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Forecasting Crude Oil Prices: A Hybrid Model Based on Wavelet Transforms and Neural Networks

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Abstract

In general, energy prices, such as those of crude oil, are affected by deterministic events such as seasonal changes as well as non-deterministic events such as geopolitical events. It is the non-deterministic events which cause the prices to vary randomly and makes price prediction a difficult task. One could argue that these random changes act like noise which effects the deterministic variations in prices. In this paper, we employ the wavelet transform as a tool for smoothing and minimizing the noise presented in crude oil prices, and then investigate the effect of wavelet smoothing on oil price forecasting while using the GMDH neural network as the forecasting model. Furthermore, the Generalized Auto-Regressive Conditional Hetroscedasticity model is used for capturing time varying variance of crude oil price. In order to evaluate the proposed hybrid model, we employ crude oil spot price of New York and Los Angles markets. Results reveal that the prediction performance improves by more than 40% when the effect of noise is minimized and variance is captured by Auto-Regressive Conditional Hetroscedasticity model.

Keywords: Crude Oil Price Forecasting; Group Method of Data Handling (GMDH) Neural Networks; Wavelet Transform; Generalized Auto-Regressive Conditional Hetroscedasticity.

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1. Introduction

Energy is a critical and strategic good in international markets and its price affects the activities and decision of governments and companies alike. Excluding unforeseen events, one could argue that the price of oil does have some determinism, which is dependent on the consumption cycles of the consumers in the long and short term intervals. Hence oil price forecasting, especially for crude oil prices, is an important issue, which has been the subject of much research in the literature.

Kaboudan et al. (2001) for short-term monthly forecasts of crude oil prices use compumetric methods. Forecasts produced by two compumetric methods-genetic programming and artificial neural networks are compared and evaluated relative to a random walk type of prediction. The results suggest that genetic programming has advantage over random walk predictions while the neural network forecast proved inferior. Wang et al. (2004) use a hybrid AI (Artificial Intelligent) system framework to integrate artificial neural networks and RES (Rule-based Expert System) with WTM (Web-based Text Mining) techniques for crude oil price forecasting and reveals that hybrid AI system is effective and feasible. Wang et al. (2005) propose a new methodology for handling complex systems—TEI@I methodology by means of a systematic integration of text mining, econometrics and intelligent techniques for crude oil price forecasting an in addition, the impact of irregular and infrequent future events on crude oil price is explored by WTM and RES techniques. Thus, a fully novel nonlinear integrated forecasting approach with error correction and judgmental adjustment is formulated to improve prediction performance within the framework of the TEI@I methodology. Moshiri and Foroutan (2006) model and forecast daily crude oil futures prices applying ARIMA (Auto Regressive Integrated Moving Average) and GARCH (Generalized Auto–Regressive Conditional Hetroscedasticity) models. They afterwards test for chaos using embedding dimension, BDS (L), Yaupon exponent, and neural networks tests. Finally, they set up a nonlinear and flexible ANN (Artificial Neural Network) model for to forecast the series. Since the test results indicate that crude oil futures prices follow a complex nonlinear dynamic process, they expect that the ANN model will improve forecasting accuracy. Naseri and Ahmadi (2006) use a hybrid artificial intelligence model for monthly crude oil price forecasting by means of feed forward neural networks, genetic algorithm and k – means clustering and they reveal that this framework is so effective. Fernandez (2006) forecasts crude oil and natural gas spot prices at a daily frequency based on two classification techniques: ANN and Support Vector Machines (SVM) and reveals at short time horizons (2-4 days), ARIMA tends to outperform both ANN and SVM. Yu et al. (2007) use a multistage neural network learning paradigm based on Empirical Mode Decomposition (EMD) for crude oil price prediction. For verification, the proposed multistage neural network learning paradigm is applied to a typical crude oil price, West Texas Intermediate, crude oil spot price prediction. Abrishami et al. (2008) use GMDH neural network based on Genetic Algorithm to model and forecast the price of Gasoline by using two approaches; Deductive Method and Technical Analysis. The results of deductive method indicate that the accuracy of prediction could reach up to 96% and in technical analysis could reach up to 99%. Mehrara et al. (2008) use a GMDH neural network model with moving average crossover inputs to predict price in the crude oil futures market. The predictions of price are used to construct buy and sell signals for traders. Compared to those of benchmark models, cumulative returns, year-to-year returns, returns over a market cycle, and Sharpe ratios all favor the GMDH model by a large factor. Gencay (1996) use foreign exchange markets to pioneer the use of technical analysis rules as inputs for neural networks, which are flexible, nonlinear models with powerful pattern recognition properties. In a series of articles, Gencay (1998a) and Gencay (1999) and Gencay et al. (1998) show that simple technical rules result in significant forecast improvements for current returns over a random walk model for both foreign exchange rates and stock indices.

In this paper, we employ the wavelet transform as a tool to smooth and minimize the noise present in the oil price series; since the noise contained in the series distorts the estimated parameters. Afterwards, the smoothing effect on the forecasting of crude oil price while using GMDH neural networks is investigated. Furthermore, the GARCH (1, 1) model is used to capture oil price series time varying variance. Therefore, this article has two new contributions. First, using a hybrid wavelet transform and neural network for oil price forecasting and second, applying variances of GARCH (1, 1) as inputs of GMDH Neural network for oil price prediction.

The paper is organized as follows. Sections 2 and 3 briefly discuss wavelet transform and wavelength theory. Section 4 reviews the GMDH neural network. Section 5 describes the methodology used in employing the wavelet transform and GARCH (1, 1) model. Section 6 describes the data sets used in this work as well as the evaluation results followed by a conclusion in Section 7.

2. Wavelet Transform

It has been well established that by representing time series in other domains (i.e. frequency, wavelet, Z transform, laplacian, etc.), certain characteristics that are not visible in the time domain are highlighted. Such characteristics may be used to better understand the underlying time series. For example, the superposition of a few sine series could lead to a complex time series, which is difficult to describe. However, by representing this complex time series in the frequency domain, we could simply observe the frequency of the sinusoidal components, which make up such a series. With wavelet analysis we gain an additional level of insight into the characteristics of the signal, by observing frequency characteristics in different time resolutions. This is in contrast to simple frequency analysis in which we observe the frequency characteristics over the entire time-series. For this reason, wavelets are considered a powerful time series analysis tool as observed by Ramsey (1999) and Ramsey (2002). In what follows we review the basic concept of wavelet transform.

3. Wavelet Theory

Wavelet transform converts a time series to the frequency domain, using a basis function, and represents the series at different time and scale resolutions. Unlike Fourier transform, where sine is the only basis function, there are several wavelet basis functions with different shapes; although all have finite energy and are compactly supported. These characterizes of wavelets allow the wavelet transform to deal with nonstationary and transient series, as well as the ability to decompose time series to different components at different scales. In the wavelet domain, a basis function is called the mother wavelet and other bases are obtained from the translation (location) and the dilation (size) of the mother wavelet. For a continues time series, one would employ the continuous wavelet transform (CWT). Genay, Seluk, and Whitcher (2001) represent the continuous wavelet transform, $W(u,s)$ as:

$$W(u,s)=\int_{-\infty}^{\infty}x(t)\Psi_{u,s}(t)dt, \qquad (1)$$

And the continuous basis (mother) wavelet, $\Psi_{u,s}(t)$ as:

$$\Psi_{u,s}(t)=\frac{1}{\sqrt{s}}\Psi(\frac{t-u}{s}), \qquad (2)$$

As we can see from equation (1), continuous wavelet transform *W* (*u*, *s*), which is a projection of time series *x*(*t*) on to the basis wavelet (i.e. $\Psi_{u,s}(t)$), is a function of two continuous variables *s* and *u*. Where *s* is a parameter for dilation (size of wavelet) and *u* is a parameter for translation (location) of the wavelet. By obtaining the wavelet with different dilation and translation values, the wavelet transform decomposes the time series into the different scale and time resolution components. As most financial series are in discrete form, discrete wavelet transform is more applicable to this work.

Similar to that of the continuous wavelet transform, in the discrete wavelet transform, the mother wavelet $\Psi_{j,k}(t)$ is defined as:

$$\Psi_{u,s}(t) = 2^{j/2}\Psi(2^{j}(t) - k),\ j,k \in Z \qquad (3)$$

Where k is the index for translation (location) of the wavelet and j is the index for dilation (size) of the wavelet. For example, as j is increased the wavelet becomes more compact (i.e. smaller in length), hence the time resolution will increase since smaller time durations are analyzed.

The set of two dimensional discrete wavelet transform coefficients $d_{j,k}$ can be obtained by the inner product of series x (t) and mother wavelets $\Psi_{j,k}(t)$:

$$d_{j,k} = \langle x(t), \Psi_{j,k}(t)\rangle = \int_{-\infty}^{\infty} x(t)\Psi_{j,k}(t)dt, \qquad (4)$$

So far I have discussed transforming the time series to the wavelet domain. Furthermore, wavelet transform has the ability to represent a time series at different resolutions (i.e., time and scale). Building on the wavelet transform, Mallat (1989) proposes the multiresolution analysis, with which a time series is decomposed to an approximation and a detailed components at different resolutions. To be able to represent multiresolution analysis of a time series, in addition to the mother wavelet function, which capture the detailed component there, is a need for another function to capture the approximation component. This function, $\ddot{\ }_{j,k}(t)$, is usually called the scaling function, and is represented by Burrus and Gopinath (1997) as:

$$\ddot{\ }_{j,k}(t) = 2^{j/2}\ddot{\ }(2^{j}(t) - k),\quad j,k \in Z \qquad (5)$$

Scaling functions always satisfy the following condition:

$$\int \ddot{\ }_{j,k}(t) = 1, \qquad (6)$$

So any square integrable function, $g(t) \in L^2(R)$, can be express as a combination of the scaling functions and the mother wavelets.

(7)

$$g(t) = \sum_{j=j0}^{\infty} c_{j0}(k)\ddot{}_{j0,k(t)} + \sum_{k=0}^{\infty}\sum_{j=j0}^{\infty} d_j(k)\Psi_{j,k}(t)$$

Where $c_j(k)$ donates the approximation coefficients (smooth) and $d_j(k)$ denotes the detailed coefficients (noisy).

4. GMDH Neural Networks

GMDH neural networks are based on the concept of pattern recognition, and in that sense such networks are a refinement of traditional methods of technical analysis. GMDH neural networks which are highly flexible, semi parametric models, have been applied in many scientific fields, including biology, medicine and engineering.

For economists, neural networks represent an alternative to standard regression techniques and are particularly useful for dealing with non-linear unvaried or multivariate relationships.

By applying GMDH algorithm a model can be represented as set of neurons in which different pairs of them in each layer are connected through a quadratic polynomial and thus produce new neurons in the next layer. Such representation can be used in modeling to map inputs to outputs. The formal definition of the identification problem is to find a function $\hat{f}$ so that can be approximately used instead of actual one, f, in order to predict output $\hat{y}$ for a given input vector $x = (x_1 x_2, x_3, ...x_n)$ as close as possible to its actual output y Therefore, given M observation of multi-input-single-output data pairs so that:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \dots x_{in}) \quad i = 1,2,\dots N \quad (8)$$

It is now possible to train a GMDH-type neural network to predict the output values $\hat{y}_i$ for any York given input vector $x = (x_{i1}, x_{i2}, x_{i3}, \dots x_{in})$, that is:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots x_{in}) \quad i = 1,2,\dots M \quad (9)$$

The problem is now to determine a GMDH-type neural network so that the square of difference between the actual output and the predicted one is minimized, in the form of:

$$\sum_{i=1}^{M} \left[\hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots x_{in}) - y_i\right]^2 \rightarrow \min \quad (10)$$

General connection between inputs and output variables can be expressed by a complicated discrete form of the Volterra functional series that is:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots \quad i = 1,2,\dots n \quad (11)$$

which is known as the Kolmogorov–Gabor polynomial (Farlow, 1984; Iba et al. 1996; Ivakhnenko, 1971; Nariman-Zadeh et al. 2002; Sanchez et al. 1997)? This full form of mathematical description can be represented by a system of partial quadratic polynomials consisting of only two variables (neurons) in the form of:

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i^2 + a_4 x_j^2 + a_5 x_i x_j \quad i = 1,2,\dots M,\ j = 1,2,\dots N \quad (12)$$

In this way, such partial quadratic description is recursively used in a network of connected neurons to build the general mathematical relation of inputs and output variables given in Equation (11). The coefficients a_i in Equation (12) are calculated using regression techniques (Farlow, 1984; Nariman-Zadeh et al, 2003) so that the difference between actual output, y, and the calculated one, $\hat{y}$, for each pair of x_i, x_j as input variables is minimized. Indeed, it can be seen that a tree of polynomials is constructed using the quadratic form given in Equation (12) whose coefficients are obtained in a least-squares sense. In this way, the coefficients of each quadratic function Gi are obtained to optimally fit the output in the whole set of input–output data pair, that is:

$$E = \frac{\sum_{i=1}^{M}(y_i - G_i)^2}{M} \rightarrow \min$$

In the basic form of the GMDH algorithm, all the possibilities of two independent variables out of total n input variables are taken in order to construct the regression polynomial in the form of Equation (12) that best fits the dependent observations $(y_i, i = 1, 2, \ldots M)$ in a least-squares sense. Consequently, $\binom{n}{2} = \frac{n(n-1)}{2}$ neurons will be built up in the first hidden layer of the feed forward network from the observations $\{(y_i, x_{ip}, x_{iq}); (i = 1, 2, \ldots M)\}$ for different $p, q \in \{1, 2, \ldots, n\}$. In other words, it is now possible to construct M data triples $\{(y_i, x_{ip}, x_{iq}); (i = 1, 2, \ldots M)\}$ from observation using such $p, q \in \{1, 2, \ldots n\}$ in the form:

$$\begin{bmatrix} x_{1p} & x_{1q} \cdots & y_1 \\ \vdots & \ddots & \vdots \\ x_{Mp} & x_{Mq} \cdots & y_M \end{bmatrix}$$

Using the quadratic sub-expression in the form of Equation (12) for each row of M data triples, the following matrix equation can be readily obtained as:

$$Aa = Y$$

where a is the vector of unknown coefficients of the quadratic polynomial in Equation (12) :

$$a = \{a_0, a_1, a_{20}, a_3, a_4, a_5\}$$

And $Y = \{y_1, y_{20}, y_3, \ldots, y_M\}^T$ is the vector of output's value from observation. It can be seen that:

$$A=\begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \hdashline 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix}$$

(17)

The least-squares technique from multiple-regression analysis leads to the solution of the normal equations as shown in Equation (18):

$$a = (A^T A)^{-1} A^T Y \qquad (18)$$

which determines the vector of the best coefficients of the quadratic Equation (18) for the whole set of M data triples. It should be noted that this procedure is repeated for each neuron of the next hidden layer according to the connectivity topology of the network. However, such a solution directly from normal equations is rather susceptible to round off errors and, more importantly, to the singularity of these equations. Recently, genetic algorithms have been used in a feed forward GMDH-type neural network for each neuron searching its optimal set of connection with the preceding layer (Nariman-Zadeh et al, 2003). Jamali et al (2006) have proposed a hybrid use of genetic algorithm for a simplified structure GMDH-type neural network in which the connections of neurons are restricted to adjacent layers. In this paper using GA for finding GMDH-type neural networks for modeling the Pareto optimized data.

5. Methodology

As discussed earlier, the wavelet transform can be used as a tool for smoothing or denoising time series. We should note, that we employ wavelet smoothing in this work instead of wavelet de-noising. This selection is due to the fact that for wavelet denoising additional parameters need to be estimated (i.e. denoising threshold), which would further complicate any analysis. We have experimented with different basis wavelets such as Haar, Daubechies, and Symlet, and have observed better results with the Haar wavelet. Similar observations were made by Kaplan (2001), who recommends the selection of Haar wavelets for financial series as a good choice, since they are not inherently smooth and are usually jagged. Using the Haar wavelet, the time series are first decomposed to detail and approximate coefficients, and then the wavelet synthesis function is used to reconstruct the series from only the approximate coefficients. In other words, we remove the second part of the Equation (7), which represents the detail (noise) coefficients. One note of importance is that the discrete wavelet transform requires the time series it operates on be of dyadic length (i.e. *length* = 2*i*, where *i* = 1 : *N*), but this requirement is not always met. A common way to deal with this issue is to extend the length of the time series so that it would become of dyadic length. This is done by padding the time series with zeros, sample mean of series, repetition of only the last value, or repeating the values of the series in a periodic form. In fact, through experimentation, we have found that the periodic padding approach provides the best results in our work.

Also we utilize neural networks with two hidden layers and a direct connection between the lagged moving average crossovers and prices. The 5 day and 50 day moving average crossover[1], and their differences and the time varying

1. Such models are all based on rules using moving averages of recent prices. A typical moving average is simply the sum of the closing prices for the last *n* number of days divided by *n*, where *n* may be from 1 to 200 days the rules for using these tools are very similar and usually involve making a decision when a short-term average crosses over a long-term average. For example, the rule may be to buy when the 5-day moving average exceeds the 50-day moving average and to sell when the 5-day average is below the 50-day average.(Gencay et al.,1996)

variance of data sets are chosen as inputs variables for the GMDH neural networks.

In order to evaluate the prediction performance, it is necessary to introduce forecasting evaluation criteria. In this study, a Root Mean Square Error (RMSE) evaluation criterion is employed, where RMSE is calculated as: (Caslla and Lehmann, 1999; Degroot, 1980)

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}e_i^2} \qquad (12)$$

Where e_i denotes the difference between forecasted and realized values and n is the number of evaluation periods. In the crude oil price forecasting, a change in trend is more important than precision level of goodness of fit from the viewpoint of practical applications.

6. Data Set and Empirical Analysis

The data sets are obtained from the Energy Information Administration website[2], which provides a wide range of information and data sets for energy products. For this work, we use the daily crude oil spot price of New York and Los Angles covering January 4th of 2003 through February 3rd of 2009, consisting of 2300 daily observation for each series.

Table 1 reports the statistical analysis of the data sets. The minimum price of New York crude oil price is 46.75, while the minimum price for Los Angeles crude oil price is 41, column 4. The skewness statistics of New York crude oil price and Los Angles crude oil price are positive, implying that these series are skewed to the right, column 6.

2. www.eia.doe.gov

Table 1 Summary Statistic of Data Sets

Oil Price	Mean	St.d	Min	Max	Skewness	Kurtosis
New York	137.385	66.732	46.75	341.55	0.941	0.098
Los Angeles	150.480	69.980	41	382.51	0.842	-0.0052

We have studied 5 cases, based on the inputs provided to the GMDH neural network:

- Case one: 5 and 50 days moving average, obtained from non-smoothed oil price data sets.
- Case two: 5 and 50 days moving average, obtained from smoothed oil price data sets.
- Case three: 5 and 50 days moving average, obtained from non-smoothed oil price data sets, plus time varying variance of oil price estimated form GARCH (1, 1).
- Case four: 5 and 50 days moving average, obtained from smoothed oil price data sets, plus time varying variance of oil price which is estimated form GARCH (1,1).
- Case five: 5 and 50 days moving average plus time varying variance which is estimated form GARCH (1, 1), obtained from both smoothed and non-smoothed data sets separately. A total of 6 series will be calculated as inputs.

In each case we use the daily data from January 4th of 2003 to October 8th of 2008 as in-sample data set for training and validation purposes and the remainder as the out of sample data set for testing purposes. Case one is chosen as a benchmark model for comparative purpose. Table 2 reports the RMSE indicator calculated for the five cases for both New York and Los Angeles crude oil prices. We observe that removing noise form the data set results in better forecasting performance, as evident from column 2 of Table 2, in which the RMSE indicator for both New York and Los Angeles oil prices falls with respect to the benchmark model. With the 3rd case (e.g. column 3), we observe that including the time varying variance of crude oil price in forecasting process will improve the performance forecasting as well. Lastly, we observe the most improvement in the fifth case, with which the RMSE indicator for Now York and Los Angeles data sets are 6.25 and 6.52, respectively. These numbers indicate a 45% and 42% decrease in the RMSE values with respect to the benchmark model.

Table 2. RMSE Results for the Estimated Models

Oil Price	Case One	Case Two	Case Three	Case Four	Case Five
New York	11.17	7.12	9.53	6.68	6.25
Los Angeles	11.39	7.46	9.76	6.99	6.52

Conclusions

Oil prices have a serious impact on political activities and economical decision of governments and industries, hence forecasting its future value accurately is of great interest to all. In this paper the GMDH neural network model was used for forecasting the price of crude oil, while assuming the price series have time varying variance. Furthermore, wavelet transform was employed as a tool for preprocessing the oil price data sets before inputting it into the GMDH neural network. We investigated five cases, each indicating a different set of inputs for the neural networks. Based on the RMSE indicators, best performance results are obtained in the case where both smoothed and non-smoothed data sets are used to calculate the moving average and the time varying variance. Hence by smoothing our data sets, we are able to obtain a more than 40% improvement in the prediction accuracy.

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پیش بینی قیمت نفت خام: یگ الگوی تلفیقی مبتنی بر تبدیل موجک و شبکه عصبی GMDH

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به طور معمول، قیمت های انرژی، مثل قیمت نفت خام، متأثر از رویدادهای معین مانند تغییرات فصلی و رویدادهای غیرمعین مانند تحولات منطقه ای می باشند. رخدادهای غیر معین که علت تغییرات تصادفی قیمت ها هستند، پیش بینی قیمت را با مشکل اساسی مواجه می کند. رویکرد اولیه به تغییرات تصادفی، فرض وجود نویز در سیستم است که تغییرات معین قیمت را متأثر می کند. در این مقاله، ما تلاش می کنیم از تبدیل موجک به عنوان ابزاری برای هموارسازی و حداقل کردن نویز موجود در سری زمانی قیمت نفت خام استفاده کنیم و سپس با استفاده از روش تلفیقی با شبکه عصبی GMDH، قیمت نفت خام را پیش بینی نمائیم.علاوه براین، با استفاده از روش GARCH ، واریانس های سری زمانی قیمت نفت خام را به الگوی تلفیقی فوق اضافه می کنیم. بدین منظور از قیمت های نفت خام بازارهای نیویورک و لس آنجلس استفاده نموده ایم. نتایج نشان می دهد که به کارگیری روش تلفیقی، بیش از ٤٠٪ الگوی شبکه عصبی بدون لحاظ تبدیل موجک و اثرات GARCH را بهبود می بخشد.

واژگان‌کلیدی: پیش بینی قیمت نفت خام، شبکه عصبی GMDH، تبدیل موجک، مدل GARC.

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