network and For each model, different number of neurons in hidden layer was tested and the minimum percentage of forecasting errors by month for the period which was covered by aggregated training set is given in table3:

Table 3-Average persentage forecast errors by training set

Month	*Model1*	*Model2*	*Model3*	*Model4*	Month	Model1	Model2	Model3	Model4
April	0.0228	0.0343	0.0444	0.0189	October	0.3961	0.2642	0.4793	0.264
May	7.4374	5.3059	0.6472	0.0214	November	0.0679	0.0259	0.0063	0.1437
June	0.0777	0.0773	0.4035	0.1809	December	0.0024	0.1917	0.2741	0.0848
July	0.066	0.0614	0.109	0.2463	January	0.0058	0.1013	0.1353	0.045
August	0.192	0.1806	1.0931	0.0321	February	0.0062	0.0188	0.3361	0.0171

September	0.1515	0.0769	0.5339	0.424	Total	0.6679	0.2175	0.4053	0.0791

Obtained results on training sets are relatively acceptable and as it is displayed in table 2, considering the factor of holidays in most months the MAPE is decreased and the sum error is significantly decreased as well. Also the atmospheric moisture factor can decrease the error but this does not have a great effect since the temperature is considered. Model 4 can be considered as the most efficient method which its error compared to model 1 has decrease to 0.07% from 0.66%.

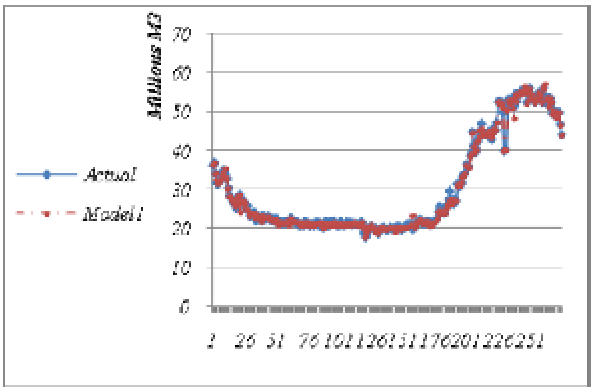

Figure 3- Real and forecasting consumption by training test

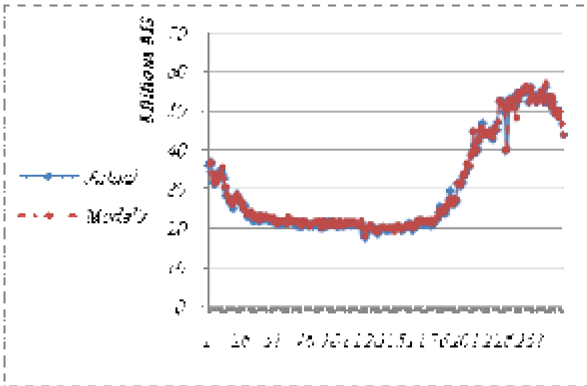

Figure 4-Real and forecasting consumption by training test

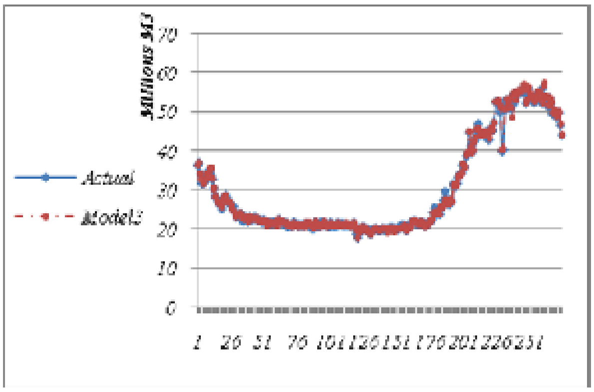

Figure 5- Real and forecasting consumption by training set

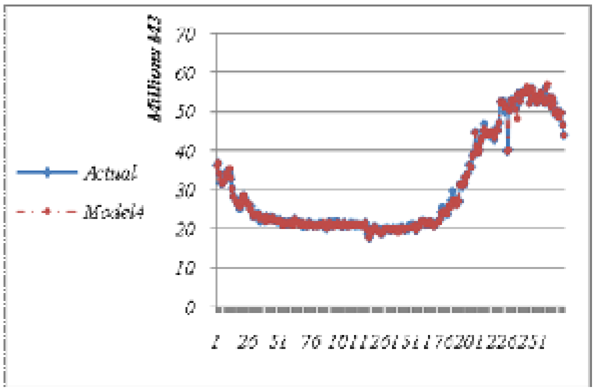

Figure 6 - Real and forecasting consumption by training set

Therefore we can use a holiday and humidity as important components of natural gas consumption. Thus model (4) is the most comprehensive model among them. We used this model to forecast natural gas consumption and also tested a designed ANN with real data from 20/2/2008 to 18/3/2008. The average percentage of forecasting error calculated in this period was 5.88%.

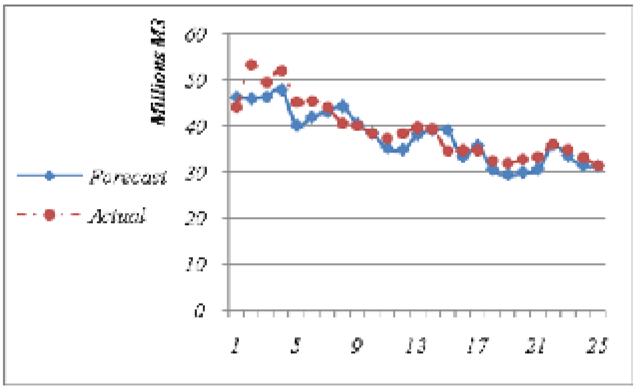

Figure 7- Real and forecasting consumption on testing set

4. Conclusion

Economic growth and energy demand are closely related. As the energy demand increases, prediction of energy consumption in different sectors is becoming more and more essential. This study aims to examine the short- term natural gas consumption of Iran by residential sector. For this propose we used artificial neural network and applied four models by various factors as inputs. The following important factors in the natural gas consumption such as the consumption of natural gas in last year, temperature, a day of week, humidity and holiday have been considered.

Results from training data sets indicate that the model is sensitive to newly defined holiday and moisture variables and the MAPE in models including both variables have been increased to 0.07 % from 0.66% in early reference models. Also in order to apply defined models results for test data sets from model estimations were compared with real data. Results of the data which was accomplished during period from 2007 to 2008 show that in most points the forecasting data are near to actual figures which proves that our model suitable for Iran.

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