DESIGN AND IMPLEMENTATION OF A FUZZY COGNITIVE MAPS EXPERT SYSTEM FOR OIL PRICE ESTIMATION

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ABSTRACT
The objective of this study is to design a fuzzy cognitive maps expert system for estimation of monthly oil price based on intelligent approaches and meta heuristics. Oil price is influenced by several elements, such as politic and social factors. In this paper a fuzzy cognitive maps (FCMs) approach is presented in order to explore the importance of these factors in oil price estimation. To this purpose, causal relationship between affective factors and oil price are depicted and relationship values between them are computed. The proposed expert system utilizes Genetic Algorithm (GA), Artificial Neural Network (ANN) and Adaptive Neural Fuzzy Inference System (ANFIS). The system is coded in .net environment by C# and Matlab and Excel are also used linked for data processing and evaluation. The expert system identifies the preferred method (from GA, ANN, ANFIS) through mean absolute percentage error (MAPE).

Keywords: Expert system, Fuzzy cognitive maps, oil price, Estimation

1. INTRODUCTION
Crude oil, sometimes called the blood of industries, plays an important role in any economies (Fan et al. 2008). The role of oil in the world economy becomes more and more significant because nearly two-thirds of the world's energy consumption comes from the crude oil and natural gas (Alvarez-Ramirez et al. 2003). The crude oil price is basically determined by its supply and demand, and is strongly influenced by many events like the weather, inventory, GDP growth, refinery operable capacity, political aspects and people's expectation. Sharp oil price movements are likely to disturb aggregate economic activity, volatile oil prices have been considerable interest to many researchers and institutions. Therefore, forecasting oil prices is an important and very hard topic due to its intrinsic difficulty and practical applications (Wang et al. 2004).

There is an array of methods that are available today for forecasting energy price. An appropriate method is chosen based on the nature of the data available and the desired nature and level of detail of the forecasts (Azadeh et al. 2010). For crude oil price forecasting, Mirmirani and Li (2004) applied VRA and ANN techniques to make ex-post forecast of US oil price movement. Lagged oil price, lagged oil supply, and lagged energy consumption were used as three endogenous variables for VAR-based forecast. Ye et al. (2006) provided a model to forecast crude oil spot prices in the short-run using high- and low-inventory variables. They showed that the non-linear-term model better captures price responses at very high- or very low-inventory levels and improves forecasting capability. Wang et al. (2005) proposed a new integrated methodology-TEI@I methodology and showed a good performance in crude oil price forecasting with back propagation neural network (BPNN) as the integrated technique. Xie et al. (2006) proposed a support vector regression (SVR) model to predict crude oil price. Similarly, Shambora and Rossiter (2007) and Yu et al. (2007) also used the ANN model to predict crude oil price. Yousefi et al. (2005) introduces a wavelet-based prediction procedure and market data on crude oil is used to provide forecasts over different forecasting horizons. Sadorsky (2006) uses several different univariate and multivariate statistical models such as TGARCH and GARCH to estimate forecasts of daily volatility in petroleum futures price returns. Amin-Naseri and Gharacheh (2007) proposed a hybrid AI approach integrating feed-forward neural networks, genetic algorithm, and k-means clustering, to predict the monthly crude oil price and obtain better results.

In this paper, we develop a fuzzy cognitive maps expert system model for forecasting monthly crude oil spot prices using readily available data. The objective of this model is to provide a forecast of monthly West Texas Intermediate (WTI) prices using readily available data. In addition, this paper examines the feasibility of applying fuzzy cognitive maps expert system in crude oil price forecasting through the contrast with ANN, ANFIS and GA models.

The rest of the paper is organized as follows: Section 2 describes fuzzy cognitive maps expert system method for crude oil price prediction. To evaluate the fuzzy cognitive maps expert system, a main crude oil price series, West Texas Intermediate (WTI) crude oil spot price is used to test the effectiveness of the proposed methodology, and its comparable results with ANN, ANFIS and GA methods. Some concluding remarks are made in section 4.

2. FUZZY COGNITIVE MAPS EXPERT SYSTEM FOR CRUDE OIL PRICE

In this section, a fuzzy cognitive maps expert system method for time series forecasting and its application in crude oil price prediction are presented. We apply ANN, ANFIS and GA in this fuzzy cognitive maps expert system model. Then present the fuzzy cognitive maps expert system method for oil price forecasting.

2.1. Fuzzy Cognitive Maps Expert System

Expert system technology has proven to benefit decision making process in businesses and accounting management of corporations. Most applications are developed in production/operations management area with lowest number of applications in the human resources area (Mearns et al. 2003). There are several applications in the area of diagnosis. They include defects diagnostic system for tire production and service (Prez-Carretero et al. 2002). Benefits of an expert system approach to productivity analysis include cost reductions due to the reduced need for manpower, faster analysis of pressing productivity problems, and more consistent appraisals and interpretation of productivity performance (Azadeh et al. 2008).

2.1.1. Fuzzy Cognitive Maps (FCM)

Cognitive maps (CMs) were introduced by Axelrod (1976) in the 1970s. CMs are signed diagraphs designed to represent the causal assertions and belief system of a person (or group of experts) with respect to a specific domain, and use that statement in order to analyze the effects of a certain choice on particular objectives. Two elements are used when realizing CMs: concepts and causal belief. Concepts represent the variables that describe the belief system of a person, while the causal belief consists in the causal dependencies between variables. Such variables can be continuous, ordinal or dichotomous (Kardaras and Karakostas, 1999). In signed cognitive maps, each relationship is linked to a sign that represents the sense of casual influence of the cause variable on the effect variable. Fuzzy cognitive map is a well-established artificial intelligence technique that incorporates ideas from artificial neural networks and fuzzy logic. FCMs were introduced by Kosko (1986) to extend the idea of cognitive maps by allowing the concepts to be represented linguistically with an associated fuzzy set rather than requiring them to be precise. In order to describe the degree of the relationship between concepts it is possible to use a number between [0,1] and [-1, 1], or use linguistic terms, such as “often”, “always”, “some”, “a lot”, etc. Figure 1 shows an example of FCM used by Kosko to define the indirect and the total effects for an FCM (Kosko 1986). Three paths connect C_1 to C_5, so there are three indirect effects of C_1 on C_5:

along path $P_1(C_1, C_2, C_4, C_5)$:

$$I_1(C_1, C_5) = \min \{e_{12}, e_{24}, e_{45}\} = \mathit{some}$$

along path $P_2(C_1, C_3, C_5)$:

$$I_2(C_1, C_5) = \min \{e_{13}, e_{35}\} = \mathit{much}$$

along path $P_3(C_1, C_3, C_4, C_5)$:

$$I_3(C_1, C_5) = \min \{e_{13}, e_{34}, e_{45}\} = \mathit{some}$$

Thus, the total effect of C_1 to C_5 is:

$$T(C_1, C_5) = \max \{I_1(C_1, C_5), I_2(C_1, C_5), I_3(C_1, C_5)\} = \mathit{much}$$

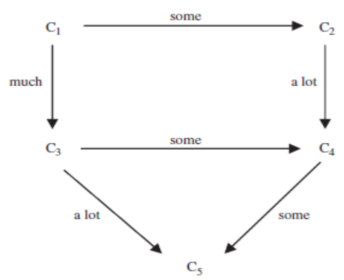

Figure 1: Example of FCM

2.1.2. Data Fuzzification

Fuzzification is a process in which the input data, precise or imprecise is converted into linguistic formation, which is easily perceptible by the human minds (Wagner et al. 2001). All relationship between concepts (indicators of the proposed oil price volatility estimation) are linguistic variables. The most typical fuzzy set membership function has the graph of a triangle. The fuzzy set membership function of our model is also a triangle. This approach translates the point $(x_1^*, \ldots, x_n^*)$ in set A to a fuzzy set A' as shown in (1). Fuzzy sets for relationship between concepts are shown in Figure 2.

$$\mu_{A'}(x) = \begin{cases} 1 - \dfrac{\left|x_1 - x_1^*\right|}{b_1}, \ldots, 1 - \dfrac{\left|x_n - x_n^*\right|}{b_n}, & \left|x_i - x_i^*\right| \le b_i \\ 0, & else \end{cases} \quad (1)$$

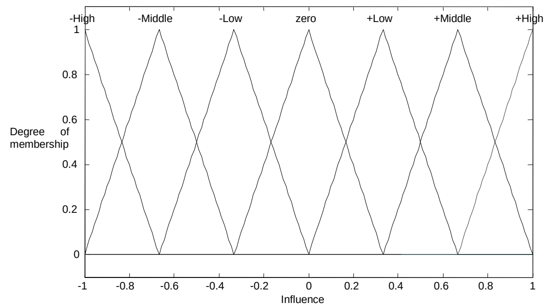

Figure 2: The fuzzy set for relationship between concepts

2.1.3. Data Defuzzification

Defuzzification is the process of producing a quantifiable result in fuzzy logic (Wilson et al. 1992). There are some methods for defuzzification such as centroid average (CA), center of gravity (CG), maximum center average (MCA), mean of maximum (MOM), smallest of maximum (SOM), largest of maximum (LOM) (Wong et al. 1995).

Our fuzzy cognitive maps expert system uses center of gravity (CG). This is because the approach provides better solution than other methods via data engine. We have the center of gravity (CG) as shown in (2):

$$y' = \frac{\int_A y\mu_{A'}(y)dy}{\int_A \mu_{A'}(y)dy} \quad (2)$$

2.2. The Proposed Fuzzy Cognitive Maps Expert System

An excellent approach is fuzzy cognitive maps expert system that can implement crude oil price forecasting in the volatile crude oil market. The flow chart of the fuzzy cognitive maps expert system is shown in Figure 3.

From Figure 3, the fuzzy cognitive maps expert system for crude oil price forecasting consists of some main components, i.e., graphical user interface module (GUI), oil price forecasting with ANN, ANFIS, GA module, oil price volatility correction with fuzzy cognitive maps module and integration module.

GUI: It is a graphical window through which users can exchange information with the fuzzy cognitive maps expert system and also users enter necessary data in system. In details, it handles all input/output between users and the fuzzy cognitive maps expert system.

Oil price forecasting with ANN, ANFIS and GA module: in this study ANN, ANFIS and GA predict the future value of oil price using the historical data. The crude oil prices data are used in this paper are monthly spot prices of West Texas Intermediate (WTI) crude oil. For a univariate time-series forecasting problem, the inputs of the network are the past lagged observations of the data series and the outputs are the future values. According to Pierson coefficient of correlation, oil price of a month before and oil price of two months before are chosen for oil price forecasting. Oil price forecasting accomplish with three methods, ANN, ANFIS and GA, then according to MAPE best forecasting is chosen between three methods. The parameters in these methods are chosen based on previous studies and also using Trial and error.

Oil price volatility correction with fuzzy cognitive maps module: Crude oil market is an unstable market with high volatility and oil price is often affected by many related factors (Wang et al. 2004). In this paper we used from nine factors that they are premier than other factors, according to experts' ideas. Eight experts draw casual graphs between these factors and volatility oil price. The experts use linguistic terms for expressing relationships between factors. Taber (1991) suggested a relation to unify different judgments of experts, based on the credibility weight of each expert. In our applications, each expert had the same credibility. At the end of the process the result of different factors effects on volatility oil price appears as in Table 1.

Table 1: The effects of different factors on volatility oil price

Effective factors	The effect on volatility oil price
World oil demand	0.78
Reduce excess capacity	0.67
Agiotage	0.42
Devaluation dollar	0.83
Financial Crisis	0.25
Government changes and internal turmoil	- 0.16
Environmental policy	0.29
OPEC cuts oil production	0.4
Natural events	0.25

Integration module: Crude oil price forecasting obtains by implementing, oil price forecasting with ANN, ANFIS, GA module and oil price volatility correction with fuzzy cognitive maps module. Indeed crude oil price forecasting obtains by adding two values of two modules.

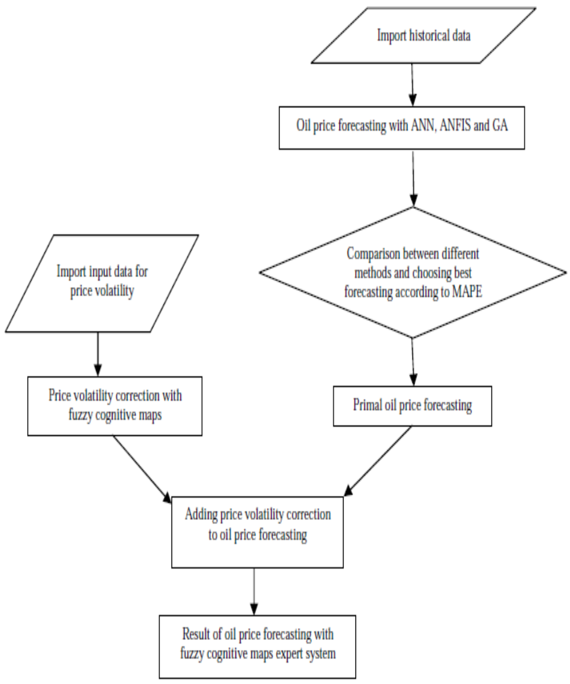

Figure 3: The overall computational flow chart of the fuzzy cognitive maps expert system

3. A CASE STUDY

In this section, we first describe the data, and then define some evaluation criteria for prediction purposes. Finally, the empirical results are presented.

3.1. Data

The crude oil price data used in this study are monthly spot prices of West Texas Intermediate (WTI) crude oil from January 1991 to December 2010 with a total of n = 240 observations. These data include train data and test data. The train data are 216 (90 percent of total data as usual) observations and the test data are 24 (10 percent of total data as usual) observations. The main reason of selecting this oil price indicator is that this crude oil price is the most famous benchmark price, which is used widely as the basis of many crude oil price formulae (Yu et al. 2008). The crude oil price data used in this study are obtainable from the energy information administration (EIA) website of Department of Energy of USA (http://www.eia.doe.gov).

3.2. Data Preprocessing

As in time-series methods making the process, covariance stationary is one of the basic assumptions and also using preprocessed data is more useful in most heuristic methods (Zhang et al. 2005), and so the stationary assumption should be studied for the models. In time series forecasting, the appropriate preprocessing method should have two main properties. It should make the process stationary and have post processing capability. The most useful preprocessed methods are presented in the sections.

The first difference method: The difference method was proposed by Box et al. (1994) In this method, transformation should be applied:

$$y_t = x_t - x_{t-1} \tag{3}$$

However, for the first difference of the logarithm method the transformation is adjusted as follows:

$$y_t = \log(x_t) - \log(x_{t-1}) \tag{4}$$

Normalization: There are different normalization algorithms which are Min-Max Normalization, Z-Score Normalization and Sigmoid Normalization.

We used these methods to estimate time series functions and finally according to mean absolute percentage error (MAPE) we didn't apply any methods for preprocessing.

3.3. Evaluation Criteria

There are four basic error estimation methods which are listed: Mean absolute error (MAE), Mean square error (MSE), Root mean square error (RMSE) and Mean absolute percentage error (MAPE). They can be calculated by the following equations, respectively:

$$\begin{aligned} MAE &= \frac{\sum_{t=1}^{n} |x_t - x'_t|}{n} \\ MSE &= \frac{\sum_{t=1}^{n} (x_t - x'_t)^2}{n}, \\ RMSE &= \sqrt{\frac{\sum_{t=1}^{n} (x_t - x'_t)^2}{n}}, \\ MAPE &= \frac{\sum_{t=1}^{n} \left| \frac{x_t - x'}{x_t} \right|}{n} \end{aligned} \tag{5}$$

All methods, except MAPE have scaled output. MAPE method is the most suitable method to estimate the relative error because input data used for the model estimation, preprocessed data and raw data have different scales (Azadeh et al. 2011).

3.4. Results and Analysis

Result of Each of the forecasting method described in the last section is presented in Table 2 in which a comparison among them is performed. Each of methods is estimated and validated by train data. The model estimation selection process is then followed by an empirical evaluation which is based on the test data.

Table 2 shows the detailed results of the simulated experiment via the four methods. It can be seen that the fuzzy cognitive maps expert system method outperforms other models in term of MAPE. Focusing on the MAPE indicators, the values of fuzzy cognitive maps expert system model are explicitly lower than those of ANN, ANFIS and GA except in the third sub-period.

The main reasons for the above conclusions are as follows. As Panas et al. (2000) reported, the crude oil market is one of the most volatile markets in the world and shows strong evidence of chaos. All methods can in principle describe the nonlinear dynamics of crude oil price. Best method between ANN, ANFIS and GA for different periods is different, so, a hybrid method that it uses from all methods is necessary and useful. Fuzzy cognitive maps expert system is resistant to the over-fitting problem and can model nonlinear relations in an efficient and stable way.

Table 2: Crude oil forecast results according to mape

Method	Full period (1991-2010)	Sub-period 1 (1991-1995)	Sub-period 2 (1996-2000)	Sub-period 3 (2001-2005)	Sub-period 4 (2006-2010)
ANN	0.0594	0.0256	0.0588	0.0525	0.0222
ANFIS	0.1534	0.0392	0.0658	0.334	0.0328
GA	0.0654	0.047	0.0799	0.0457	0.0285
FCM expert system	0.0474	0.0245	0.0423	0.0386	0.0216

Actual values and forecasting values with fuzzy cognitive maps expert system for test data are shown in Figure 3.

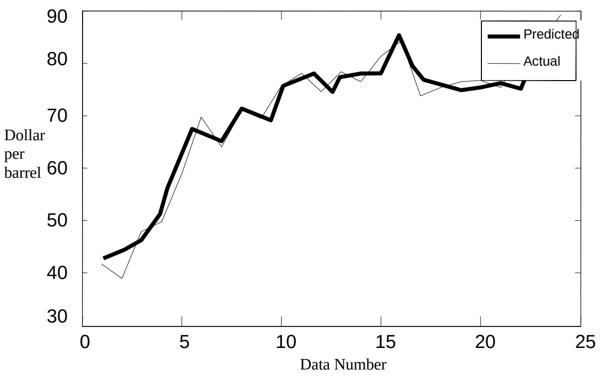

Figure 3: WTI crude oil price forecast based on fuzzy cognitive maps expert system for test data

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