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Application of neural network for forecasting gas price in America

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Abstract

This paper presents a neuro-base approach for gas price forecasting of American consumers. in order to forming a neural network structure, effecting parameters on gas price are analyzed and gas production and consumption, import and export gas ,natural gas supplies held in storage,oil price are selected as inputs. this approach is structured as multi-level artificial neural net work(ANN)base on supervised muliti-layer perceptron (MLP),train with the levbergenberg-marquard algorithm .actual data from 1949-2010 is extracted from American energy information administration (EIA) .samples from 1949-2005 are used to train the multi-level ANN and the rest from 2005 to 2010 are used for network test. Result shows multi-level ANN is train well.

Keywords: neural network, MLP, forecasting, levenberg-Marquard

1. INTRUDUCTION

Due to increasing gas demand for industrial and domestic consumption in developing and developed countries such as India,China,Brazil, gas will be most significant economical parameter. Due to effective of gas price on the other economical

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parameters, decided to forecast gas price movement. In economics, the issue forecasts are divided in four main categories:

1. Technical analysis

In finance, technical analysis is security analysis discipline for forecasting the direction of prices through the study of past market data, primarily price and volumeTechnical analysis [7].

2. Fundamental analysis

Fundamental analysis of a business involves analyzing its financial statements and health, its management and competitive advantages, and its competitors and markets. When applied to futures and forex, it focuses on the overall state of the economy, interest rates, production, earnings, and management [7].

3. Random walk theory

The theory that stock price changes have the same distribution and are independent of each other, so the past movement or trend of a stock price or market cannot be used to predict its future movement. In short, this is the idea that stocks take a random and unpredictable path. A follower of the random walk theory believes it's impossible to outperform the market without assuming additional risk. Critics of the theory, however, contend that stocks do maintain price trends over time - in other words, that it is possible to outperform the market by carefully selecting entry and exit points for equity investments [7].

4. Chaos non linear dynamic approach

Since 1990, new and expanded efforts in relation to stock price prediction using new mathematical techniques, long time series and advance tools were initiated that the result was the emergence of chaos and nonlinear dynamics [7].

Some economical sophisticated believe that stock market is a nonlinear dynamics system which called chaos theory. Chaos theory analyzes a process under the assumption that part of process is deterministic and part of process is random .chaos is a nonlinear process which appear to be random. In essence, a chaotic system is a combination of a deterministic and a random process .the deterministic process can be characterized using regression fitting. While the random process can be characterized by statically parameters of a distribution function thus, using only deterministic or statically techniques will not fully capture the nature of a chaotic system. As mentioned in previous subsection, complex time series can decompose in to linear and nonlinear components; linear components can be modeled by using ARIMA-based econometrical linear forecasting model, but ARIMA model doesn't perform well in modeling nonlinear components in most situations[9],[11],[12]. It is therefore necessary to find a nonlinear modeling technique to fit the nonlinear components of time series. In this study, artificial neural networks (ANN) are used. The application of artificial neural networks for stock market and energy forecasting problems have resulted in several research papers. B. Abramson et al. (1997) have developed a neural networks model to predict the price oil [3]. Z. Tang et al. (1993) ,using feed forward neural network model to forecast time series[15]. G.P. Zhang et al. (2001) simulate study of artificial neural networks for non linear time series forecasting [6].HUS et al. (2003), has collected empirical data to formulate an artificial neural network model to predict the regional peak load of Taiwan [5]. Wang Shouyang et al. (2005), suggest hybrid model (ARIMA, neural network, expert system) to crude oil price forecasting[14].A.Kazemi et al. (2011), present a MLP artificial network for residential and commercial energy demand forecast[1].

In this study gas price predictor for American consumer using MLP with Levenberg-Marquart method in training is designed. Actual data from 1949-2010 is extracted from American energy information administration (EIA) and samples from 1949-2005 are used to train the multi-level ANN and the rest from 2005 to 2010 are used for network test. The test of this paper organized as fallow: in section 1 advantage of neural network over other technique will be describe and at section 3 and 4 we will introduce neural networks and Levenberg algorithm and in section 5 our propose model will be discussed and the last result will be presented.

2. COMPARE ANN WITH OTHER COMPUTER TECHNI QUES

Many other computer based techniques have been employed to forecast the price. They range from charting programs to sophisticated expert systems. Fuzzy logic has also been used. Expert systems process knowledge sequentially and formulate it into rules. They can be used to formulate trading rules base on technical indicators. In this capacity, expert systems can be used in conjunction with neural networks to predict price. In such a combined system, the neural network can perform its prediction, while the expert system could validate the prediction based on its well-known trading rules. The advantage of expert systems is that they can explain how they derive their results. With neural networks, it is difficult to analyze the importance of input data and how the network derived its results. However, neural networks are faster because they execute in parallel and are more faults tolerant. The major problem with applying expert system to forecasting price is difficulty in formulating knowledge of the markets because we ourselves do not completely understand them. Neural networks have an advantage over expert system because they can extract rules without having them explicitly formulized .in a highly chaotic and only partially understood environment, such as the stock market, this is an important factor. It is hard to extract information from experts and formalize it in a way usable by expert system .expert system are only good within their domain of knowledge and do not work well when there is missing or incomplete information. Neural networks handle dynamic data better and can generalize and make “educated guesses” [9]. Thus neural networks are more suited to the price forecasting than expert system [4], [13].

3. ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network (ANN) is an information processing paradigm inspired by biological nervous system. The human learning process may be partially automated with ANN, which can be configured for a specific application. 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. An artificial neuron is composed for some connections, which receive and transfer information, also there is a net function designed for collect all information (weights x inputs + bias) and send it to the transfer function, which process it and produces an output .ANNs consists of an inter-connection of a number of neurons. There are many varieties of connection under study, however, here, only one type of network, which is called the multi-layer preceptron (MLP) will be discussed. an MLP is a network of a simple neurons called perceptrons.The basic of a single perceptron was introduced by Rosenblat in 1958[8].the perceptron computes a single output from multiple real-valued inputs by forming a linear combination according to its inputs weights and then possibly putting the output through some nonlinear activation function. Using supervised learning, these networks can learn the mapping from one data space to other using examples. In MLPs, the data are feed forward into the network without feedback. These networks are so versatile and can be used for forecasting. To build a model for forecasting, there are two main phases in ANN: the learning or training phase and testing phase. The learning phase is critical because it determines the type of future tasks able to solve. Once trained the network, the test phase is followed, in which the representative features of the input are processed .after calculated the weights of the network, the value of the last layer neurons are compared with the wished output to verify the suitability of the design[1], [11].

The MLPs most popular learning rule is error back propagation (BP) algorithm as shown in figure (1).

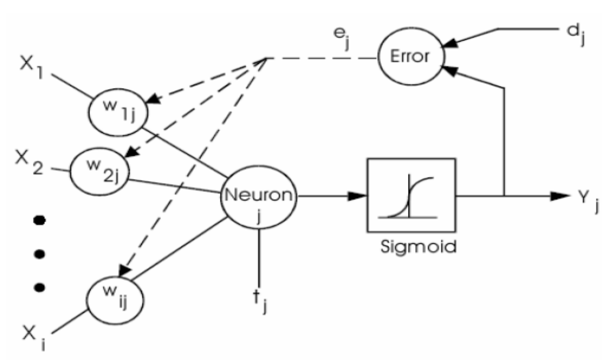

Fig1. back propagation algorithm

BP learning is a kind of supervised learning introduced by Werbos and later developed by Rumelhart and McClelland [2].following formula shown how weights and biases in BP algorithm will be updated.

$$\hat{F}(k)=\sum_{i=1}^{n(l)} e_i^2(k)=e(k)\times e(k)^t \qquad (1)$$

$$\begin{Bmatrix} w_{ij}^1(k+1)=w_{ij}^1(k)-\alpha\dfrac{\partial\hat{F}(K)}{\partial w_{ij}^1(k)} \\ b_i^1(k+1)=b_i^1(k)-\alpha\dfrac{\partial\hat{F}(K)}{\partial b_i^1(k)} \end{Bmatrix} \qquad (2)$$

Where e: error, $\hat{F}(k)$: performance index w and b are weight and bias respectively, α is learning rate. The update error back-propagation with Levenberg-Marquardt method will be described in next section.

4. LEVENBERG-MARQUARDT ALGORITHM

Levenberg-marquart(LM) algorithm is an iterative technique that locates the minimum of a multivariable function that is expressed as the sum of squares of non-linear real-valued function .it has become ,widely adopted in abroad spectrum of discipline .LM can be thought of as a combination of steepest decent and gauss-Newton method when the current solution is far from the correct one, the algorithm behaves like a steepest method :slow ,but guaranteed to converge .when the current solution is close to correct solution ,it becomes a gauss-Newton method

The Levenberg-Marquardt algorithm is a very simple, but robust, method for approximating a function. Basically, it consists in solving the equation:

$$(J^t.J+\lambda \mathrm{I})\delta=J^tE \qquad (3)$$

Where J is the Jacobian matrix for the system, λ is the Levenberg's damping factor, **δ** is the weight update vector that we want to find and E is the error vector containing the output errors for each input vector used on training the network. The δ tells us by how much we should change our network weights to achieve a (possibly) better solution. The $j^t.j$ matrix can also be known as the approximated Hessian.

The λ damping factor is adjusted at each iteration, and guides the optimization process. If reduction of E is rapid, a smaller value can be used, bringing the algorithm closer to the Gauss–Newton algorithm, whereas if iteration gives insufficient reduction in the residual, λ can be increased, giving a step closer to the gradient descent direction [10].

5. FACTOR AFFECTING NATURAL GAS PRICE

Natural gas prices are mainly a function of market supply and demand. Because there are limited short term alternatives to natural gas as a heating fuel and as a fuel for electricity generators during peak demand periods, changes in supply or demand over a short period may result in large price changes. Prices themselves often act to balance supply and demand.

Factors on the supply side that affect prices include natural gas production, net imports, and underground storage levels. Increases in supply tend to pull prices down, while decreases in supply tend to push prices up. Increases in prices tend to encourage production and imports and sales from storage inventories, and declining prices tend to have the opposite effects.

Factors on the demand side include economic conditions, winter and summer weather, and petroleum prices. (Petroleum fuels may be an economical substitute for natural gas for manufacturers, power generators, and large building owners.) Higher demand tends to lead to higher prices, while lower demand can lead to lower prices. Increases and decreases in prices tend to reduce or increase demand.

Now some of above parameter describe according (EIA) as fallow:

1. *Domestic supply*

Most of the natural gas consumed in the United States comes from domestic production. Lower production can lead to higher prices, but those higher prices, in turn, can lead to increased drilling for natural gas and eventually increased production.

2. *Pipeline import*

In 2010, pipeline imports amounted to almost 16% of total natural gas consumption. About 99% of the pipeline-imported natural gas came from Canada with the remainder from Mexico.

3. *Economy condition*

Economic activity is a major factor influencing natural gas markets. When the economy improves, the increased demand for goods and services from the commercial and industrial sectors generates an increase in natural gas demand. This is particularly true in the industrial sector, which is the leading consumer of natural gas as both a plant fuel and as a feedstock for many products such as fertilizer and pharmaceuticals.

4. *Natural Gas Supplies Held in Storage (net withdrawals)*

The overall supply picture is also influenced by the level of gas held in underground storage fields. Natural gas in storage is a critical supply component during the heating season that helps satisfy sudden shifts in supply and demand, accommodates stable production rates, and supports pipeline operations and hub services. Levels of natural gas in storage typically increase during the refill season (April through October), when demand for natural gas is low, and decrease during the heating season (November through March), when space heating demand for natural gas is high. Natural gas in storage represents an incremental source of supply immediately available to the market, which can ameliorate the effects of increased demand for natural gas, or other supply disruptions, on prices.

5. *Oil price*

Some large-volume gas consumers (primarily industrial consumers and electricity generators) can switch between natural gas and oil, depending on the prices of each. Because of this interrelation between fuel markets, when oil prices fall, the shift in demand from natural gas to oil pulls gas prices downward. When oil prices rise relative to natural gas prices, there may be switching from oil to natural gas, pushing gas prices upward.

6. *Political matters*

Policy is major factor on fuel price. As example Arab oil embargo 1973/74 shocked oil price from 7 to 12 dollar per barrel ,Iranian revolution of 1978/97 and Iran –Iraq war of 1980-88 increase oil price from 14 to 36 dollar per barrel, also Persian gulf-war 1990-91 cause increase oil price in the word. According to policy and oil price correlation, also decrease network input, oil price only used as input.

7. *Weather season*

During cold months, residential and commercial end users consume natural gas for heating, which places upward pressure on prices. If unexpected or severe weather occurs, the effect on prices intensifies because supply is often unable to react quickly to the short-term increased level of demand. Temperatures also can have an effect on prices in the cooling season as many electric power plants that are operated to meet air conditioning needs in the summer are fueled by natural gas. Hotter-than-normal temperatures can increase gas demand and push up prices.

6. PORPOSAL MODEL FOR ANNUAL GAS PRICE FORECASTING

After considering of effecting parameter on gas price also network simplicity, four factors are selected as inputs: net import (import-export), (production-consumption), net withdrawals, oil price, as shown in table (1).

TABLE1. MAIN NETWORK INPUTS, OUTPUT

inputs				output
In1	In2	In3	In4	out
Net import	Dry (production) – (Consumption)	Net withdrawals	Oil price	Gas price

The inputs value normalization will increase the numerical stability of neural network processing ,while the output values normalization is necessary because of the transfer function characterize .we will normalize the input between[-1,1]and output also. with trial and error also considering few samples, for preventing over fitting, main ANN that used in this study is two layer back propagation one hidden layer with three neuron with non linear function and one neuron with linear function at output incorporating Levnberg-Marquart for training as shown in figure (2).

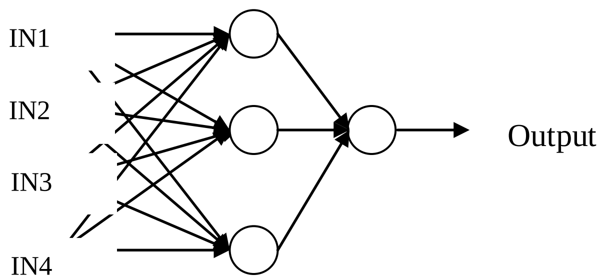

Fig 2. Main neural network structure

The main network was trained with extracted data of EIA; training data was set 75% including the validation dataset, while the test data represents the 25% of all data. This job done by matlab7 software. After designing ,training and testing main neural network(ANN5), weights and biases have been calculated , now need next year parameter to earn next year gas price ,but we do not know them so they must be predicted. Hence for forecasting them each main network's input will be considered as a time series and from econometric method, such as ARIMA or for more desirable to achieve result, application of neural network in time series can be used, but our approach is using of neural network[1]. hence for each input ,we design networks(ANN1,ANN2,ANN3,AAN4) that their outputs will be inputs to major network(ANN5) as represented in figure (3)

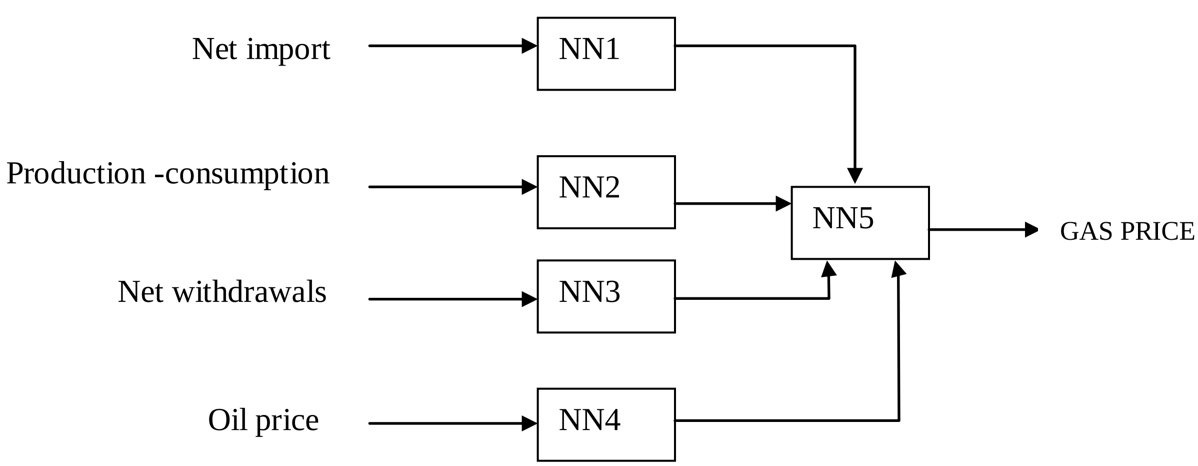

Fig 3. Proposal network

for calculating of(k+1)th each parameters ,we can assume a window that is contain a certain value of previous year and value of next year will be network output .now with applying four networks which have been designed to major network (ANN5) future year gas price will be computed please attention to fallowing formula :

$$in1_{k+1} = ANN_1(win[1],...,win[n-1],win[n]) \quad (4)$$

$$in2_{k+1} = ANN_2(win[1],...,win[n-1],win[n]) \quad (5)$$

$$in3_{k+1} = ANN_1(win[1],...,win[n-1],win[n]) \quad (5)$$

$$in4_{k+1} = ANN_4(win[1],...,win[n-1],win[n]) \quad (7)$$

$$price_{k+1} = ANN5(in1_{k+1}, in2_{k+1}, in3_{k+1}, in4_{k+1}) \quad (8)$$

7. RESULT

Network train with MSE and epoch equal 0.011 and 31 respectively as shown in figure (4).

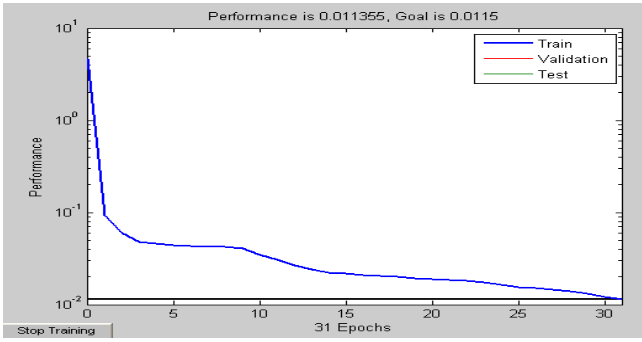

Fig 4. Network training

Figure (5) shows actual output and forecasting output obtain from network training.we reach to MSE equal to .78 for output training.

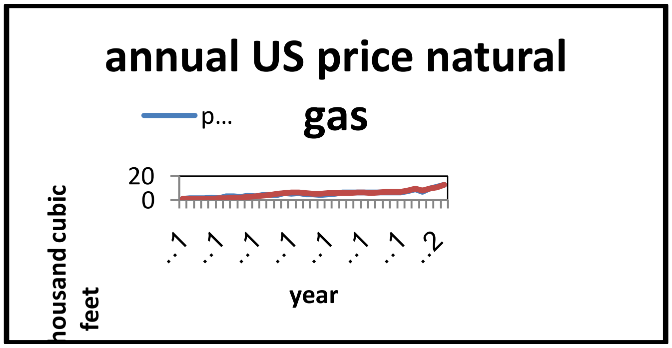

Fig 5.actual output and training output

Table (2) shows actual value and output of network testing and figure (6) shows its bar graph.

TABLE 2.ACTUAL AND PREDICTED OUT PUT

Year	2006	2007	2008	2009	2010
Real	13.73	13.08	13.89	12.14	11.21
Predict	12.86	13.026	12.17	11.75	11.48

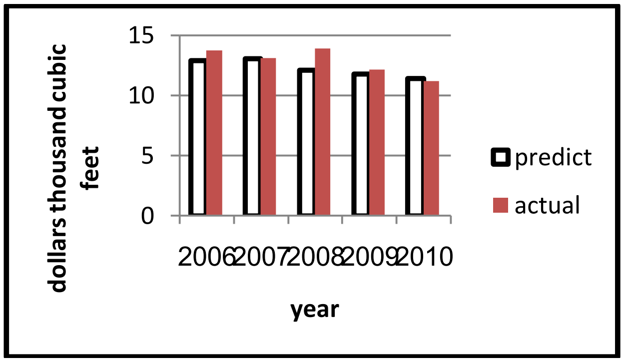

Fig 6.actual and prediction output in test

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