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A flexible neural network-fuzzy mathematical programming algorithm for improvement of oil price estimation and forecasting

Ali Azadeh *, Mohsen Moghaddam, Mehdi Khakzad, Vahid Ebrahimipour

Department of Industrial Engineering and Center of Excellence for Intelligent Based Experimental Mechanics, College of Engineering, University of Tehran, Iran

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ABSTRACT

This paper presents a flexible algorithm based on artificial neural network (ANN) and fuzzy regression (FR) to cope with optimum long-term oil price forecasting in noisy, uncertain, and complex environments. The oil supply, crude oil distillation capacity, oil consumption of non-OECD, USA refinery capacity, and surplus capacity are incorporated as the economic indicators. Analysis of variance (ANOVA) and Duncan's multiple range test (DMRT) are then applied to test the significance of the forecasts obtained from ANN and FR models. It is concluded that the selected ANN models considerably outperform the FR models in terms of mean absolute percentage error (MAPE). Moreover, Spearman correlation test is applied for verification and validation of the results. The proposed flexible ANN–FR algorithm may be easily modified to be applied to other complex, non-linear and uncertain datasets.

0. Significance

Estimation and forecasting of oil price trend is a dilemma and cumbersome task due to lack of significance historical data and limitations on information regarding earlier values of economic indicators affecting the oil price trend. This, in turn, intensifies the amounts of parametric noise, complexity, and uncertainty associated with estimation of oil price trend with respect to economic indicators. This study makes use of a 23 years dataset of economic indicators which is a bit small for conducting an accurate analysis on oil price trend using conventional forecasting methods. Hence, fuzzy regression (FR) artificial neural networks (ANNs), as well-known and robust intelligent forecasting methods, have been employed to cope with the noise accompanied with the small dataset and complexity and uncertainty of the dataset in its nature. The proposed flexible algorithm is able to find the preferred forecasting method using a comprehensive statistical analysis on the results obtained from ANNs and FR models to efficiently estimate the oil price trend as a decisive in today's competitive commerce.

1. Introduction

Oil price is one of the most crucial factors which has an effect on domestic and global economy. Fluctuations in oil price could in some way result in variation in the price of other products and accordingly the profit of several companies. Oil is identified as the largest and most actively traded commodity all over the world accounting for over 10% of total world trade (Verleger, 1993). In today's competitive markets, traders and investors are broadly interested in using economic indicators to understand fundamentals of the market. In oil trade, the most effectual economic indicators are those which provide information regarding petroleum industry. The main economic indicators for oil price forecasting are oil supply, crude oil distillation capacity, oil consumption of non-OECD, USA refinery capacity, and surplus capacity (see www.eia.doe.gov). Due to the importance of oil price in future, several researchers and practitioners are concerned with estimation of oil price in future.

Forecasting methods can be categorized according to the timescale involved in the forecast. Forecasting methods can be classified into three major categories including short-term, medium-term, and long-term (González-Romera, Jaramillo-Morán, & Carmona-Fernández, 2007). Table 1 presents the timescales and some applications of the three mentioned forecasting categories.

The main idea of the above classification is based on application of forecasting methods in different circumstances. Note that the data variation in quantitative forecasting methods increases from short-term to long-term timescales. In other words, variation of data in short-term forecasting is very low while in long-term forecasting, data variation has higher values. Shortly, conventional forecasting methods, whether short-term, medium-term, or long-term, can be classified as follows (Makridakis, Wheelwright, & Hyndman, 1998):

– *Qualitative methods*: applied in situations where no mathematical model is available, often due to the incompleteness of data to be representative of the future.

* Corresponding author. Tel.: +98 21 88021067; fax: +98 21 82084194.
E-mail address: aazadeh@ut.ac.ir (A. Azadeh).

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Table 1
Forecasting methods according to timescale and related oil price forecasting literature.

Timescale	Type of decision	Application instances	Oil price forecasting literature
Short-term Up to 3–6 months	Operating	Distribution, scheduling, inventory management and control	Fesharaki (1990), Ye, Zyren, and Shore (2005) and Malik and Nasereddin (2006)
Medium-term 3–6 months to 2 years	Tactical	Workforce changes, equipment leasing	Fesharaki (1990)
Long-term Above 2 years	Strategic	Research and development, expansions and investment, policy making	Fesharaki (1990), Suárez (1990), Rehrl and Friedrich (2006) and Chen and Chen (2007)

- *Regression methods*: applied to investigate the relationship (linear or non-linear) between a variable and a number of other independent variables.
- *Multiple equation methods*: applied to determine the interactions between a number of dependent variables via a series of equations.
- *Time series methods*: applied to find the value of a single variable which varies with time where its future values are related to its previous values (see Medeiros and Pedreira (2001) for example).

Different forecasting methods have been presented and used in literature for different purposes. All previous studies proposed a forecasting method as the most superior method based on their findings. However, adopting a forecasting method without considering the case conditions could lead to distortion in results. For example, in presence of complexity and non-linearity of the input dataset, ANNs are more likely to outperform other popular forecasting methods while as the nature of the input dataset gets fuzzier, FR models are expected to yield better results than ANNs. As a result, in this paper a flexible intelligent algorithm is proposed to tackle optimum long-term forecasting of the oil price trend. The unique feature of the proposed algorithm lies in integration of well-known and mostly-used ANN and FR models so as to find the preferred method with most accurate estimates. To do so, a comprehensive statistical analysis using analysis of variance (ANOVA), Duncan's multiple range test (DMRT), and Spearman correlation test is then performed on the results of ANN and FR models. The proposed flexible algorithm can be easily applied to uncertain, noisy, non-linear, and complex environments due to utilizing ANNs and FR. The proposed algorithm facilitates the decision-making process in different case conditions and provides a comprehensive framework for long-term forecasting of the oil price.

The remainder of this paper is organized as follows. Section 2 presents and discusses previous studies related to this work. Section 3 presents the proposed flexible ANN–FR algorithm for oil price forecasting. In Section 4, a case study along with the algorithm implementation procedure is presented. Results analysis is scrutinized in Section 5 and the concluding remarks are drawn in Section 6.

2. Related works

Several methods have been utilized in literature for forecasting of oil price; e.g. vector error correction model (Coppola, 2008), univariate model (Abosedra, 2005), present value model of rational commodity pricing (Knetsch, 2007), congruent econometric model (Albacete, 2010), option-implied and ARCH-type models (Hog & Tsiaras, 2010). However, the recent models are not capable of handling both noise and uncertainty associated with oil price indices.

In recent years, ANNs have attracted researchers for forecasting purposes (Sharda, 1994). The unique forecasting features of ANNs make this method more applicable and useful in comparison with the conventional forecasting methods (Zhang, Patuwo, & Hu, 1998). Admittedly, there may be few cases in which ANNs like regression models reveal some drawbacks in terms of comprehensiveness for policy making in face of uncertain and noisy data (see for example Cheng & Wei, 2009).

ANNs, as one of the most popular forecasting methods, has recently attracted researchers for forecasting of the oil price trend. For instance, Haidar, Kulkarni, and Pan (2008) applied a three-layered feed-forward ANN for short-term forecasting of crude oil prices. They considered a number of features such as crude oil futures prices, dollar index, gold spot price, heating oil spot price and S&P 500 index as indicators. An empirical mode decomposition based neural network ensemble learning paradigm was presented by Yu, Wang, and Lai (2008a, 2008b) in order to forecast the crude oil spot price. Alizadeh and Mafinezhad (2010) proposed a framework based on ANNs and crisis index for forecasting of Brent crude oil price. Ma (2009) developed an immune clustering neural algorithm for forecasting of oil price time series in which the number and position of hidden layers were defined by symbiotic evolutionary and immune algorithm. Kuo, Hit, and Chen (2009) proposed a radial basis function neural network for oil price forecasting. They applied self-organizing map neural network to determine the initial activation function parameters and then used a hybrid of particle swam optimization and genetic algorithm to train the radial basis function neural network. Other studies also exist in literature which applied ANNs for oil price forecasting (e.g. Jinliang, Mingming, & Mingxin, 2009; Kaboudan, 2001; Lackes, Börgermann, & Dirkmorfeld, 2009; Moshiri & Foroutan, 2006; Pan, Haidar, & Kulkarni, 2009; Qunli, Ge, & Xiaodong, 2009; Sun & Lai, 2006; Yang, Zhu, & Liu, 2006; Yu, Lai, Wang, & He, 2007).

Despite application of FR models in various forecasting problems (Wang & Tsaur, 2000) there are few studies in literature which applied FR for oil price forecasting. Chen and Chen (2007) used conventional regression (CR) to study the long-term relationship between real oil prices and real exchange rates according to a monthly panel of G7 countries from 1972 to 2005. Ringlund, Rosendahl, and Skjerpen (2008) estimated the relationship between the oilrig activity in different non-OPEC regions and the crude oil price by using dynamic regression models based on the latent components capturing trend and seasonality. Cong, Wei, Jiao, and Fan (2008) applied multivariate vector auto-regression method to study the interactive relationships among the oil price shocks and Chinese stock market.

Based on this motivation, this study proposes a comprehensive flexible and intelligent framework for improving oil price estimation and forecasting. Several studies considered the oil price modeling and analysis. However, such studies do not consider the integrated noise, complexity, non-linearity, and uncertainty associated with the oil price data. What is more, there is a need for such approaches to cope with such chaotic and hostile markets. This is why this study presents a flexible approach based on fuzzy mathematical programming and neural network along with CR to cover all aspects of noise and uncertainty in oil markets in general and in oil price forecasting in particular through using the most common economic indicators in oil price estimation and forecasting.