A Fundamental Analysis based Neuro-fuzzy Approach for Modeling the Effects of Crude Oil Ending Stocks Variations on Oil Price

Ali Ghaffari[1], Mansour Nikkhah Bahrami[2], Seyed Mahdiar Ghaffari[2]

[1] Mechanical Engineering Department, KN Toosi University of Technology, 322 West Mirdamad Ave., Tehran, Iran
[2] Engineering Department, University of Tehran, North Kargar Ave., Tehran, Iran
ghaffari@kntu.ac.ir, mbahrami@ut.ac.ir, mahdiar@email.com

Abstract. Intelligent computing tools such as artificial neural network (ANN) and fuzzy logic approaches are proven to be efficient when applied individually to a variety of problems. Recently there has been a growing interest in combining both these approaches, and as a result, neuro-fuzzy computing techniques have evolved. In the last decade, various neuro-fuzzy systems have been developed. Among them, adaptive neuro-fuzzy inference system (ANFIS) provides a systematic and directed approach for model building and gives the best possible design parameters in minimum time. They have got wide acceptance for modeling many financial systems, among technical analysts. The technical analysis is only and only based on the history of the price movement. One such problem frequently encountered is the crude oil price (COP) modeling. Supply and demand are the essential factors which affect the crude oil market, such as any other financial system. One of the most important factors influencing demand is crude oil ending stocks (COES). In this paper, contrary to the classic neuro-fuzzy modeling methods, next to the time-series of the oil price, we have also considered the fundamental analysis by studying the effects of weekly COES variations as a fundamental factor. Final results show that employing COES cause better performance and less error in modeling.

Keywords: fuzzy and neuro-fuzzy systems, fundamental analysis, financial systems, crude oil ending stocks, oil price.

1 Introduction

In financial problems, two kinds of analyses are commonly used for prediction of the future prices: Technical analysis and fundamental analysis.

Technical analysis is the examination of past price movements to forecast future price direction. Technical analysts are sometimes referred to as "chartists" because they rely almost exclusively on charts for their analysis. Technical analysis is applicable to stocks, indices, commodities, futures or any tradable instrument where the price is influenced by the forces of supply and demand. Price refers to any combination of the open, high, low or close for a given commodity/security over a specific timeframe. The time frame can be based on intraday (tick, 5-minute, 15-

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minute or hourly), daily, weekly or monthly price data and last a few hours or many years. In addition, some technical analysts include volume and/or open interest figures with their study of price action. It's been said, "A technical analyst knows the price of everything, but the value of nothing". Technicians, as technical analysts as they are called, are only concerned with two things: What is the current price? What is the history of the price movement?

The price is the end result of the battle between the forces of supply and demand for any particular item. The objective of analysis is to forecast the direction of the future price. By focusing on price and only price, technical analysis represents a direct approach. Fundamentalists are concerned with "why" the price is what it is. For technicians, the "why" portion of the equation is too broad and many times the fundamental reasons given are highly suspect. Technicians believe it is best to concentrate on "what" and never mind why. Why did the price go up? It is simple, more buyers (demand) than sellers (supply). After all, the value of any item is only what someone is willing to pay for it. Who needs to know why? You may never know why.

Aside from technical analysis, another primary approach to analyze currency market fluctuations is called fundamental analysis. Fundamental analysis is the examination of economic indicators, asset markets and political considerations when evaluating a nation's currency in terms of another. The key to fundamental analysis is to gather and interpret this information and act before the information is incorporated into the currency price. The lag time between an event and its resulting market response presents a trading opportunity for the fundamentalist [1].

Fuzzy-rule based approach in modeling is a soft computing technique which has recently received attention in financial systems. First introduced by Zadeh [15], fuzzy logic and fuzzy set theory are employed to describe human thinking and reasoning in a mathematical framework. Fuzzy-rule based modeling is a qualitative modeling scheme where the system behavior is described using a natural language [11]. The last decade has witnessed many applications of a fuzzy logic approach in financial systems forecasting [3,8,13]. The principal of designing these systems is neuro-fuzzy computing. Neural networks identify the models and adapt themselves to be able to consider the environmental variations, and fuzzy inference systems combine the human knowledge, concluding, and decision-making. The coalition of these two perfect approaches, next to the modern optimization techniques creates a new structure called neuro-fuzzy and soft computing and finally caused forming adaptive neuro-fuzzy inference systems (ANFIS).

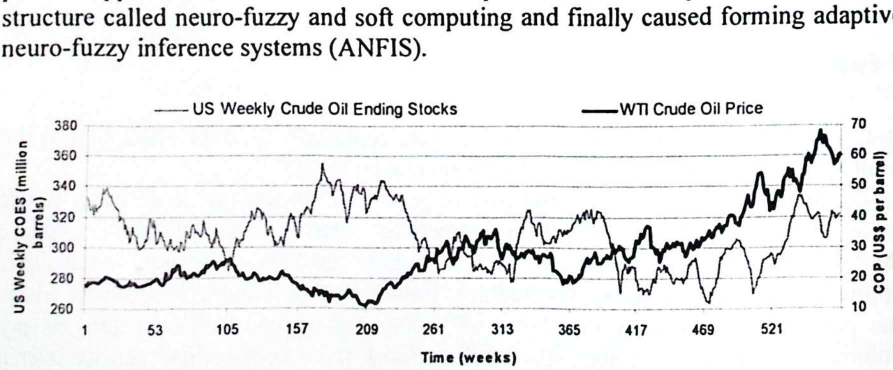

Fig. 1. The trends in WTI crude oil price and US weekly crude oil ending stocks (1995-2005).

Crude oil reserves of industrial countries such as US and China have key role in estimating the crude oil demand by fundamental analysts. In Fig. 1, we can visualize the trends in the West Texas Intermediate (WTI) crude oil price and US weekly COES from 1995 to 2005. While there is a continuous trend in the price, the relationship depicted in Fig. 1 indicates that in short- term variations both the trends parallel each other in an opposite direction. Often when US COES goes down, the price rises.

The main purpose of this paper is to try and investigate the determinants of weekly COES variations in the crude oil price on the basis of short-term horizons. For this purpose a predicting model with oil price time series inputs employed. One additional input that presents weekly COES variations added to the model, and using the error criterions we analyze the effects of this change.

2 Neuro-fuzzy Computing

Fuzzy set theory extends the degree of membership of an arbitrary element of the universe in a set to the interval [0, 1]. In the case of classical set theory there is just 0 (non-membership) and 1 (membership). If, for instance, 170 cm is the value to distinguish between tall male and short male persons in central Europe by classical sets, a height of 171 cm is assumed as tall whereas a height of 169 cm is assumed as short [7]. Fuzzy set theory permits a soft, gradual transition between the two sets, which is closer to common sense [14,16].

Hence, fuzzy sets are defined by membership functions which represent the gradual membership of all elements of the universe in the respective fuzzy set (Ross 1995). Contrary to classical sets, elements of a fuzzy set can also be members of other fuzzy sets in the same universe. In addition, fuzzy logic works with linguistic variables (i.e. fuzzy sets such as 'height of a male central European' with the values or labels 'short', 'medium', 'tall') which are connected by means of extensions of logical operators such as AND or OR.

Fuzzy inference systems (FIS) are integrated structures consisting of several units that transform information from the input space to the output space by means of fuzzy if-then rules. Fuzzy if-then rules or fuzzy conditional statements are expressions of the form IF A THEN B, where A and B are labels of fuzzy sets characterized by appropriate membership functions [15]. Fuzzy if-then rules may differ only in the types of membership functions in the consequent parts. The consequent part may be defined by either a fuzzy set or a non-fuzzy equation of input variables as given by Takagi and Sugeno [12].

An adaptive neural network (ANN) is a superset of all kinds of feed-forward neural networks with supervised learning capability. It is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, parts or all of the nodes are adaptive, what means that each output of these nodes depends on the parameter(s) pertaining to a particular node, and the learning rule specifies how these parameters should be changed to minimize a prescribed error measure.

The basic learning rule of ANNs is based on gradient descent and the chain rule.

There are numerous other numerical learning algorithms available, such as those of Gauss-Newton, Levenberg-Marquardt, etc., which could replace the gradient descent method in the hybrid learning algorithm given in Section 2.2. Nevertheless, they have not been considered in this study because the chosen algorithm performed quite well.

ANFIS are feed-forward ANNs which are functionally equivalent to FISs. An FIS is typically designed by defining linguistic input and output variables as well as an inference rule base. However, the resulting system is just an initial guess for an adequate model. Hence, its premise and its consequent parameters have to be tuned based on the given data in order to optimize the system performance. In ANFIS this step is based on a supervised learning algorithm.

2.1 ANFIS Architecture

ANFIS which was proposed by Jang [5], is a multi-layered feed-forward neural network with a supervised learning scheme which is equal to Takagi-Sugeno-Kang (TSK) fuzzy inference system [10, 12].

A common architecture of an ANFIS is shown in Fig. 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. For simplicity, we consider two inputs x_1, x_2 and one output f. The ANFIS used in this paper implements a first-order Sugeno fuzzy model. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques. For a first order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as

$$\text{Rule 1: if } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1 \text{ then } f_1 = p_1x_1+q_1x_2+r_1 \tag{1a}$$
$$\text{Rule 2: if } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2 \text{ then } f_2 = p_2x_1+q_2x_2+r_2 \tag{1b}$$

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the design parameters that are determined during the training process. As in Fig. 2, the ANFIS consists of six layers:

Layer 0: Input Layer. It has n nodes where n is the number of inputs to the system.

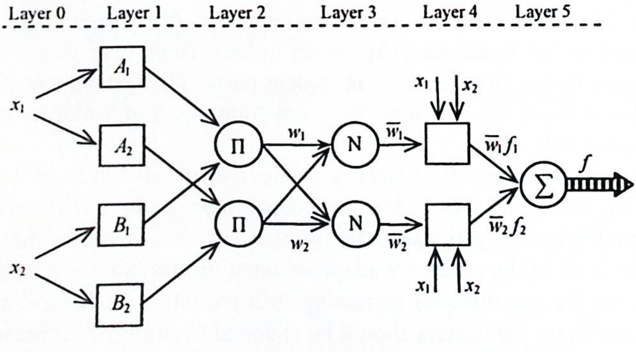

Fig. 2. The ANFIS architecture for a two-input Sugeno fuzzy model with two rules.

Layer 1: Fuzzification Layer. Each node represents a membership value to a linguistic term as a Gaussian function with the mean

$$\mu_{A_i}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)^2}. \tag{2}$$

where σ_i and c_i are parameters of the function. These are adaptive parameters. Their values are adapted by use of the back propagation algorithm during the learning stage. As the values of the parameters change, the membership functions of the linguistic term A_i change. These parameters are called premise parameters. In that layer there are $n \times m$ nodes where m is the number of membership functions.

Layer 2: Inference Layer. The nodes in this layer multiply the incoming signals and send the output as shown in the below equation.

$$w_i = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2). \tag{3}$$

The membership values represented by $\mu_{A_i}(x_1)$ and $\mu_{B_i}(x_2)$ are multiplied in order to find the firing strength of a rule where the variable x_1 has linguistic value A_i and x_2 has linguistic value B_i in the antecedent part of Rule i. There are m^n nodes denoting the number of rules in Layer 2. Each node represents the antecedent part of the rule.

Layer 3: Normalization Layer. This layer normalizes the strength of all rules according to the equation

$$\overline{w}_i = \frac{w_i}{\sum_{j=1}^{R} w_j}. \tag{4}$$

where w_i is the firing strength of the ith rule which is computed in Layer 2. Node i computes the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. There are m^n nodes in this layer.

Layer 4: Consequent Layer. The ith node in this layer computes the contribution of the ith rule towards the model output with the function

$$O_i = \overline{w}_i f_i = \overline{w}_i (p_i x_1 + q_i x_2 + r_i). \tag{5}$$

where $\{p_i, q_i, r_i\}$ is the parameter set in the consequent part of the first-order Sugeno fuzzy model.

Layer 5: Output Layer. The function of this layer is the summation of the net outputs of the nodes in Layer 4. The output is computed here as

$$O = \sum_i O_i = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \tag{6}$$

2.2 Estimation of Parameters

The parameters for optimization in an ANFIS are the premise parameters $\{a_i, b_i, c_i\}$, which describe the shape of the MFs, and the consequent parameters $\{p_i, q_i, r_i\}$, which describe the overall output of the system. The basic learning rule of an adaptive network, the back-propagation algorithm [9], which is based on the gradient descent rule, can be successfully applied to estimate these parameters. However, Jang [4] argues that the gradient descent method is generally slow and is likely to get trapped in local minima. Jang has proposed a faster learning algorithm, which combines the gradient descent method and the least squares estimate (LSE) to identify parameters, as described below:

The adaptive network has one output and is assumed to be

$$\text{output} = F(\vec{I}, S)\,. \tag{7}$$

where $\vec{I}$ is the set of input variables and S is the set of parameters. If there exists a function H such that the composite function $H \circ F$ is linear in some of the elements of S, then these elements can be identified by the least squares method. More formally, if the parameter set S can be decomposed into two sets

$$S = S_1 \oplus S_2\,. \tag{8}$$

(where $\oplus$ represents the direct sum) such that $H \circ F$ is linear in the element S_2, then applying H to Eq. (7), we have

$$H(\text{output}) = H \circ F(\vec{I}, S)\,. \tag{9}$$

which is linear in the elements of S_2. Now given values of elements of S_1, the P training data can be plugged into Eq. (9) to obtain the matrix equation:

$$AX = B\,. \tag{10}$$

where X is the unknown vector whose elements are parameters in S_2. Let $|S_2| = M$, then the dimensions of A, X and B are $P \times M$, $M \times 1$ and $P \times 1$, respectively. Since P (number of training data pairs) is usually greater than M (number of linear parameters), this is an over-determined problem and generally there is no exact solution to Eq. (10). However, a least square estimation (LSE) of X can be sought that minimizes the squared error $\|AX - B\|^2$.

From the ANFIS architecture presented in Fig. 2 it is observed that given the values of the premise parameters, the overall output can be expressed as linear combinations of consequent parameters. More precisely, the output f can be rewritten as,

$$\begin{aligned} f &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= (\overline{w}_1 x_1) p_1 + (\overline{w}_1 x_2) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x_1) p_2 + (\overline{w}_2 x_2) q_2 + (\overline{w}_2) r_2 \end{aligned} \tag{11}$$

which is linear in the consequent parameters (p_1, q_1, r_1, p_2, q_2 and r_2). As a result, the total number of parameters (S) in an ANFIS can be divided into two such that S_1 = set of premise parameters and S_2 = set of consequent parameters. Consequently the hybrid learning algorithm, which combines the back propagation gradient descent and least squares method, can be used for an effective search of the optimal parameters of the ANFIS. More specifically, in the forward pass of the hybrid learning algorithm, the node output goes forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the error signal propagates backwards and the premise parameters are updated by gradient descent. As mentioned earlier, the consequent parameters thus identified are optimal under the condition that the premise parameters are fixed. Accordingly, the hybrid approach converges much faster since it reduces the dimension of the search space of the original back-propagation method. A detailed description of this algorithm can be found in [6].

3 Model Development

Like other neural networks, ANFIS also requires a training process to examine the relationships between each pair of inputs and the corresponding outputs. The sample data applied to this paper are composed of weekly data from the beginning of 1995 through 2004 for a total of 500 observations. The first 80% of the data is training data set, and the last 20% serves as the testing data set whose purpose is to see how well the ANFIS model predicts the corresponding set of data output values. The error criterion of the supervised training is the smaller mean absolute percentage error (MAPE), the smaller root mean squared error (RMSE) and the larger R-squared (R^2).

We have employed MATLAB Fuzzy Logic Toolbox to model the ANFIS structure [2]. The goal is to estimate the West Texas Intermediate (WTI) crude oil price in one week in front, so if $P(t)$ represents the average price of t, the output of both models would be $P(t+1)$ that is the average price at $t+1$. The first model is a technical analysis based (TA-based) model, while in the second one a combination of technical analysis and fundamental analysis is used for prediction of the future oil prices. Here, the latter is called technical-fundamental analysis based (TFA-based) model. These two ANFIS models are developed during the analysis with the corresponding input vectors as follows:

TA-based Model $\quad P(t+1) = f(P(t-3), P(t-2), P(t-1), P(t))$

TFA-based Model $\quad P(t+1) = f(P(t-3), P(t-2), P(t-1), P(t), \Delta COES(t))$

where $\Delta COES(t) = COES(t) - COES(t-1)$ and $COES$(t) corresponds to the US weekly crude oil ending stock at time t.

4 Results

To assess the models' performances, several criteria are used and shown as below.

Root Mean Square Error (RMSE). Evaluates the residual between real and forecasted oil price. This index assumes that larger forecast errors are of greater importance than smaller ones; hence they are given a more than proportionate penalty

$$\mathrm{RMSE} = \left[\frac{\sum (P_t - O_t)^2}{n}\right]^{0.5}. \tag{14}$$

R-squared (R^2). Represents the

$$R^2 = 1 - \frac{\sum (P_t - O_t)^2}{\sum (P_t - \overline{P}_t)^2}. \tag{12}$$

where P_t is the real price, O_t is the model output, and $\overline{P}_t$ is the average of P_t values.

Mean Absolute Percentage Error (MAPE). Is calculated according to the equation

$$\mathrm{MAPE} = 100 \times \frac{1}{n} \times \sum \frac{|P_t - O_t|}{|P_t|}. \tag{13}$$

The errors of developed models are shown and compared to the errors of a TA-based ANN model in Table 1. TA-based model has the testing MAPE equal to 2.1944.

Table 1. Prediction by ANN, TA-based ANFIS model and TFA-based ANFIS model

	ANN Model	ANFIS Model	
	TA-based	TA-based	TFA-based
R^2	0.7863	0.8293	0.9619
MAPE	4.5729	3.9438	2.4724
RMSE	5.1246	4.2310	2.5736

Fig. 3 illustrates the real data and ANFIS output for testing data in the TA-based model. It is seen that in recent years that the oil market has reached high prices, the model performance is too low and causes a large error in forecasting the future oil prices.

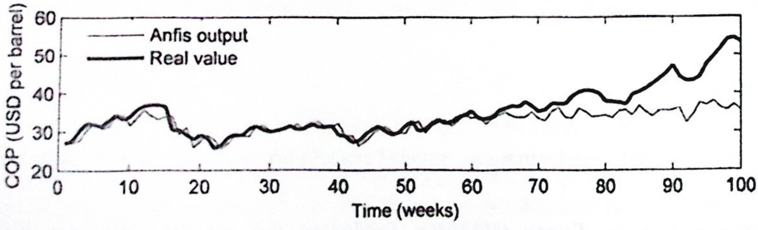

Fig. 3. Real values and outputs for the technical analysis based model.

In Table 1 it is observed that the performances of both ANFIS models are better than ANN model. In addition, we can visualize that adding weekly COES variations cause much better performance in TFA-based ANFIS model. The trends in WTI oil price and predicted price by TFA-based model are seen in Fig. 4.

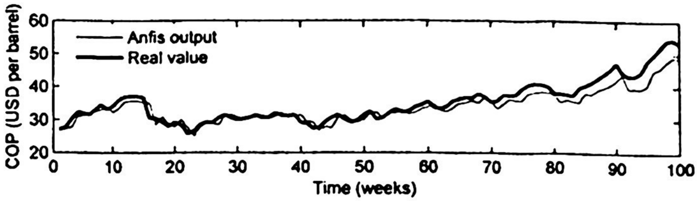

Fig. 4. Real values and outputs for the technical-fundamental analysis based model.

5 Conclusions

In this paper, we propose the use of a fundamental-technical analysis based adaptive neuro-fuzzy inference system (ANFIS) to forecast the future WTI oil prices. We study the role of USA weekly COES in the price variations. Using weekly data sets means that there are 52 observations per year, so for a suitable training, the training and testing data sets cover a wide domain. But the crude oil market follows different behavioral models in different temporal domains. That is the main reason for the low performance of the first model. As Fig. 5 shows, the training data set and testing data set are belonged to two different domains with different structures. In this case, adding weekly COES variations input to the model is a good approach to reach a suitable output.

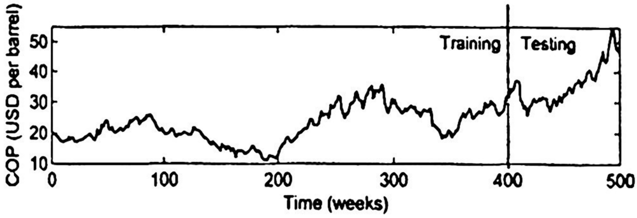

Fig. 5. Training and testing data sets.

The ANFIS preserves the full potential of ANN models, and simplifies the model building process. The results of the study are highly encouraging and suggest that an adaptive neuro-fuzzy approach is viable for modeling the price time series. Though there are other fundamental factors e.g. crude oil imports and exports, refinery operable capacity, percent utilization of refinery operable capacity, US$/Euro exchange rate, temperature and some other social and financial matters that we do not consider them in this paper, but we leave them as a topic for future research. The analyses of the results indicate that the performance of ANFIS models for prediction of future prices is significantly improved if a combination of technical analysis and fundamental analysis is used.

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