Forecasting of petroleum-based energy consumption in Iran using Artificial Neural Network (ANN)

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Abstract
Petroleum-based resources provide different products including transportation fuels, fuel oils for heating and electricity generation, asphalt and road oil, and the feedstocks used to make chemicals, plastics, and synthetic materials found in nearly everything we use today. Optimal prediction and forecasting of petroleum-based resource consumption would help energy policy makers and practitioners to take appropriate strategic decisions in this sector. In this paper, an Artificial Neural network (ANN) approach is proposed to optimum forecasting of petroleum-based energy consumption in Iran. Oil and natural gas together make petroleum. The most important and effective environmental and economic factors in petroleum resource consumption are considered in the applied ANN. The ANN trains and tests data with Multi-Layer Perceptron (MLP) approach which has the lowest mean absolute percentage error (MAPE). The obtained results justify the efficiency of the proposed approach in prediction of petroleum-based energy consumption.

Keywords: Petroleum-based resources, Strategic decision making, Artificial neural network, Prediction and forecasting.

1. Introduction
Energy consumption has increased remarkably over the past decades all over world due to the increasing population and the economic development. Energy is considered as an important factor in the economic and social development of a country and consequently in the people’s wealth. Energy consumption predictions are essential and are required in the studies of capacity expansion, energy supply strategy, capital investment, revenue analysis and market research management. Energy consumption and emissions of the world are increasing at alarming rates. Continued carbon dioxide, carbon mono oxide and nitrogen oxide emissions are likely to lead to catastrophic problems such as the greenhouse effect. These emissions are driven by several factors, the most prominent being energy consumption from fossil fuels and the level of economic activity. Hence, efforts have been made to analyze the energy consumption and carbon dioxide, carbon mono oxide and nitrogen oxide emissions in different countries or regions of the world. Several studies considered the relationship between energy consumption and these emissions (Chang, 2010; Fei et al., 2011).
Energy is broadly classified into two main groups: Renewable and Non-renewable. Renewable energy is the energy which is generated from natural sources i.e. sun, wind, rain, tides and can be generated again and again as and when required. They are available in plenty and by far most the cleanest sources of energy available on this planet. According to the 2009 International Energy Outlook by the Energy Information Administration, ‘‘Renewables are the fastest growing source of world energy with consumption increasing by 3.0 percent per year’’. The increased attention on renewable energy sources can be attributed to a number of factors. The recent concerns over the volatility of oil prices and the environmental consequences of carbon emissions are all contributing factors to the current interest in renewable energy sources. Moreover, the emergence of government policies such as renewable energy production tax credits, installation rebates for renewable energy systems, renewable energy portfolio standards, and the establishment of markets for renewable energy certificates has been critical in the promotion of renewable energy as a viable component of the energy portfolio for various countries (Bowden and Payne, 2009). Non-Renewable energy is the energy which is taken from the sources that are available on the earth in limited quantity. Non-renewable sources are not environmental friendly and can have serious effect on our health. They are called non-renewable because they cannot be re-generated within a short span of time. Non-renewable sources exist in the form of fossil fuels, natural gas, oil and coal. A

lot of papers studied the relationship between energy consumption with oil and gas price. Wong et al. (2013) examined the elasticities of various types of energy consumption and energy R&D to change in oil prices and income of some OECD countries using the Nerlove partial adjustment model (NPAM). He at al. (2014) analyzed the response behaviors of different customers to typical energy prices. Lee and Chiu (2011a) considered the dynamic relationship among nuclear energy consumption, real oil price, oil consumption, and real income in six highly industrialized countries. Lee and Chiu (2011) considered the short-run dynamics and long-run equilibrium relationships among nuclear energy consumption, oil prices, oil consumptions, and economic growth for developed countries. Sadorsky (2009) examined the relationship between energy consumption, CO2 emissions and oil prices in the G7 countries. Apergis and Payne (2014) explored a long-run integrated relationship between renewable energy consumption, real GDP, carbon emission, real coal prices and real oil prices. Berry (2005) considered renewable energy consumption as a hedge of natural gas price.

The rest of this paper is organized in the following sections. In Section 2, the relevant literature is reviewed. The structure of the proposed ANN method is discussed in Section 3. In Section 4, the obtained results are presented and discussed. Section 5 presents conclusion of this paper.

2. Literature Review

In this section, some papers that examined prediction of energy consumption are introduced. Ekonomou (2010) applied artificial neural network (ANN) to predict the Greek long-term energy consumption. The results of ANN method were compared with the results produced by a linear regression method and a support vector machine method. Conclusions indicate that ANN method outperform the other methods. Apergis and Payne (2010) considered the relationship between renewable energy consumption and economic growth within a multivariate framework. This study reveals a long-run equilibrium relationship between real GDP, renewable energy consumption, real gross fixed capital formation, and labor force with the respective coefficients positive and statistically significant. Say and Yücel (2006) studied the relationship between the total energy consumption (TEC) and total CO2 (TCO2) emission. Regression analysis was performed for modeling the strong relationship between TEC and TCO2. Also, TEC was forecasted as a function of country population and gross national product (GNP). Apergis and Payne (2012) considered the relationship between renewable and non-renewable energy consumption and economic growth within a multivariate framework. This study shows a long-run equilibrium relationship between real GDP, renewable energy consumption, non-renewable energy consumption, real gross fixed capital formation, and the labor force with the respective coefficient estimates positive and statically significant. Ediger and Akar (2007) estimated the future primary energy demand of Turkey using the autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) methods. Results show that ARIMA forecasting of the total primary energy demand is more reliable than the summation of the individual forecasts. Liu et al. (2011) introduced the development status of renewable energy and other main CO2 mitigation options in power generation in China. They also made a preliminary prediction of the development of renewable energy in the country for future decades. Menyah and Wolde-Rufeal (2010) considered the casual relationship between carbon dioxide emissions, renewable and nuclear energy consumption and real GDP for the US. Results of econometric evidence indicate that nuclear energy consumption mitigates CO2 emissions, but renewable energy consumption has not reached a level that can reduce significant amount of emissions.

Apergis and Payne (2011) used multivariate panel data for 88 countries categorized into four panels. They explored a long-run equilibrium relationship between real GDP, coal consumption, real gross fixed capital formation, and the labor force for the high, upper middle, and lower middle income country panels. They also explored bidirectional causality between electricity consumption and economic growth in both the short- and long-run for the high income and upper-middle income country panels. Acaravci and Ozturk (2010) found the long-run relationship between electricity consumption and economic growth in 15 transition countries. Vlahinic-Dizdarevic and Zikovic (2010) examined the causal relationship between energy variables and GDP. The empirical results provide clear support of causality that runs from real GDP growth to all energy variables. Zikovic and Vlahinic-Dizdarevic (2011) found that oil consumption causes economic growth in less developed countries, while economic growth causes oil consumption in highly developed European countries. Chontanawat et al. (2006) tested causality between energy and GDP for some OECD and non-OECD countries. They found that causality from aggregate energy consumption to GDP and from GDP to energy consumption is more prevalent in the developed OECD countries compared to the developing non-OECD countries. Narayan and Prasad (2008) considered the relationship between electricity consumption and real GDP for 30 OECD countries. They found that electricity consumption causes real GDP in eight countries. The results indicate that electricity conservation policies negatively impact real GDP in these countries.

3. Structure of the proposed ANN approach

Artificial neural networks are accounted as mathematical models for modeling of sophisticated systems. They can be used for classification and regression problems. These networks are huge complexes of parallel processors called Neuron which are acting coordinately for problem solving and transfer the data through synapses. Transferring the input data into the meaningful outputs is the aim of neural network. These networks have got the ability to learn and system learns to revise its errors through some algorithms. Learning is done in a comparative way in these systems, i.e. through the examples the synapses weight is changed in way that system will give a reasonable answer in case of new input data (Basheer and Hajmeer, 2000). Neural networks are non-linear learning mathematical systems. In fact, neural networks may be used in problems in which there is no certain correlation between inputs and outputs. Relative position of cells in networks (numbers and grouping and connection type) is called topology or network architecture. In fact, topology is the hardware connection of neurons to each other which is paired with respective software (mathematical method of data flow and weights estimation) will nominate the functionality of the neural network.

Artificial neural networks include three layers called input layer, hidden layer and output layer. The input layer shows the input of the model and the output layer shows the output of the model. The hidden layer is built out of some nodes that try to map the input model on the outputs in the optimization process. There exist many architectonics for the neural networks, but there is a special emphasis on the most used one (the multi-layer perceptron (MLP)) in this investigation. This model can be written as (1):

$$y_t = a_0 + \sum_{j=1}^{n} a_j f\left(\sum_{i=1}^{m} \beta_{ij}\, y_{t-1} + \beta_{0j}\right) + \varepsilon_t$$

Where m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function. {αj, j = 0, 1, …, n} is a vector of weights from the hidden to output nodes and {βij, i = 1, 2, …, m; j = 0, 1, …, n} are weights from the input to hidden nodes. α0 and β0j are weights of arcs leading from the bias terms which have values always equal to 1. Note that Equation (1) indicates a linear transfer function is employed in the output node as desired for forecasting problems. Therefore, we use sigmoid and linear transfer functions in hidden and output layers, respectively. The MLP's most popular learning rule is the error back propagation algorithm. Back Propagation learning is a kind of supervised learning introduced by Werbos (Werbos, 1974). At the beginning of the learning stage all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input–desired output pattern pairs. Each input–output pair is obtained by the offline processing of historical data. These pairs are used to adjust the weights in the network to minimize the sum squared error (SSE) which measures the difference between the real and the desired values over all output neurons and all learning patterns. After computing SSE, the back propagation step computes the corrections to be applied to the weights. The ANN models are researched in connection with many power system applications, short-term forecasting being one of the most typical areas. Most of the suggested models use MLP networks (Park et al., 1991). The attraction of MLP has been explained by the ability of the network to learn complex relationships between input and output patterns, which would be difficult to model with conventional algorithmic methods.

There are three steps in solving an ANN problem which are (1) training, (2) generalization and (3) implementation. Training is a process that network learns to recognize present pattern from input data set. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. For this reason, each ANN uses a set of training rules that define training method. Generalization or test evaluates network ability in order to extract a feasible solution when the inputs are unknown to network and are not trained to network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process the values of inter-connection weights are adjusted so that the network produces a better approximation of the desired output. ANNs learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself and its operation can be unpredictable. In this paper the effort is made to identify the best fitted network for the desired model according to the characteristics of the problem and ANN features.

At the present work, the most important and effective factors which have direct impact on petroleum resource consumption are considered. These factors are partitioned into two components including environmental and economic factors. Environmental factors consist of emission of the most important greenhouse gases including carbon dioxide, carbon monoxide, and nitrogen oxide. Economic factors include oil price, gas price, and GDP. Output values include petroleum resource consumption over the monthly periods.

4. Results and Discussion

In order to recognize the number of first and second neurons in hidden layers, several MLP networks are generated and tested. The transfer function for the first layer and all hidden layers are sigmoid and for the last one is linear. Back propagation (BP) algorithm is used to adjust the learning procedure. Table 1 shows different MLP specifications and MAPE results for petroleum resource consumption in Iran.

According to Table 1, the best structure of the ANN method is related to iteration 5 of the table. In other words, for the used data of the studied case, the best numbers of neurons in the first and second hidden layers are 4 and 3, respectively.

Table 1: Different MLP specifications for petroleum resource consumption

MLP model number	1	2	3	4	5	6	7	8	9	10
Number of neurons in the first hidden layer	3	3	4	4	4	5	5	6	6	8
Number of neurons in the second hidden layer	1	2	1	2	3	1	2	2	3	2
Learning method	BP	BP	BP	BP	BP	BP	BP	BP	BP	BP
MAPE (%)	2.47	5.27	4.11	4.08	**2.19***	3.28	3.27	2.81	3.39	6.09

The MAPE is calculated as follows:

$$\text{MAPE}(\%) = \frac{\sum_{t=1}^{n} |x_t - x'_t / x_t|}{n} \times 100$$

The data for 20 periods (months) is considered to test the efficiency of the proposed ANN model. The MAPE of the prediction for the test data is %2.09 which is an acceptable and reasonable amount of error.

5. Conclusion

Planning for utilization of petroleum-based energy resources is needed to an efficient tool for prediction of petroleum resource consumption. Artificial Neural Networks have proved their capabilities as a precious prediction tool in real world applications. In this paper, the ANN model for prediction of petroleum resource consumption is presented. For this model a number of effective input parameters were introduced and applied in the structure of ANN model. Considering the literature, the most important environmental and economic factors are considered for optimal prediction and forecasting of petroleum resource consumption. Environmental factors consist of emission of the most important greenhouse gases including carbon dioxide, carbon monoxide, and nitrogen oxide. Economic factors include oil price, gas price, and GDP. Output values include petroleum resource consumption over the monthly periods. The acquired results show the applicability of the proposed ANN model in optimal prediction and forecasting of petroleum-based energy consumption. Also, the proposed approach has a general structure which could be applied for forecasting purposes in different areas.

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