CRUDE OIL PRICE FORECASTING THROUGH NARX MODELLING

AS A DYNAMIC ARTIFICIAL NEURAL NETWORKS

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Abstract

This paper presents a model based on multilayer feedforward neural network used to forecast crude oil price direction on the short term, up to 20 days. After testing pre-processing data methods, we use a dynamic Nonlinear Auto Regressive model with exogenous input (NARX) as a form of ANN in order to take account for the time factor.

As a feedback dynamic neural model, we integrate the output from time series model to feed NARX model. Our NARX model uses data running from 1 January 2002 to 31 December 2015. Results obtained from this training offer a good understanding of the crude oil price dynamic and we observe that predictive trend carried out in the fact.

Keywords: Crude oil price forecasting, Prediction models, Artificial Neural Networks, NARX

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1. Introduction

As one of the most strategic resource of the world, crude oil is a key variable for global economy. Crude oil prices variations are observed by both market actors and financial practitioners. In order to reduce the negative effect of the price fluctuations, forecasting direction of crude oil price is essentially not only for oil exporting and oil importing countries but also for minimizing shocks on other energy markets. Forecasting its price is necessary but it is a challenging task because many factors influence their trends and level price volatility, unforeseen events like weather conditions, financial speculations and shocks, foreign exchange rates variations, OPEC oil policy, dollar index, gold, heating oil spot price... wars, embargoes and political events. (Panas and Ninni, 2000).

Usually, time series analysis is a method of forecasting that focuses on the historical behavior of dependent variable. Oil prices are assumed to be normally distributed in many studies but their departure from normal distribution was disregarded due to misinterpretation of Central Limit Theorem. In fact, crude oil prices are non-Gaussian. Forecasting crude oil prices through fundamental method is a complex task due to uncertainty, noisiness and non-stationary inbuilt in indicators that drive them. Therefore, time series models provide an alternative to analyze and predict future movements based on past behavior of oil prices.

The most common models in time series forecasting, particularly in the parametric estimation method, are the autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) models. ARIMA is a basic linear forecasting model, which uses a lagged series. Because of its simplicity and good performance, ARIMA used to be applied to many time series analyses. GARCH is based on the idea of non-consistent variance in a general time series, and can be applied to the volatility analysis of a time series.

Recently, machine-learning methodologies, such as artificial neural networks (ANN), are used in many forecasting studies, as the versatility of these models allows them to be applied to any time series data. Because an ANN is not based on an asymptotic theory in econometrics, it has a wide and increasing range of applications.

Indeed, Artificial Neural Networks have seen an explosion of interest over the last few years, and have being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology and physics.

In this contribution, we present a dynamic Artificial Neural Networks called a Nonlinear Autoregressive model with external output (NARX), this one using a time factor, allowing a dynamic model and should improve the ability and generate a greater prediction.

This paper proceeds as follows: section 2 presents a brief literature review, section 3 describes methodology used, section 4 deals with data and analysis and section 5 concludes this paper.
2. Literature Review

Since the oil crisis in 1973, many studies focused on forecasting crude oil price. We present here a brief review of the key papers, surveyed on the various techniques used to forecast crude oil price: both traditional and statistical econometric models. Descriptions of static and dynamic artificial neural networks displayed in the section 4.

Amano (1987) was one of the first to use an econometric model for forecasting oil price. Through cointegration analysis, Gulen (1998) succeed to predict the WTI crude oil price. Morana (2001) used a semi-parametric approach based on GARCH to forecast Brent crude oil price on short term.

In their early work, Ye et al. (2002) used a linear regression for forecasting WTI crude oil spot price on short term by using OECD oil inventory levels and stocks. Few years later, Ye et al. (2006) included in their modelling nonlinear variables such as low and high inventory variables to the linear forecasting model.

Others methods were carried out. By utilizing the error correction models, Lanza et al. (2005) worked on crude oil prices. Starting from OPEC behavior, Dees et al. (2007) modelled a linear model of the oil market to forecast both oil demand, oil supply and prices.

At the same time, Moshiri et al.(2006) worked on the chaos and nonlinearity in crude oil prices. They compared ARMA (Autoregressive Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models for the daily forecasting of crude oil prices to FNN (Feedforward Neural Network) and concluded that the latest is the best candidate for modelling and forecasting.

It appears that both traditional statistical and econometric techniques are able to capture only linear process in data time series. Because the oil price is characterized by both high nonlinearity and high volatility, these models are inappropriate to forecast the oil price.

Studies on the relation between spot prices and futures prices have been very experienced by many researchers. They displayed the importance of efficiency, prediction ability, lead and lags.

Among them, Narayan (2007) and Agnolucci (2009) used GARCH model to predict spot and futures crude oil prices. Murat and Tokat (2009) worked on this relation. They showed the capacity of futures prices to predict spot price variations through random walk model.

More recently, Mohammadi et al. (2010) compared issues from different GARCH models in order to forecast crude oil price. In the same posture, Kang et al. (2009) tested CGARCH, FIGARCH and IGARCH models to forecast volatility of crude oil markets in order to measure the best one.

Ksaier et al. (2010) used the Hurst exponent in order to determine the existence of a long memory phenomenon in the daily oil return series (WTI), they concluded that unlike the GARCH and IGARCH models, the selected FARIMA-FIGARCH model is able to capture persistence in the volatility of crude oil price and FIGARCH model generates a best forecasting accuracy.
In this contribution, we use a dynamic ANN model for crude oil price forecasting on short term. It is a nonparametric, nonlinear model. Because ANN lets the data speak for itself there is not a a priori assumption and feedforward network with nonlinear function allows to approximate any function.

Shambora et al. (2007) experienced an ANN model to forecast the crude oil price. The target of the model is the predicted prices. They concluded that ANN outperforms other techniques. For the same purpose of forecasting, Yu et al. (2007) proposed a multiscale neural network to predict oil price. This model performed better than a single-scale one.

Lackes et al. (2009) experienced a layer backpropagation FNN to predict crude oil price trend on short term but also on mid-term and long term (i.e. 3 months). They concluded that prediction modelling with 5 neurons was less rich than with 2 neurons on the long term.

ANN model was also tested by Haidar et al. (2009) to forecast crude oil prices on the short term (3 days). They displayed that the futures prices offer more information to the spot prices and increases forecasting ability.

It appears that these empirical studies that display ANN performance have a better accuracy prediction than the other models.

3. Methodology

Artificial Neural Network (ANN) is an information processing system developed as generalizations of mathematical models of human neural biology (Figure 1). ANN is composed of nodes or units connected by directed links. Each link has a numeric weight (W is the weight matrix). Note that in Figure 1 we have included a bias b with the purpose of setting the actual threshold of the activation function.

Figure 1. Mathematical model of the artificial neuron

\[
v_i = \sum_{j=1}^{d} w_{ij} x_j \\
y_i = f(v_i) = f(\sum_{j=1}^{d} w_{ij} x_j) \\
w = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1d} \\
w_{21} & w_{22} & \cdots & w_{2d} \\
\vdots & \vdots & \ddots & \vdots \\
w_{m1} & w_{m2} & \cdots & w_{md} \end{bmatrix}
\]
Where f is the activation function, \( x_j \) is the input neuron \( j \), \( y_i \) is the output of the hidden neuron \( i \), and \( W \) is the weight matrix. The Neural Networks learns by adjusting the weight matrix. Therefore, the general process responsible for training the network is mainly composed of three steps:
1. Feed forward the input signals
2. Back propagate the error
3. Adjust the weights

Training the Neural Networks is divided into four steps:
1. Data selection: Data selection step restricts subsets of data from larger databases and different kinds of data sources. This phase involves sampling techniques, and database queries.
2. Data pre-processing: data preprocessing represents data coding, enrichment and clearing which involves accounting for noise and dealing with missing information.
3. Data transformation: has the purpose to convert data into a form suitable to feed the NN.
4. Neural Networks selection and training.

### 3.1 Dynamic Neural Networks

Neural networks can be classified into dynamic and static categories, and dynamic neural networks can also be classified into feedback and no feedback categories.

In no feedback dynamic neural networks, the output of the network depends not only on the current input to the network, but also on the previous inputs to the network. In feedback dynamic neural networks, the output of the network depends not only on the current input to the network, but also on the previous inputs, outputs, or states of the network. One principal application of dynamic neural networks is in time series prediction.

Time series prediction studies the trends of process time series of the predicted target. Neural Networks time series tools in MATLAB provide three categories to solve three different kinds of nonlinear time series problems:
- Nonlinear autoregressive with external input (NARX)
- Nonlinear autoregressive (NAR)
- Nonlinear input-output

NARX used in our paper is a feedback dynamic neural network, and it also can be seen as the Back Propagation Neural Networks that depends on the previous inputs and outputs to the network. The structure of NARX network used in the paper as shown in Figure 1.

### 3.2 Nonlinear Autoregressive Network with Exogenous Inputs (NARX):

The NARX models are commonly used in the system of identification area (Xie et al., 2009). All the specific dynamic networks discussed so far have either been focused networks, with the dynamics only at the input layer, or feed-forward networks. The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time series modelling.
Figure 2 illustrates the standard NARX network. The standard NARX network used here is a two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This network also uses tapped delay lines (d) to store previous values of the input, \( x(t) \) and output, \( y(t) \) sequences. First, load the training data and use tapped delay lines with two delays for both the input and the output, so training begins with the third data point. There are two inputs to the series-parallel network, the \( x(t) \) sequence and the \( y(t) \) sequence. Notice that the \( y(t) \) sequence is considered as a feedback signal, which is an input that is also an output (target). The model can be summary by the Eq. 1:

\[
y_t = f(y_{t-1}, \ldots, y_{t-d}, x_{t-1}, \ldots, x_{t-d})
\]

where, \( y_t \) is the output of the NARX network and also feedback to the input of the network and tapped delay lines (d) that store the previous values of \( x_t \) and \( y_t \) sequences.

4. Data Selection and Case study

4.1 Data
Most governments and private sector players on the oil market consider the WTI as the benchmark for the international crude oil price. The crude oil prices on other markets are influenced by fluctuations in the WTI oil market (He K, Yu L, Lai KK 2012).

In this study, our data sample contains 5 daily (5-day / week) time series over the period from January 1st, 2002 to December 31th, 2015, namely crude oil price, Euro/Dollar exchange rate, stock price, US 10 Year Treasury and VIX (Volatility Index as a “fear index”). These data sets retrieved from DATASTREAM sources.

- US interest rate: Decreasing interest rates level will make lendings more accessible and will stimulate crude oil demand, which, in turn, will contribute to the oil prices increase.
- SP500 index: This index, characterizing state of financial markets, is included here to represent general financial situation and its possible effects on oil prices. According to a number of previous studies there is a strong relationship between crude oil prices and stock markets.
- Euro-Dollar Exchange rate: is referred as a factor of daily changes in crude oil prices, there is a negative correlation between crude oil prices and Euro-Dollar exchange rate, stronger U.S Dollar leads to lower crude oil prices and weaker U.S. Dollar leads to higher crude oil prices (see graph below).
Daily evolution
Stock Prices

Daily evolution
Interest Rate
4.2 Analysis Model

In this contribution, nonlinear autoregressive with exogenous input (NARX) model (Figure 3), constructed by using MATLAB neural network toolbox, is used in order to obtain future prediction values of a time series, $y(t)$, from past values of this time series and past values from other time series, $x_i(t)$. In these experiments, we conducted NARX with different numbers of hidden layers, numbers of tapped delay lines ($d$) and one output neuron with two-layer feed-forward networks (hyperbolic tangent transfer function in the hidden layer and linear transfer function in the output layer) were used.

Training automatically stops when generalization improving, as indicated by an increase in the Mean Square Error (MSE) of the validation samples.
According to the Figure 4, all values of $R$ are above 0.998 during training of the neural network. This shows that the output produced by the neural network model is closely similar to the target and that the model is adequate.

The model specification is trained by experimenting number of nodes and number of tapped delay lines. The number of neurons in the hidden layer is determined by trial and error method. First, the trials initialize at error with 2 nodes. Then, the process is repeated until 15 nodes were used. On the other hand, the number of tapped delay lines was initialized at 2 steps up until 4 steps. A comparison of the MSE value for all networks was carried out. The lowest MSE value will be selected as optimum network. Based on training method, the lowest MSE value is obtained with 12 nodes in hidden layers and 2 tapped delay lines. This result is also supported by a high $R$ value (0.99855) at 12 nodes that means a close relationship between Output and Target. Hence, 12 hidden nodes with 2 tapped delay lines are selected as optimum network.
4.3 Prediction Model

From our results, it appears that thanks to neural networks, the direction of crude oil prices can be predicted (red curve), with a high accuracy. From the training regression plot displayed supra (Figure 4), we obtain the model fit (blue curve) which corresponds to the observed trend. Indeed, we observe a high correlation and low mean squared error term. Dynamic Neural Network can be helpful for investors and policy makers by giving information about the future direction of the oil price market.

5. Conclusion

In this paper, after surveyed a brief review of literature on forecasting crude oil price, we presented a NARX model for forecasting crude oil prices on the short term. Indeed, taking account the variation of crude oil price and nonlinearity of its time series, traditional and statistical econometric models to forecast crude oil prices are inappropriate. So we chose a dynamic ANN as a nonlinear artificial model - after a description of this approach - to predict crude oil price on short term. In this intention, we test the ability of NARX method to make accurate prediction. We conclude that artificial neural networks offer a greater predictive ability for crude oil price forecasting. Our future research continues to investigate other techniques, which could lead to improving the short term forecast.
References


