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Forecasting Crude Oil Price Using Artificial Neural Networks: A Literature Survey

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Abstract

The literature on forecasting the « black gold » price is vast. This paper provides a literature review on the various techniques that have been used to forecast crude oil price. We mainly focused on the researches that have utilized artificial neural network models in their forecasting study. Therefore, a detailed description of this model will be presented in this paper.

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1. Introduction

As the most important strategic resource around the globe, crude oil is the “key” commodity for the world’s economy. Therefore, forecasting crude oil price has always been considered as a very challenging task which drew the interest of researchers, practitioners and institutions. The price of oil is essentially determined by its supply and demand (Hagen, 1994; Stevens, 1995), it is also strongly related to irregular and unforeseen events caused by weather, wars, embargoes and revolutions (Aloui et al. 2012). Moreover, the important role of financial activity, and especially that of the speculation, in oil price formation has recently become such a strongly debated issue (Kilian and Murphy, 2011; Fattouh, 2012 ; Kilian et al., 2013 ; Beidas-Strom and Pescatori, 2014). Many other factors like Gross Domestic Production growth, stock levels inventories, foreign exchange rates, world population, political aspects and investors’ expectations can significantly affect the price of oil (Bernabe et al., 2004; Ghouri, 2006; Nelson et al., 1994; Yousefi and Wirjanto, 2004). Furthermore, the time to ship crude oil from one country to another can affect directly their price because oil prices vary in different regions of the worldwide (Wang et al., 2005a). All these factors can explain the nonlinear evolution and chaotic behavior of crude oil prices and therefore the high volatility of crude oil market (Plourde and Watkins, 1994; Yang et al., 2002). The oil price fluctuations have a direct effect on the nation’s economy (Hamilton, 1996, 2010; Blanchard and Gali, 2007; Kilian, 2008); therefore, it is of vital importance to predict oil price.

The present paper is organized as follows. Section 2 outlines the numerous studies which used traditional and statistical econometric models to forecast crude oil price. Then, a detailed description of artificial neural network model was introduced. In addition, we present the existing literature on crude oil price forecasting using this model. Finally, we conclude in section 3.

2. Crude Oil Price Prediction: A Literature Review

2.1 Application of Traditional and Statistical Econometric Models

Among many and different forecasting models that have been developed to predict the "black gold" price, the traditional statistical and econometric methods are the first ones to be applied by academic researchers.
The first research about forecasting oil market is proposed by Amano (1987). The author used a small-scale econometric model for oil market prediction. Huntington (1994) utilized a sophisticated econometric model for predicting oil price in the 1980s. In another work, Gulen (1998) applied cointegration analysis to predict the WTI crude oil price. Barone-adesi et al. (1998) suggested a semi-parametric approach based on the filtered historical simulation technique to forecast oil price. Based on the GARCH properties of the oil price volatility, Morana (2001) employed a semi-parametric approach investigated by Barone-adesi et al. (1998) to short-term forecast of Brent crude oil price. In another work, Tang and Hammoudeh (2002) utilized a nonlinear regression to predict OPEC basket price. Using OECD petroleum inventory levels and relative stock inventories, Ye et al. (2002, 2005) adopted a simple linear regression model for short-term monthly prediction of WTI crude oil spot price. In a related study, Ye et al. (2006) included nonlinear variables such as low- and high- inventory variables to the linear forecasting model suggested by Ye et al. (2002, 2005) to predict short-run WTI crude oil prices. Using OECD stocks, non-OECD demand and OPEC supply, Zamani (2004) applied an econometrics forecasting methodology to short term quarterly WTI crude oil spot

price. Lanza et al. (2005) investigated crude oil and product prices by utilizing the error correction models. Sadorsky (2006) applied multiple univariate and multivariate statistical models such as GARCH, TGARCH, AR, and BIGARCH to daily forecast of volatility in petroleum futures price returns. Slightly more recent, Dees et al. (2007) developed a linear model of the world oil market to predict oil demand, supply, and prices focusing mainly on OPEC behavior. Murat and Tokat (2009) investigated the relationship between futures and spot crude oil prices and therefore tested the ability of futures prices to forecast spot price movements using random walk model. Cheong (2009) adopted ARCH models to forecast crude oil markets. On the other hand, more recent studies have applied GARCH as well as different models of the GARCH family to predict oil price. For example, Narayan and Narayan (2007) and Agnolucci (2009) used GARCH model to forecast spot and futures crude oil prices. In a related research, Mohammadi and Su (2010) compared the forecasting results of various GARCH-types models in order to predict the crude oil price. Kang et al. (2009) proposed CGARCH, FIGARCH and IGARCH models to forecast volatility of crude oil markets. For the same pupose, Wei et al. (2010) extended the study of Kang et al. (2009) by applying linear and nonlinear GARCH-class models.

As results of the application of linear techniques, a significant error has been demonstrated between actual and predicted oil prices. With these models, several exogenous variables have been employed to predict oil price, however; inventory, supply and demand are the mostly used factors. Supply and demand are relatively inelastic to price changes, subsequently, an inventory adjustment can be slow to happen which explains the major part of the difference between real and forecasted prices, especially for the short run (Hamilton, 2008). On the other hand, traditional statistical and econometric techniques are usually able to capture only linear process in data time series (Weigend and Gershenfeld, 1994). However, the oil prices behavior is characterized by a high nonlinearity and irregularity. Therefore, the mentioned models are not the appropriate choice to forecast the oil price.

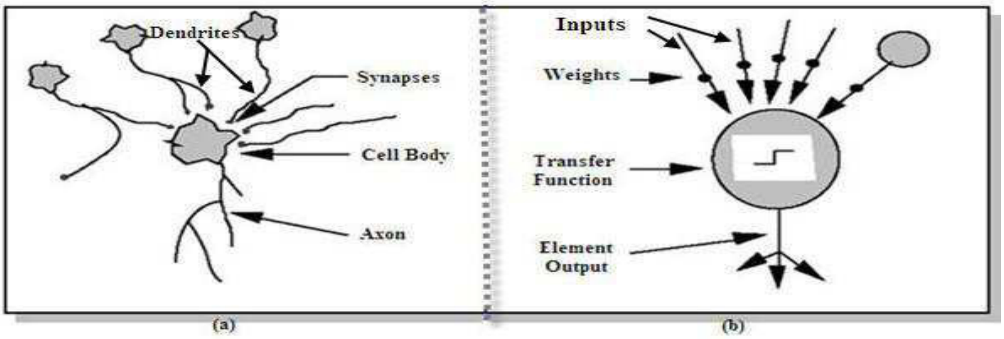
2.2 Artificial Neural Network (ANN): Model Description

2.2.1 Definition and Neuron Model Evolution

2.2.1.1 Definition

ANN is an input-output mathematical model inspired from human brain functioning by adopting the same mode of acquiring knowledge through learning process. Fig. 1 summarizes an analogy between biological and artificial neuron.

Figure 1. Analogy between biological neuron (a) and artificial neuron (b)



2.2.1.2 Neuron Model Evolution

a) McCulloch & Pitts (1943) neuron model

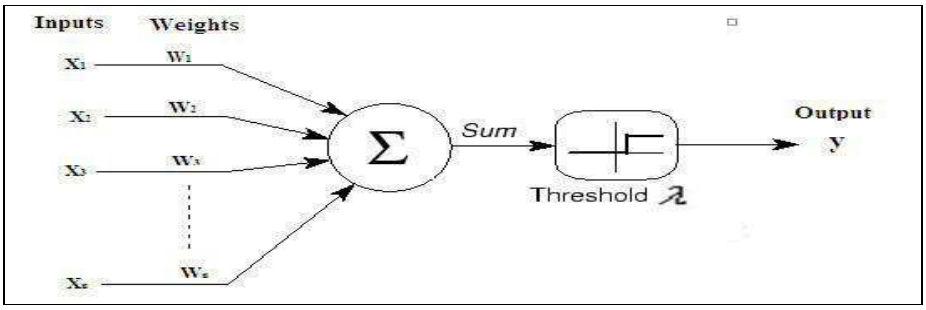
McCulloch and Pitts (1943) proposed the first artificial neuron also called formal neuron. Mathematically, the McCulloch-Pitts neuron model can be written as follows:

$$y = f\left(\sum_{i=1}^{n} w_i x_i - \lambda\right) \qquad (1)$$

Where $x_1, x_2, \ldots, x_n$ represent the McCulloch-Pitts neuron inputs that are exclusively binary values (zeros or ones), $w_1, w_2, \ldots, w_n$ are the connections' weights received by the neuron. f is the sign function, λ is the threshold and y is the output of McCulloch-Pitts neuron defined as:

$$f((x_1, \ldots, x_n), (w_1, \ldots, w_n)) = \begin{cases} 1, & if \sum_{i=1}^{n} w_i x_i \geq \lambda \quad (2) \\ 0, & if \sum_{i=1}^{n} w_i x_i < \lambda \quad (3) \end{cases}$$

Figure 2. Illustration of McCulloch & Pitts (1943) neuron



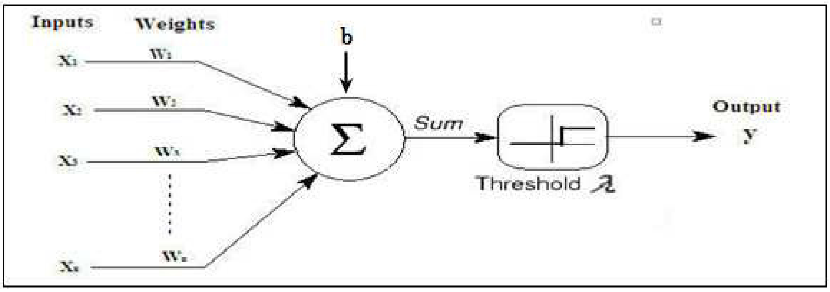
b) Perceptron model (Rosenblatt 1958)

Rosenblatt (1958) introduced an improved version of McCulloch-Pitts neuron model, a perceptron, as the first artificial neuron introducing the learning rule. The perceptron splits the space of input variables into two regions according to a linear decision boundary called linear separator. Thus, the following equation describes the perceptron output :

$$f((x_1, \ldots, x_n), (w_1, \ldots, w_n), b) = \begin{cases} 1, & if \sum_{i=1}^{n} w_i x_i + b \geq \lambda \quad (4) \\ 0, & if \sum_{i=1}^{n} w_i x_i + b < \lambda \quad (5) \end{cases}$$

Where $x_1, x_2, ..., x_n$ represent the Rosenblatt's neuron inputs, $w_1, w_2, ..., w_n$ are the synaptic weights received by the neuron. f is the sign function, λ is the threshold and b represents the bias measure.

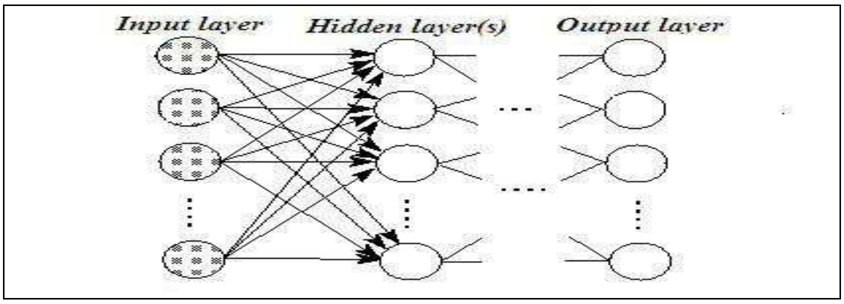
Figure 3. Illustration of Rosenblatt's (1958) neuron



c) Multilayer perceptron model

Perceptron neural nets without hidden layers suppose only binary values of input-output as well as only two layers which explains the capability of the model to treat only the linearly separable functions. Windrow and Hoff (1960) introduce a learning rule called the delta rule consisting in modifying the connections' weights in order to reduce the difference between desired and actual output value. Therefore, the output value can take any value instead of 0 and 1. Minsky and Papert (1969) highlighted, in their book, the utility of adding one or more hidden layers to detect the complex features present in the inputs. The multilayer perceptron net was trained, traditionally, based on the backpropagation learning algorithm (detailed in the next section) developed by Rumelhart et al. (1986).
The multilayer perceptron is composed of a layer of input units, one or more hidden layers and an output layer (see Fig .4).

Figure 4. Illustration of multilayer perceptron net



In this network system, the information propagates in a single direction''forward'': the input units pass the information to the neurons in the first hidden layer, the outputs from the first hidden layer are subsequently passed to the next layer, and so forth. Thus, the network output (for example, with one hidden layer) is :

$$y_k = h\left\{ \sum_{j-1}^{J} w_2(j,k)\, g\left[\sum_{i=1}^{I} w_1(i,j)\, x_i + b_1(j) \right] + b_2(k) \right\} \tag{6}$$

Where: x_i are the input variables of the network; I is the number of input variables; J is the total number of nodes in the hidden layer; K is the number of neurons in the output layer; g and h are, respectively, the transfer/activation function of the first and the second layer; w_1 is the weights matrix of the hidden layer; w_2 is the weights matrix of the output layer; b_1 and b_2 are the bias vectors of the hidden layer and of the output layer, respectively. To note, at least one transfer function (see the next section for more description of transfer function) of the hidden layer must be nonlinear (Hornik et al., 1989).

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2.2.2 Operating Keys

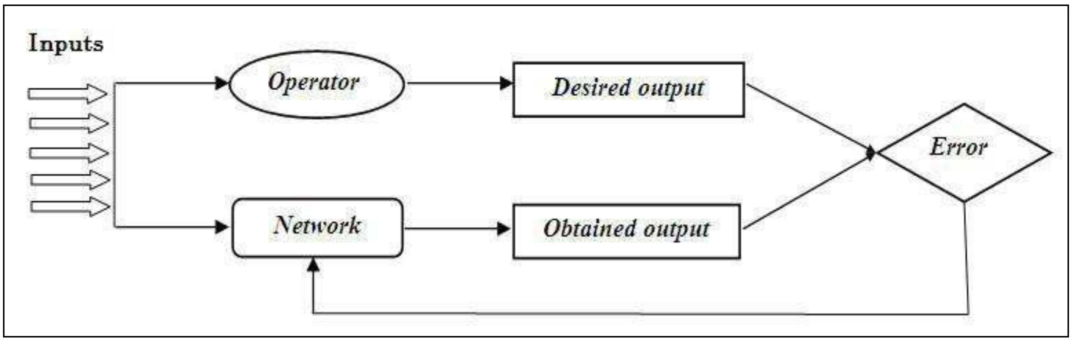
2.2.2.1 Learning Mode

The learning process of the neural net consists in the adjustment of connections' weights between neurons until achieving better network response. In fact, there are three modes of learning :

a) Supervised learning

In the supervised learning, the presence of an external operator is indispensable. The role of the operator is to provide to network both the inputs and the desired responses. Then the network is forced to converge to a specific final state (target output) by modifying the synaptic weights. Weights are usually initiated randomly and the learning rule adopted to adjust weights is the rule of error correction (the error is the difference between the desired value and the calculated response by the net). This type of learning is mostly used by neural networks trained with backpropagation learning algorithm (defined later). Fig. 5 schematizes this category of learning.

Figure 5. Supervised learning

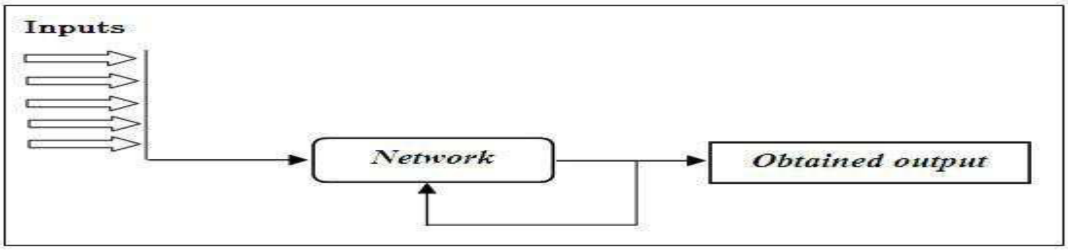


b) Unsupervised learning

In the unsupervised learning, there is no external operator that supervises the process of learning, only inputs were provided to the network. Weights will be adjusted on the basis of a competitive learning rule and the outcomes of the network will have the same trend as similar inputs. The most famous ANN based on unsupervised learning is the self-organizing map

(SOM) of Kohonen[1]. The Kohonen's SOMs are widely applied in several fields such as text classification, pattern recognition, clustering, etc. Fig .6 depicts an explanatory diagram of this class of learning.

Figure 6. Unsupervised learning



c) Reinforcement learning

''Reinforcement learning is learning what to do-how to map situations to actions-so as to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them'' (Sutton and Barto, 1998. Reinforcement Learning: An Introduction. MIT Press, Cambridge, MA, A Bradford Book, p. 4).

2.2.2.2 Learning Algorithm: The Backpropagation Rule

The learning algorithm is designed to estimate the optimum weights. Therefore the good choice of the learning rule is needed to deduce a good quality of estimation. In this context, the most used algorithm is the backpropagation algorithm. This rule consists in adjusting the synaptic connections in order to minimize the error between the calculated or estimated response (0_k) and the desired response (d_k) of the network.

The backpropagation algorithm can be applied to any type of error function. Thus, it is necessary to define an error function to be minimized. This function could be for example ; the root mean square error defined as follows:

$$E = \frac{1}{K}\sum_{k=1}^{K}\left(d_k - 0_k\right)^2 \qquad (7)$$

Where K is the number of network responses.

The weights **W** $\left(W_i, W_h\right)$ are firstly initialized randomly, where W_i and W_h are the random vector of weights generated, respectively, by the input layer and hidden layer. Using these connections weights $\left(W_i\right)$ each hidden nodes performs a weighted sum ($\sum\left(W_i X\right)$) of its

[1] For more details see the seminal work of Kohonen (1982).

inputs **X** and then applies the activation function $f(.)$. Thus, $f(\sum(W_i X)$ represents the inputs of the output layer (supposing that the network presents only one hidden layer), thereafter the output neurons are calculated as follows :

$$O_k = g\left(W_h f(\sum(W_i X))\right) \tag{8}$$

where f and g is the transfer function in the hidden and output layer, respectively.

By using the backpropagation rule as a learning algorithm of ANN model, the sigmoid activation/transfer function is the most frequently utilized (Van der Baan and Jutten, 2000).

After computing the output of the network, the next step consists in comparing the obtained response to the desired response of the network, therefore takes the error that must be reduced.

To update the weights of neurons, the error signal is back propagated to the inputs by modifying synaptic weights such that the error between the calculated and desired output will be minimized in the next iteration (t+1).

$$W(t+1) = W(t) + \Delta W(t) \tag{9}$$

Where $\Delta W(t) = -\varepsilon \frac{\delta E}{\delta W}$, *with ε is the learning rate and E is the output error.*

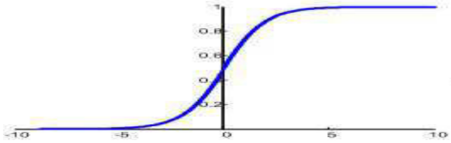
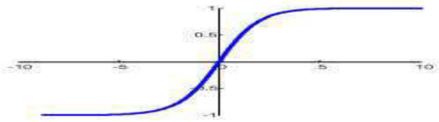
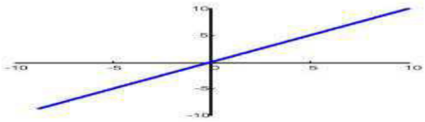
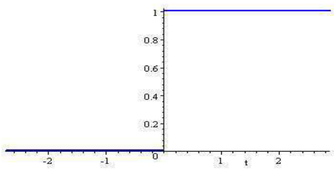
The process will be repeated many times until obtaining a negligible output error $\delta E \simeq 0$.

2.2.2.3 Activation/Transfer Functions

An activation or transfer function $f(\cdot)$ is a mathematical function applied to the weighted sum ($\sum(WX)$) to determine the activation or the state of each neuron of the net : $f\left(\sum(WX)\right)$. The activation function plays a crucial role in the convergence of the learning algorithms. Therefore, a pertinent choice of this element is required in the specification of an ANN model (Gomes et al., 2011).

As known, there are several types of activation functions, however, the sigmoid and hyperbolic tangent functions are the most widely used (Haykin, 1999). Table 1 presents mathematical definitions as well as graphical representations of some activation functions.

Table I. Activation/Transfer functions

Function	***Definition***	***Graphic illustration***
Sigmoid	$\dfrac{1}{1+\exp^{[-(WX)]}}$	
Hyperbolic tangent	$\dfrac{\exp^{(WX)}-\exp^{[-(WX)]}}{\exp^{(WX)}+\exp^{[-(WX)]}}$	
Identity	WX	
Heaviside	$\begin{cases} 0 \text{ si } WX < 0 \\ 1 \text{ si } WX \geq 0 \end{cases}$	

2.2.2.4 Stopping Criteria

The goal of using stopping criterion is to decide when to finish learning process of an ANN to avoid overfitting problem. According to Shao et al. (2011), the most applied stopping parameters are, a predefined error output value (the difference between the target output and the ANN computed output) for training phase, a predetermined number of learning iterations to reduce this error and finally, a threshold value of learning rate defined as a stop index of training process.

2.2.3 Performance Criteria

The use of forecasting evaluation measures is a necessary step to gauge the predictive capability of the ANN model. To verify the predictive ability, several performance criteria can be used as good indicators of forecasting performance. Table 2 presents the most frequently utilized performance criteria to judge the quality of prediction of the employed model (Zhang et al., 1998).

Table II. Performance measures

Definition	*formulas*
Sum **S**quared **E**rror (**SSE**)	$SSE=\sum_{i=1}^{n}(d_i-0_i)^2$
Mean **S**quared **E**rror (**MSE**)	$MSE=\frac{1}{N}\sum_{i=1}^{n}(d_i-0_i)^2=\frac{SSE}{N}$
Root **M**ean **S**quared **E**rror (**RMSE**)	$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{n}(d_i-0_i)^2}=\sqrt{MSE}$
Mean **A**bsolute **E**rror (**MAE**) index or Mean Absolute Deviation (**MAD**)	$MAE=\frac{1}{N}\sum_{i=1}^{n}\lvert d_i-0_i\rvert$
Mean **A**bsolute **P**ercentage **E**rror (**MAPE**)	$MAPE=\frac{1}{N}\sum_{i=1}^{n}\left\lvert\frac{d_i-0_i}{d_i}\right\rvert*100$
Normalized **M**ean **S**quared **E**rror (**NMSE**)	$NMSE=\frac{\sum_{i=1}^{n}(d_i-0_i)^2}{\sum_{i=1}^{n}(d_i-\overline{d_i})^2}=\frac{SSE}{\sum_{i=1}^{n}(d_i-\overline{d_i})^2}=\frac{MSE}{\frac{1}{N}\sum_{i=1}^{n}(d_i-\overline{d_i})^2}$

*N is the size sample

2.3 Application of ANN Models

This section presents a large search of literature survey on forecasting crude oil price based on ANN model. Kaboudan (2001) and Rast (2001) are the first to introduce the ANN technique in order to predict the price of crude oil. Kaboudan (2001) compared two compumetric techniques as genetic programming (GP) and ANN to random walk (RW) model to forecast the monthly crude oil prices. For this purpose, the author used several monthly time series over the period from 1993 to 1999, namely crude oil spot prices, world crude production, OECD consumption, world crude stocks, change in US stocks and lagged FOB crude oil price of US imports. Based on MSE measure, he concluded that genetic algorithm forecasting model (MSE=1.85) outperformed the RW (MSE=2.29) and also the neural network technique (MSE=3.54). In the same year, Rast (2001) employed fuzzy neural networks methodology for forecasting the future crude oil price. He used oil futures prices time series into two different oil market states (contango, i.e. purchasing the oil today is less expensive than purchasing it by utilizing the future contract; while in the backwardation state, the use of futures contracts will cost less). Based on the performance forecast results, he showed that the proposed model improve the prediction accuracy (6.95%) more than the classical technique as the feedforward neural network (-22.34%) for the out of sample set.

In another research, Mirmirani and Li (2004) applied two different techniques to forecast the evolution of U.S. oil price. A vector autoregression (VAR) is the first technique, modeled based on three explanatory variables: oil prices, petroleum consumption and oil supply. While money supply, oil supply and petroleum consumptions are used as inputs of the second tool "the backpropagation neural network (BPNN) with genetic algorithm (GA)". The forecasting accuracy was evaluated based on monthly data over the period between January 1986 and November 2002 using two performance criteria: (RMSE) and (MAE). By comparing the results of these metrics, ANNs with GA model (RMSE=1.2354, MAE=0.8629) offers much better performance than VAR technique (RMSE=4.69861, MAE=4.18883).

In another work, Wang et al. (2005b) applied a TEI@I methodology to monthly crude oil price forecasting by combining web-based text mining (WTM), rule-based expert systems (RES), autoregressive integrated moving average (ARIMA) model and ANN technique. WTM was utilized to extract the irregular events, from internet, that can affect the variability of crude oil price. The impact of the retrieved information was therefore measured by using RES. The ARIMA model is employed for modeling the linear part of crude oil price time series, while the BPNN was used to handle the nonlinear part. By utilizing the online retrieved information and the monthly WTI crude oil spot prices ranging from January 1970 to December 2003, the proposed model was compared to single ARIMA, single ANN and to the simple integration of ARIMA- ANN. To verify the effectiveness of the nonlinear integration approach, three performance criteria, RMSE, direction statistics (D_{stat}) and the hit ratio are used. The empirical results show that the TEI@I methodology significantly performs the best in terms of all evaluation statistics used (e.g. the hit rate for the nonlinear integration over the entire period of evaluation (2000-2003) was equal to 85.42% whereas only 70.83% for the simple integration and for the same period the RMSE was equal to 1.0549 for the nonlinear integration whereas 2.0350, 2.3336 and 2.3392 for the simple integration, ANN and ARIMA, respectively. Also, the higher D_{stat} ($\approx$ 100%) was achieved with the nonlinear integrated forecasting approach, 85.42% for the simple integration, 70.83% for ANN tool and the lowest D_{stat} was found with ARIMA model (54.17%).

In the study of Moshiri and Foroutan (2006), three competing tools are proposed such as a feedforward neural network (FNN), ARMA (autoregressive moving average) and generalized autoregressive conditional heteroskedasticity (GARCH) models for the daily prediction of crude oil futures prices. The data used in this forecasting study are the daily crude oil futures prices covering the period between April 4th, 1983 and January 13th, 2003. Three performance metrics (MAE, MSE and RMSE) were utilized to evaluate the forecasting results of the proposed models. On the basis of these computed measures, they concluded that ANN (MAE=2.04, MSE=8.14 and RMSE=2.85) performs significantly better than ARMA (MAE=4.81, MSE=29.27 and RMSE=5.41) and also than GARCH model (MAE=2.90, MSE=15.25 and RMSE=3.90).

In next work, Xie et al. (2006) applied a support vector machine (SVM) model to predict crude oil price using monthly WTI spot prices over the period from January 1970 to December 2003. The proposed method was compared to ARIMA and BPNN. As results and focusing on two forecasting performance criteria (RMSE and Dstat), they found SVM forecaster performs better than the two other models. However, the BPNN surpass SVM and ARIMA for two sub-periods among four tested sub-periods.

Slightly more recent, Shambora and Rossiter (2007) used an ANN model to predict the crude oil futures prices by utilizing technical analysis crossover rules as inputs. To train the model, daily nearby crude oil futures contract prices over the period from April 16th, 1991 to

December 1st, 1997 are employed. The outputs of the neural network represent the predicted prices which are considered as trading signals. Therefore, an empirical investigation of profitability has been conducted using several means and statistical measures and factors. Besides, the authors compared the neural network model to three benchmark trading strategies such as buy-and-hold strategy, traditional technical trading strategy and a naïve RW strategy. As results of this empirical study, the profitability of ANN performs better than the other benchmark models indicating inefficiency of the crude oil futures market.

In another study, Amin-naseri and Gharacheh (2007) proposed a hybrid artificial intelligence tool to forecast the monthly WTI crude oil price. The hybrid model is composed of three popular artificial intelligence (AI) techniques such as the FNN, GA and the K-means clustering. To assess effectiveness of the proposed model, the authors compared the prediction results of the hybrid model with the forecasts of four single models namely Short term energy outlook, GP, AI framework system[2], and ANN technique. The WTI Crude oil price time series used in their empirical study were selected from January 1983 to December 2006 for the first experiment (comparison with the first model) while from January 1974 to December 1999 for the second (comparison with GP) and running from January 1983 to December 2002 for the third experiment (comparison with the third model). Finally, the oil price data of the fourth and last experiment (comparison with ANN) was selected over the period from January 1974 to December 2001. Based on nine performance criteria (MAE, MAPE, Max AE, SSE, MSE, RMSE, D_{stat}, U2-Theil (RMSE of the model/ RMSE of RW process) and the squared correlation coefficient (R^2)), hybrid model results outperform significantly others techniques in terms of the majority of performance measures used for empirical comparison study.

For the same purpose of predicting crude oil price, Liu et al. (2007) employed a fuzzy neural network approach. More precisely, a combined three forecasting tools were applied in this work as the radial basis function (RBF) neural network, markov chain based semiparametric method and wavelet decomposition analysis. For the simulation task, the authors used Brent crude oil price ranging from May 20th, 1987 to August 30th, 2006. To assess the simulation forecasting results, MSE was used as a performance evaluation metric. Based on this criterion, the authors showed that the proposed forecasting method outperforms the others single models (1.02980, 2.70602, 2.81591 and 4.52168 respectively for combined forecasting tool; markov chain based semiparametric model, RBF neural network and wavelet analysis).

Also, Yu et al. (2007) proposed a multiscale neural network learning paradigm based on empirical mode decomposition method to predict the WTI crude oil price. The decomposition method consists on decomposing the original daily crude oil price time series, running from 01st/01/1998 to 30th/10/2006, into different intrinsic mode components that can be used as inputs of neural network. After training process and based on input strength indicator, only six components are retained among nine as inputs of neural network model for prediction task. To evaluate this task, the proposed model was compared to single- scale neural network learning paradigm for two different neural network architectures[3] . According to NMSE and R^2, the comparison results showed a superiority of the multiscale learning paradigm for both architectures. For the same neural network design, the multiscale neural network learning paradigm performs better than the single-scale learning paradigm and especially with (6:15:1) architecture which represents the lowest error (0.0084) and the highest R^2(0.9876).

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[2] See the research paper of Wang et al. (2004) for more explanation of this approach.

[3] The first neural network configuration used is (9:15:1) that represents 9 intrinsic mode components utilized as inputs, 15 hidden nodes and one output and the second neural network design adopted is (6:15:1) .

Gori et al. (2007) utilized adaptive neuro-fuzzy inference system (ANFIS) to predict monthly oil prices. The future oil price depends only on its past price history. The proposed model has been trained focused on price data ranging from July 1973 to January 1999, and from February 1999 to December 2003 for checking and verification purpose. The authors concluded that ANFIS methodology can provide a good forecasting ability.

In their research study, Haidar et al. (2008) developed a three layer backpropagation FNN to predict the short-term of crude oil spot price. Two groups of daily variables were considered as inputs of the forecasting model. The first represents the WTI crude oil futures prices while the second is composed of S&P 500, gold spot price, dollar index and the heating oil spot price. These features were selected over the period from 1996 to August 2007. Based on several performance criteria such as the hit rate, information coefficient (IC), RMSE, R^2, MSE, MAE and SSE, Haidar and his colleagues concluded that futures contracts mainly 1 and 2 months to maturity improve the prediction results, and also outperform all other inputs for one step forecast. Moreover, they found that heating oil spot price improves the forecasting ability of the employed model for multiple steps prediction.

Moreover, Yu et al. (2008) used an empirical mode decomposition (EMD) based neural network learning approach to forecast both WTI and BRENT crude oil prices. The proposed learning paradigm applies the decomposition technique with three-layer FNN and an adaptive linear neural network (ALNN) in the price forecasting task. In this research, they have utilized a daily data of crude oil price over the period between 01st/01/1986 to 30th/09/2006 and from 20th/05/1987 to 30th/09/2006 for WTI and BRENT, respectively. For the purpose of testing and verification, the authors have compared the proposed model with five others techniques such as the EMD-FNN-Averaging, EMD-ARIMA-ALNN, EMD-ARIMA-Averaging, standard FNN and the single ARIMA. Based on two main indicators as the RMSE and D_{stat}, the empirical results have shown that the EMD-FNN-ALNN significantly perform the best for the two time series under study ($RMSE_{(WTI)}$=0.273 and $D_{stat(WTI)}$=86.99%; $RMSE_{(BRENT)}$=0.225 and $D_{stat(BRENT)}$=87.81%).

Recently, Lackes et al. (2009) proposed the backpropagation FNN to forecast crude oil price development in short-term (one week ahead), mid-term (one month ahead) and long-term (one quarter ahead). They used a lot of available relevant factors (supply and demand as well as economic and political influencing features) which have a meaningful influence on the crude oil market from 1999 to 2006. Several network architectures were built and the three layer perceptron was shown as the optimal design. More precisely, Lakes and his colleagues aimed at forecasting the trend of WTI price development and not the exact WTI price value. Hence, they employed five neurons in the output layer that represent five trend classes ('strong decrease', 'decrease', 'constant price', 'increase', 'strong increase'), they also tried with two output neurons corresponding an 'increase' and a 'decrease' trend prediction. Based on the measure of the hit rate as the forecasting performance criterion, they concluded that the trend prediction with two classes was explicitly superior than trend forecasting with five classes, especially in the mid and long term which reach more than 90% whereas 69% in short-term.

In another recent study, Kulkarni and Haidar (2009) presented an ANN model with backpropagation algorithm to predict the crude oil spot prices on the short term (three days ahead). Moreover, these authors tested the relationship between futures and spot crude oil prices. Using WTI crude oil spot prices and futures prices (1, 2, 3 and 4 months to maturity) time series for the period ranging from September 1996 to August 2007 and based on hit rate and RMSE as performance criteria, they concluded that the futures prices especially futures contracts 1 and 2 add newer information to the spot price and therefore, improve the prediction accuracy of the crude oil price direction for the short term.

Furthermore, Ghaffari and Zare (2009) combined the ANNs and the fuzzy logic approaches to predict the daily variation of the WTI crude oil price. Furthermore, they applied a smoothing algorithm to the daily crude oil spot prices running from January 5th, 2004 to April 30th, 2007. By comparing the smoothing procedure model (model 1) to the model without smoothing procedure (model 2), the empirical findings showed a great advantage of the smoothing algorithm to improve accuracy of the model predictions. The authors determined the percentage of the correct prediction (PCP) and found therefore that PCP of model (1) surpasses the PCP of model (2) for several arbitrary selected periods. For example, for the period (1st/5/2007-31st/5/2007), the PCP equals to 45.45% and 68.18% for model (1) and (2), respectively. These findings highlighted the reliability of the proposed model (model 1) and especially the capability of the smoothing procedure to reduce the unforeseen short term disturbances while maintaining the dynamic crude oil process.

In the same year, Qunli et al. (2009) simultaneously applied a wavelet transform and RBF neural network for crude oil price forecasting. The wavelet transform of Mallat algorithm decomposed the original crude oil price into three decomposed levels which are used as the input layer of the network. Hence, the proposed network was composed on four input nodes, for hidden nodes and one output neuron that represent the future crude oil price. The world crude oil price used in this research was the Europe (UK) Brent Blend spot price covering the period running from January 1997 to October 2008. Focusing on the simulation results, the authors showed that the wavelet decomposition method improves the forecasting accuracy.

In another research, Alizadeh and Mafinezhad (2010) proposed an intelligent forecasting tool as the general regression neural network to forecast monthly Brent crude oil price. As input of the proposed network, the authors employed six factors, namely, US refinery capacity, US gross domestic product growth, US dollar nominal effective exchange rate, OPEC total liquid capacity, OPEC crude oil production ceiling allocation and US gasoline ending stocks. A crisis index was also used to overcome unforeseen world events that can affect oil price behavior. In this research, Alizadeh and his colleague investigated the forecasting ability of general regression neural network model in two different conditions (normal and critical). In normal conditions, they only utilized six main factors as inputs due to absence of important crisis. In this case, the error simulations showed a good prediction. While in critical conditions, the authors included the crisis index to inputs therefore significantly more important prediction results were demonstrated. In March 2008, the error simulation value was equal to 2.58 and 41.31 for the model included crisis index and without crisis index respectively. Based on these results, the authors concluded that introducing crisis index in critical situation periods presents a great importance to improve the forecasting accuracy of crude oil price.

Abdullah and Zeng (2010) applied the machine learning and ANNs-quantitative approach to forecast the monthly WTI crude oil price. A combination of qualitative and quantitative data, varying from January 1984 to February 2009, was used as inputs of the proposed model. The qualitative data was derived from online news, whereas the quantitative variables represent a total of 22 sub-indicators of population, economy, inventory, supply and demand. By focusing on the results of three performance measures such as NMSE (0.00896), RMSE (2.2690) and Dstat (93.33%); the authors showed the reliability of this prediction tool. To validate this finding, the authors compared this approach to two other hybrid models as TEI@INonlinear Integration model and EMD-FNN-ALNN model based on RMSE and Dstat metrics.

Corresponding to RMSE comparison results, the ANN-quantitative model (2.2690) performs less than TEI@INonlinear Integration model (1.0579) and also less than EMD-FNN-ALNN model (0.2730). Nevertheless, TEI@INonlinear Integration forecasting model presents the highest D_{stat} (95.83%) and slightly less important D_{stat} value (93.33%) with ANN-quantitative, however, 86.99% with EMD-FNN-ALNN model. Consequently, the high directional accuracy (93.33%) proved the effectiveness of this predicting tool.

More recently, Jammazi and Aloui (2012) employed a hybrid model combining the multilayer BPNN and the Haar A Trous wavelet decomposition to forecast the short term crude oil price. The crude oil data frequency used in this empirical investigation is the monthly spot price of WTI over the period ranging from January 1988 to March 2010. To provide the best forecasting simulation results, the authors used different neural network architectures as well as three kinds of transfer function as the sigmoid, the bipolar sigmoid and the hyperbolic tangent. Four performance metrics (MSE, MAE, hit rate and R^2) were chosen by the authors to testify the forecasting ability of the proposed technique. The comparative empirical findings show that the hybrid model, which combine 3 input-3 hidden nodes to hyperbolic tangent transfer function (MSE=3.59066, MAE=1.10108, hit rate=80% and R^2=0.9988), outperforms the multilayer BPNN (MSE=4.48590, MAE=1.40342, hit rate=76% and R^2=0.9892).

In a more recent research, Xiong et al. (2013) proposed an EMD analysis based on the FNN modeling incorporating the slope-based technique (SBM) to forecast the crude oil price for multi-step-ahead. To investigate the forecasting performance of the proposed model, the authors have examined and compared three multi-step-ahead prediction strategies including iterated strategy, direct strategy, and MIMO (multiple-input multiple-output) strategy using the weekly WTI spot price over the period (07^{th}/01/2000-30^{th}/12/2011). On the basis of prediction accuracy[4] and computational load, they concluded that the employed EMD-SBM-FNN model using the MIMO strategy is the best compared to others strategies. To justify this conclusion, let's refer back to the example of 12-step-ahead where MASE is equal to 0.991, 0.948 and 0.914 respectively for EMD-SBM-FNN strategy, direct EMD-SBM-FNN strategy, and MIMO EMD-SBM-FNN strategy. Table 3 presents a summary of literature on oil price prediction.

Table III. A Survey on world oil price prediction

Author(s)	**Technique(s)**	**Periods**
Kaboudan (2001)	GP, ANN, RW	1993 - 1999
Rast (2001)	Fuzzy neural networks	NA
Mirmirani and Li (2004)	BPNN with GA and VAR	01/1986 - 11/2002
Wang et al. (2005)	TEI@I methodology (nonlinear integration) ARIMA ANN Simple integration (ARIMA+ANN)	01/1970 – 12/2003
Moshiri and Foroutan (2006)	ANN, ARMA, GARCH	04/04/1983 - 13/01/2003

[4] The prediction accuracy has mainly been evaluated based on symmetric MAPE (SMAPE) and mean absolute scaled error (MASE) performance criteria.

Xie et al. (2006)	SVM , ARIMA, BPNN	01/ 1970 - 12/ 2003
Shambora and Rossiter (2007)	ANN	16/04/1991 - 01/12/1997
Amin-naseri and Gharacheh (2007)	FNN, GA, K-means clustering	01/1983 – 12/2006
Liu et al. (2007)	Fuzzy neural network	20/05/1987 - 30/08/2006
Yu et al. (2007)	Multiscale neural network learning paradigm	01/01/1998 - 30/10/2006
Gori et al. (2007)	ANFIS model	07/1973 – 12/2003
Haidar et al. (2008)	Three layer backpropagation FNN	1996 - 08/2007
Yu et al. (2008)	EMD-FNN-ALNN, EMD-FNN-Averaging, EMD-ARIMA-ALNN, EMD-ARIMA –Averaging, FNN and ARIMA	(WTI: 01/01/1986 - 30/09/2006) and (BRENT: 20/05/1987 - 30/09/2006)
Lackes et al. (2009)	Backpropagation FNN	1999 - 2006
Kulkarni and Haidar (2009)	ANN	09/1996 – 08/2007
Ghaffari and Zare (2009)	ANFIS	05/01/2004 - 30/04/2007
Qunli et al. (2009)	Wavelet transform and RBF neural network	01/1997 -10/2008
Alizadeh and Mafinezhad (2010)	General regression neural network	NA
Abdullah and Zeng (2010)	Machine learning, ANNs-quantitative	01/ 1984 - 02/2009
Jammazi and Aloui (2012)	Multilayer BPNN and the Haar A Trous wavelet decomposition	01/1988 – 03/2010
Xiong et al. (2013)	EMD-SBM-FNN EMD-SBM-FNN strategy, direct EMD-SBM-FNN strategy, MIMO EMD-SBM-FNN strategy	07/01/2000-30/12/2011

*NA: not available

3. Conclusion

In this paper, we surveyed a literature on forecasting crude oil price. Firstly, we began by introducing numerous studies which have used traditional and statistical econometric models to forecast crude oil prices. These methods are usually able to handle only linear time series data. However, crude oil market is the most volatile commodities market. Therefore, forecasting oil price via nonlinear models is the appropriate choice. ANN is the most popular nonlinear AI model used to predict crude oil price. Therefore, we have well described this approach. Finally, we presented the existing literature on forecasting crude oil price using ANNs models. As conclusions drawn from these studies, neural network approach has shown a strong predictive ability, in this field of research.

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