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A Multi-level Artificial Neural Network for Residential and Commercial Energy Demand Forecast: Iran Case Study

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Abstract. This paper presents a neuro-based approach for Iran annual residential and commercial energy demand forecasting by several socio-economic indicators. In order to analyze the influence of economic and social indicators on the residential and commercial energy demand, gross domestic product (GDP), total number of households, energy prices and investment for construction are selected. This approach is structured as a multi-level artificial neural network (ANN) based on supervised multi-layer perceptron (MLP), trained with the back-propagation (BP) algorithm. This multi-level ANN is designed properly. This paper indeed proposed a multi-level network by which the inputs to the ending level are obtained as outputs of the starting levels. Actual data of Iran from 1967-2007 is used to train the multi-level ANN and illustrate capability of the approach in this regard. Comparison of the model predictions with data of the evaluation stage shows validity of the model. Furthermore, the energy demand for the period of 2008 to 2020 is estimated.

Keywords: ANN, MLP, BP algorithm, Forecasting, Energy demand, Residential and commercial sectors

1. Introduction

Energy is central to achieving the interrelated economic, social and environmental goals toward sustainable development of each country. As the total number of households and standard of living increase, the demand for energy is also increasing. The fast growth on the GDP per capita leads the energy demand for residential and commercial to increase. Residential and commercial sectors takes the biggest shares in energy consumption in Iran; achieving to about 35% of the total energy consumption. Thus, residential and commercial energy demand forecasting becomes an essential function in planning for the future to design more efficient systems and control the demand by a proper price mechanism as well.

Various technical and statistical methods for energy forecasting have been proposed in the last few decades with varying results. However, no technique or combination of techniques has been consistently successful enough to forecast energy demand. On the other hand, ANNs are being used extensively in forecasting different types of energy demands. ANNs have been applied to the energy forecasting problem with considerable success. There is some evidence that an ANN yields more useful insights than a regression based model and that ANNs architecture used to forecast energy demands presents higher accuracy than a traditional polynomial fit method [1]. The applications of artificial neural networks for energy forecasting problems have resulted in several research papers. In 2002 Kermanshahi and Iwamiya have developed an artificial neural networks model to predict the peak electric load in Japan up to 2020 [2]. Hsu and Chen have

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collected empirical data to formulate an artificial neural network model to predict the regional peak load of Taiwan in 2003 [3]. In this year a neural network approach has been formulated for the gasoline consumption prediction in Lebanon by Nasr, Badr and Joun [1]. In 2006 Murat and Ceylan have developed a model based on artificial neural network for the prediction of transport energy demand in Turkey [4]. In 2008 Azadeh, Ghaderi and Sohrabkhani have formulated a neural network model to predict the annual electricity consumption in high energy consuming industrial sectors in Iran [5].

In this paper residential and commercial energy demand of Iran is forecasted using MLP trained by BP algorithm considering economic and social indicators for the time span 2008 to 2020. For the estimation, time series data covering the period 1967 to 2007 are used. The remaining parts of the paper are organized as follows. In section 2, ANNs are introduced. Details of the proposed forecast strategy and numerical results are described in section 3. A brief review of the paper and future research are given in section 4.

2. Artificial Neural Networks

ANNs are computational modeling tools that have recently emerged and found extensive acceptance in many disciplines for modeling complex real-world problems. In an ANN model, a neuron is an elemental processing unit that forms part of a larger network. ANNs consist of an inter-connection of a number of neurons. There are many varieties of connections under study, however, here, only one type of network, which is called the multi-layer perceptron (MLP) will be discussed. A MLP consists of (i) input variables, (ii) an output layer with nodes representing the dependent variables (i.e., what is being modeled), and (iii) one or more hidden layers containing nodes to help capture the nonlinearity in the data. Using supervised learning, these networks can learn the mapping from one data space to other using examples. In MLPs, the data are fed forward into the network without feedback. These networks are so versatile and can be used for forecasting.

To build a model for forecasting, the network is processed through three stages: (1) The training stage where the network is trained to predict future data based on past and present data. (2) The testing stage where the network is tested to stop training or to keep in training. (3) The evaluation stage where the network ceases training and is used to forecast future data and to calculate different measures of error.

The MLPs most popular learning rule is the error BP algorithm. BP learning is a kind of supervised learning introduced by Werbos and later developed by Rumelhart and McClelland [6]. 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, target pattern pairs. Each input–output pair is obtained by 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 target values over all output neurons and all learning patterns. After computing SSE, the backpropagation step computes the corrections to be applied to the weights.

3. The multi-level ANN model development and application

In this section residential and commercial energy demand of Iran from 2008 to 2020 is forecasted regarding socio-economic indicators using a multi-level ANN model. The structure of the designed multi-level ANN is given in Fig. 1. The main ANN (ANN7) takes investment for construction, total number of households, GDP, natural gas price, gas oil price, kerosene price, dummy1 (which indicates the especial conditions of the country in the revolution years and the years just after the war), dummy 2 (which indicates the effect of development of natural gas systems in Iran) and residential and commercial energy demand in the last year as inputs and produces the residential and commercial energy demand. The inputs to ending level are obtained as outputs of the starting levels. The investment for construction, total number of households, GDP, natural gas price, gas oil price and kerosene price are forecasted using ANNs.

Data related with residential and commercial energy demand modeling have been collected from different sources. The investment for construction has been collected from Institute for International Energy Studies (IIES). Natural gas price, gas oil price and kerosene price have been collected from National Iranian Oil Products Distribution Company (NIOPDC). GDP and residential and commercial energy consumption have been collected from Iran Ministry of Energy and the total number of households has been collected from Statistical Center of Iran. All values given for the economic variables are normalized based on the fixed prices of 1997 (1997=100). Table 1 summarizes the ANNs inputs and output.

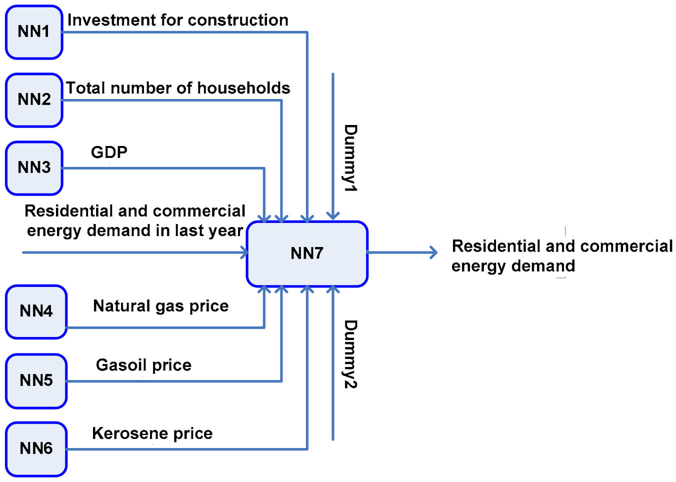

Fig. 1: Structure of the designed multi-level ANN

TABLE I. ANNS INPUTS AND OUTPUT.

ANN	Inputs	Output
1	1- Growth rate of investment for construction in the last year 2- Growth rate of investment for construction in two last years	Investment for construction
2	1- Growth rate of total number of households in the last year 2- Growth rate of total number of households in two last years	total number of households
3	1- Growth rate of GDP in the last year 2- Growth rate of GDP in two last years	GDP
4	1- Growth rate of natural gas price in the last year 2- Growth rate of natural gas price in two last years	natural gas price
5	1- Growth rate of gas oil price in the last year 2- Growth rate of gas oil price in two last years	gas oil price
6	1- Growth rate of kerosene price in the last year 2- Growth rate of kerosene price in two last years	kerosene price
7	1- investment for construction, 2- total number of households, 3- GDP, 4- natural gas price, 5- gas oil price, 6- kerosene price, 7- dummy1, 8-dummy 2, 9- residential and commercial energy demand in the last year	residential and commercial energy demand

The study spans the time period from 1967 to 2007. This period is used to train, test and evaluate the ANN models. The training of the models is based on a 33 year training set, 1967 to 1999, while the test stage covers the period between 2003 and 2007. Also, the evaluation stage covers the period from 2000 to 2002. All data are normalized before to be applied to each ANN.

Normalization (scaling) of data within a uniform range (e.g., 0–1) is essential (i) to prevent larger numbers from overriding smaller ones, and (ii) to prevent premature saturation of hidden nodes, which impedes the learning process. This is especially true when actual input data take large values. There is no one standard procedure for normalizing inputs and outputs. One way is to scale input and output variables (z_i) in interval $[\lambda_1, \lambda_2]$ corresponding to the range of the transfer function [7]:

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

where x_i is the normalized value of z_i , and $z_i^{\max}$ and $z_i^{\min}$ are the maximum and minimum values of z_i in the database.

A computer program, written in MATLAB programming language, is used for estimating investment for construction, total number of households, GDP, natural gas price, gas oil price, kerosene price and residential and commercial energy demand. The implementation procedure for ANNs is as follows:

1. Divide the available data into training, test and validation set.
2. Select architecture and training parameters.
3. Train the model using the training set.
4. Test the model using the test set.

5. Repeat steps 2 through 4 using different architectures and training parameters.

6. Select the best network architecture from the training and test set.

7. Assess this final network architecture using the validation set.

Several MLP networks were generated and tested. The transfer function for the first layer was sigmoid and for the second layer was linear. The BP algorithm was used to adjust the learning procedure. For forecasting residential and commercial energy demand the MLP network with 9–3–1 construction based on definition (1) had the best output with estimated 3.59% average absolute error percentage (AAEP) on the validation data. The AAEP is calculated from the following equation:

$$AAEP = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{a(t)-T(t)}{T(t)}\right| \tag{6}$$

where $a(t)$ is the estimated residential and commercial energy demand and $T(t)$ is the actual value of residential and commercial energy demand.

For forecasting investment for construction, total number of households, GDP, natural gas price, gas oil price and kerosene price MLP networks with 2–6–1, 2–4–1, 2–3–1, 2–6–1, 2–5–1 and 2-6-1 construction had the best output with estimated 4.77%, 0.23%, 1.92%, 8.32%, 4.21%, and 6.97% AAEP on the validation data. The estimation of investment for construction, total number of households, GDP, natural gas price, gas oil price and kerosene price are given in Fig. 2, 3, 4, 5, 6 and 7. These graphs show the actual data versus the ANN results. The investment for construction will reach to a level of 107.25 trillion Rials, total number of households is 26.74 million, GDP is 797.24 trillion Rials, natural gas price is 18.37 Rials/Kilo, gas oil price is 55.27 Rials/Liter and kerosene price is 70.27 Rials/Liter in 2020.

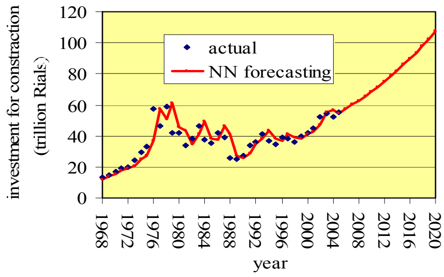

Fig.2 : Estimated investment for construction

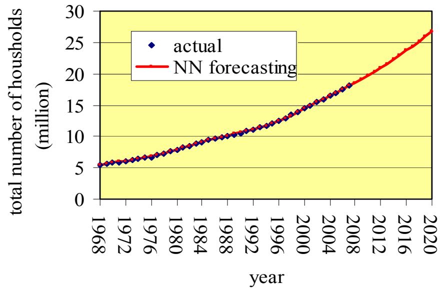

Fig.3 : Estimated total number of households

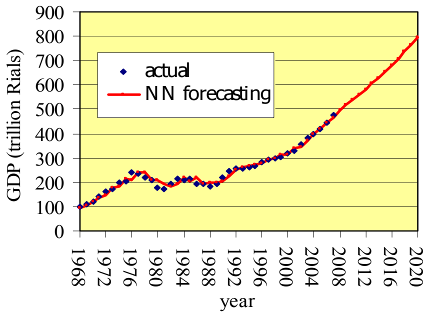

Fig.4 : Estimated GDP

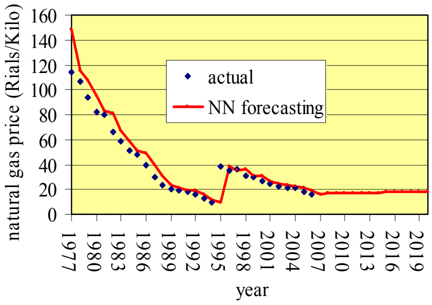

Fig.5 : Estimated natural gas price

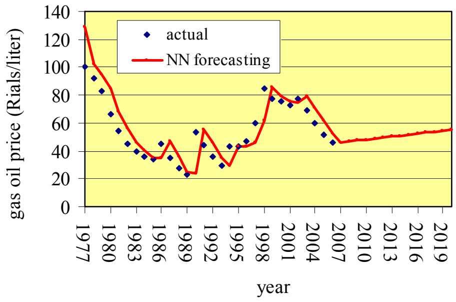

Fig.6 : Estimated gas oil price

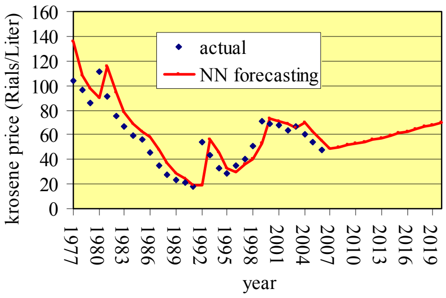

Fig.7 : Estimated kerosene price

After selecting the best architecture ANNs, the estimated investment for construction, total number of households, GDP, natural gas price, gas oil price and kerosene price from 2008 to 2020 are passed to the network and the residential and commercial energy demand for these years are forecasted. The estimated residential and commercial energy demand from 2008 to 2020 can be seen in Table 2. The residential and commercial energy demand will reach to a level of 594 MBOE in 2020.

TABLE II. FORECASTED RESIDENTIAL AND COMMERCIAL ENERGY DEMAND

Years	residential and commercial energy demand (MBOE)	Years	residential and commercial energy demand (MBOE)	Years	residential and commercial energy demand (MBOE)
2008	403	2013	492	2017	552
2009	423	2014	508	2018	567
2010	442	2015	523	2019	580
2011	459	2016	538	2020	594
2012	476				

4. Conclusions

This paper focused on forecasting the annual residential and commercial energy demand regarding socio-economic indicators using multi-level artificial neural networks. An ANN was designed to take the investment for construction, total number of households, GDP, natural gas price, gas oil price, kerosene price and residential and commercial demand in the last year as inputs and produces the residential and commercial energy demand. The investment for construction, total number of households, GDP, natural gas price, gas oil price and kerosene price were forecasted using ANNs. Actual data from 1967 to 2007 were used and residential and commercial demand of Iran from 2008 to 2020 was forecasted.

4.1. Future research

This paper considered seven standard variables as inputs to the main ANN for forecasting residential and commercial energy demand. Other input variables like the average energy usage of the appliance, technological developments, etc., may be inserted in to the model. Also, a future study may incorporate integration of a genetic algorithm and an ANN to foresee whether the estimated error is further decreased.

5. Acknowledgements

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