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Comparing Functional Link Artificial Neural Network And Multilayer Feedforward Neural Network Model To Forecast Crude Oil Prices

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Abstract

In this paper a trigonometric functional link artificial neural network (FLANN) model using backpropagation rule is applied to predict the next day's spot price of US crude oil. The daily observations of these variables: US dollar index, S&P 500 stock price index, gold spot price, heating oil spot price and US crude oil spot price are employed as inputs of the proposed model. By comparing with multilayer backpropagation feedforward neural network (FNN), more accurate predictions were shown by applying the FLANN model. In fact, several performance criteria are used to assess the forecasting power of the proposed model such as the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the hit rate. For checking the forecasting robustness of the proposed model, in addition to the other input variables, the US crude oil and biofuels production are also used to predict the next month's spot price of crude oil. Comparatively, similar conclusion was deduced and the FLANN model performs better than the standard FNN. These findings can be explained by the simplicity of FLANN structure since it consists of a single layer with only one neuron at the output thus a lower computational load on the network.

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1. Introduction

Considering the high volatility of international crude oil markets, forecasting the crude oil price is an extremely challenging task. Up to now, a wealthy literature has been focused on this topic. The econometric and statistical models (such as random walk model, error correction models, vector autoregression (VAR) technique, (G)ARCH class models) are among the first methods which have been used to forecast the price of crude oil. However, these techniques failed to offer good prediction results due to the nonlinear aspect of crude oil market. Therefore, the applicability of the statistical forecasting approaches has been mainly challenged by the artificial neural network (ANN) models in predicting the crude oil prices. Hamdi and Aloui (2015) have recently presented a detailed bibliographic review in this field of research.

In the presented study, we carry out a comparison of the functional link artificial neural network (FLANN) and multilayer feedforward neural network (FNN) model to predict the West Texas Intermediate (WTI) crude oil price. In fact, there are two main reasons to select these two techniques in our predictive analysis. First, the FNN is the most applied tool in predicting crude oil price due to it's universal approximator property (Hornik et al., 1989). Second, and to the best of our knowledge, the FLANN model is employed for the first time to forecast the crude oil market.

This technique is very recently used for classification and prediction in data mining. For solving classification problems, we cited these works (Misra and Dehuri, 2007 ; Dehuri and Cho, 2010a, 2010b ; Mili and Hamdi, 2012 ; among them). On the other hand, there are few studies that address the use of FLANN as a predictive tool (Chen and Ou, 2009 ; Majhi et al., 2009a ; Tai and Ahn, 2012). However, there are a certain number of researches that have specially focused on stock market prediction by using FLANN model (Majhi et al., 2009b ; Patra et al., 2009 ; Padhiary and Mishra, 2011 ; Mohapatra and Raj, 2012 ; Kumar and Kailas, 2012 ; Bebarta et al., 2012 ; among them).

The remainder of the present paper is structured as follows. Section 2 is devoted to a comparative analysis between FLANN model and multilayer FNN to predict crude oil price. More precisely, we begin by presenting the data used for daily forecasts of WTI crude oil price. Second, we describe the two proposed forecasting models. Then, we present the empirical results to evaluate the short (one day ahead) and mid-term (one month ahead) forecasting ability of the applied models. Later, we conclude in section 3.

2. Comparison of FLANN and multilayer FNN to Predict WTI Crude Oil Price: Experimental Study

2.1. Data Description

For short-term prediction, the daily data from January 4, 2010 to December 31, 2013 of the US dollar index, S&P 500 stock price index, gold spot price, heating oil spot price and US crude oil spot price, are employed as inputs of the proposed models. Those inter-market data were chosen by Haider et al. (2008) to forecast WTI crude oil price. The energy data (crude oil spot price and heating oil spot price) are provided by US Energy Information administration website: http://www.eia.doe.gov/. Other variables such as US dollar index and S&P 500 stock price index were retrieved from the official site of Federal Reserve Bank of St. Louis: http://research.stlouisfed.org/. Finally, the gold prices were downloaded from world gold council: http://www.gold.org/.

According to the most previous studies on forecasting crude oil price, the hypothesis which assume that the past history of price is the only independent variable to forecast the future is valid, but really it's not sufficient. According to the price theory, market prices are mainly related to the law of demand and supply (Weber, 2012). However, these key variables are not available on daily frequency; therefore, a careful selection of input factors is required for crude oil short-term forecast. The choice of the used variables can be explained by the following reasons:

As suggested by Haider et al. (2008), S&P 500 index represents the overall market performance; gold price is less volatile than crude oil which can reflect the real trend in the commodities market; heating oil price indicates the seasonality in the energy market and the US dollar index prove the strenght of the USD versus other international currencies [1]. Moreover, Ismail et al. (2009) indicate that S&P 500 index and US dollar index have an influence on gold prices, therefore on crude oil prices. Recently, Mensi et al. (2013) show that information circulates from the S&P 500 to the commodity markets especially gold and WTI crude oil markets.

The data is divided into two parts: training and testing data sets. The daily data covers the period of 04/01/2010 to 31/12/2012 are used to train the network and the rest of the data (approximately one financial year of 2013) are used for testing. The training set is primarily intended to define the optimal parameters of the network (connection weights and bias) while the test set is not involved in the learning process and it is only adopted to assess the performance of the network.

2.2. The FLANN Model: Structure and Learning Process

2.2.1. FLANN Structure

The construction of a FLANN is shown in Fig. 1. FLANN is a single layer flat structure first introduced by Pao (1989). Specifically in this network, the hidden layers are reduced by renovating the input pattern to a higher dimensional space such that in the expected higher dimensional space the patterns become linearly separable. Due to the absence of hidden layer, FLANN provides computational advantage over the multilayer perceptron model. Unlike the multilayer perceptron, it performs pattern enhancement by using a set of functional expansion functions of either an element or the entire pattern. In fact, there are several conventional nonlinear functional expansions such as trigonometric, Chebyshev and power series. Generally, in a FLANN, the functional expansion is carried out by using trigonometric functions (Patra and Pal, 1995; Nanda and Tripathy, 2011). In a recent research, Mili and Hamdi (2013) have elaborated an empirical comparative study between trigonometric, power series, Chebyshev polynomials and Chebyshev Legendre polynomials functional expansion functions. These authors concluded that the trigonometric functional expansion is the most adequate choice in a FLANN model. Therefore, the trigonometric functional expansion was employed in our experimental analysis.

In our study, a 5-dimensional input pattern given by $X=[X_1,X_2,\ldots X_5]^T$ expanded to higher-dimensional pattern by trigonometric functions as $X^*=[1,X_1,\cos(\boldsymbol{\pi}X_1), \sin(\boldsymbol{\pi}X_1), \cos(2\boldsymbol{\pi}X_1),$

[1] Major currencies index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden.

$\sin(2\pi X_1)\ldots.X_2, \cos(\pi X_2), \sin(\pi X_2), \cos(2\pi X_2), \sin(2\pi X_2)\ldots.X_1{*}X_2\ldots{*}X_N]^T$. Hence after the input patterns, the trigonometric expansion, $X^*=F=[f_1(X),f_2(X),\ldots.f_N(X)]T$, $\{f\}^N{}_{i}=1$ is a set of bias function, where $X=[X_1, X_2, \ldots X_N]^T$ is the input vector and $W_j=[W_{j1},W_{j2},\ldots W_{jN}]^T$ is the weight vector. Then sum of the network is:

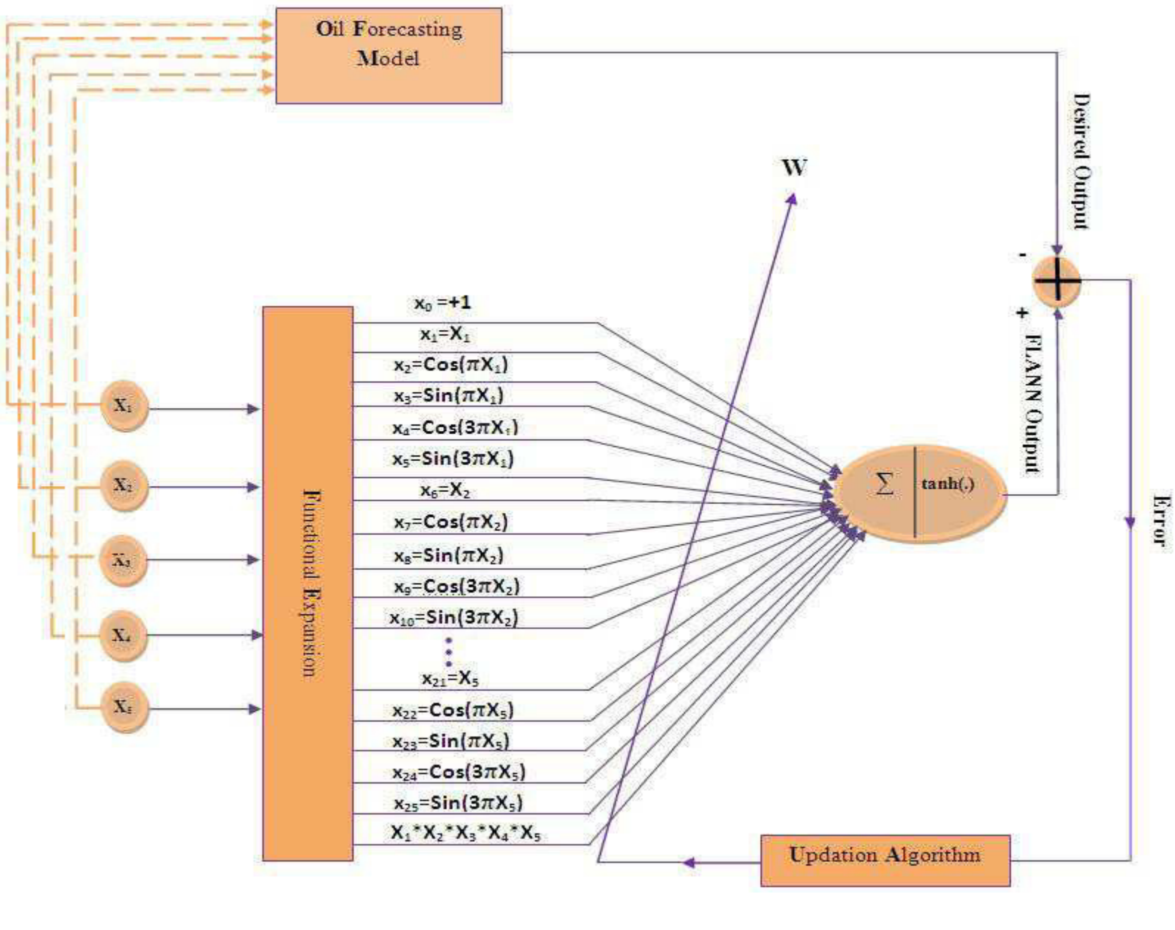
$$s_j = \sum_{i=1}^{N} W_{j,i} F_i(X) \tag{1}$$

For five input vector $X=[X_1,X_2,\ldots.X_5]^T$, the functional expansion $F=[x_0,x_1,x_2,\ldots x_{25},x_{26}]$ where $x_0= +1$, is bias of the network. Where x_1,x_2,x_3,x_4,x_5 are five expansion of first input X_1, i.e. are $x_1=X_1$, $x_2=\cos(\pi X_1)$, $x_3=\sin(\pi X_1)$, $x_4=\cos(3\pi X_1)$, $x_5=\sin(3\pi X_1)$, x_6,x_7,x_8,x_9,x_{10} are the expansion of X_2, i.e. $x_6=X_2$, $x_7=\cos(\pi X_2)$, $x_8= \sin(\pi X_2)$, $x_9=\cos(3\pi X_2)$, $x_{10}= \sin(3\pi X_2)$. Similarly for X_5, x_{21}, x_{22}, x_{23}, x_{24} and x_{25} are the expansions i.e. $x_{21}=X_5$, $x_{22}=\cos(\pi X_5)$, $x_{23}=\sin(\pi X_5)$, $x_{24}= \cos(3\pi X_5)$, $x_{25}=\sin(3\pi X_5)$, the last pattern $x_{26}=X_1{*}X_2{*}X_3{*}X_4{*}X_5$. Hence the total expansion is 27 including the bias of the structure.

The M-dimensional linear output is given by $s=W^TF$, where $s=[s_1,s_2,..s_M]^T$ and $W=[W_1,W_2,\ldots W_M]^T$ is a N×M weight matrix. The output of the FLANN structure is given by :

$$Y = [y_1, y_2, \ldots y_M]^T = tanh(s_j) \cong \tanh\left\{\sum_{i=1}^{N}\sum_{j=1}^{M} W_{j,i} F_i(X)\right\} \tag{2}$$

Figure 1. FLANN structure



2.2.2. FLANN Learning Process

Learning process involves updating the weights of FLANN in order to minimize the error of the system. Error is always considered as a cost function. Here gradient descent algorithm is used to reduce the cost function. For k^{th} index, the error of the system is determined as follows:

$$E_k = \frac{1}{2}(d_k - y_k)^2 = \frac{1}{2}e_k^2 \tag{3}$$

Where d_k and y_k are respectively the desired and the estimated output at k^{th} index. The goal of the learning algorithm is to minimize the error E_k. The output of the FLANN is computed and the error $e_k=(d_k-y_k)$ is obtained. For minimizing e_k, backpropagation algorithm is used.

$$W_{k+1} = W_k + \Delta W_k = W_k + \left(-\alpha \frac{\partial E_k}{W_k}\right) \tag{4}$$

Where α is the momentum parameter. The gradient of the cost function is given by:

$$\frac{\partial E_k}{\partial W} = e_k \frac{\partial y_k}{\partial W} \tag{5}$$

The update rule for the FLANN system is given by:

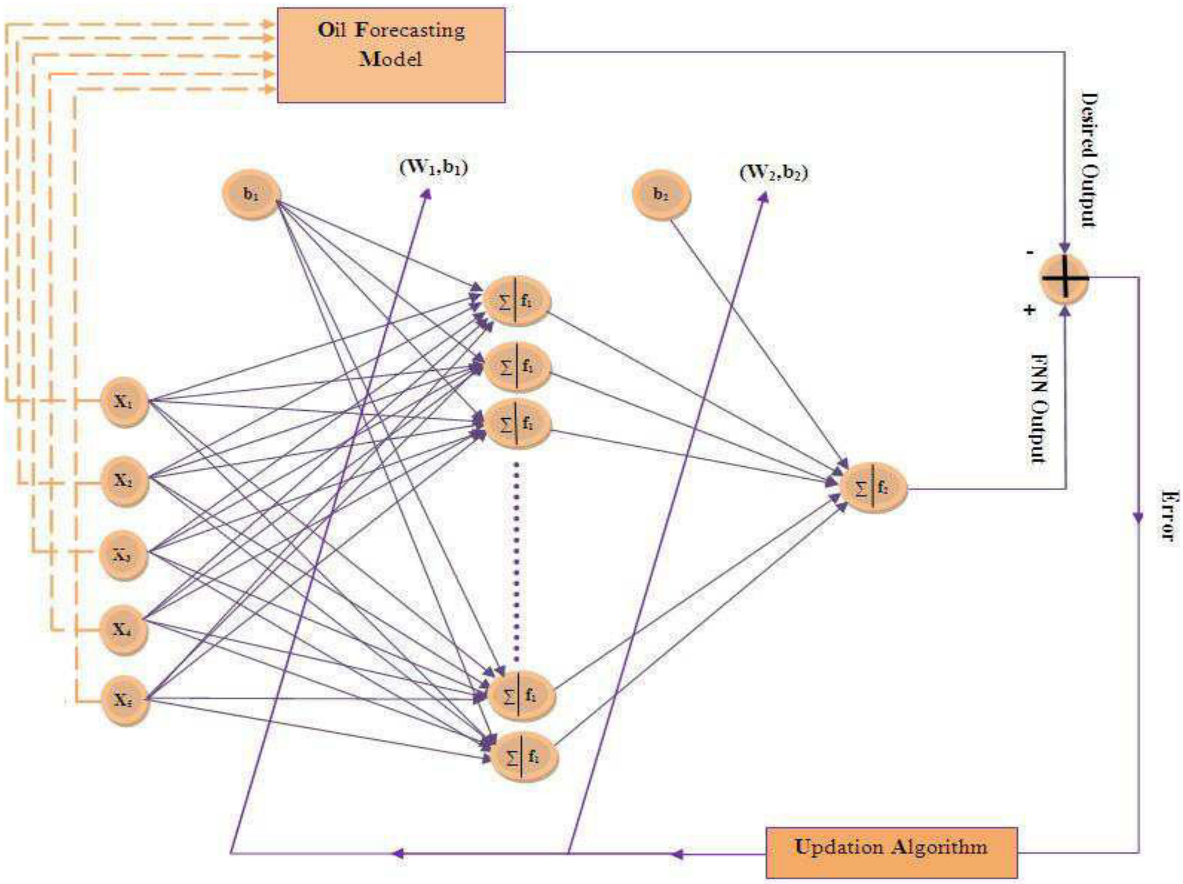
$$W_{j,i}(k+1) = W_{j,i}(k) + \alpha\, e_j\,(k) \times F_i(x) \tag{6}$$

2.3. The Multilayer FNN Model : Structure and Optimal Design

2.3.1. FNN Structure

The multilayer FNN model is the most popular ANN wich is usually trained using backpropagation algorithm (Rumelhart et al., 1986). The multilayer FNN consists of an input layer, one or more hidden layers and an output layer. The multilayer FNN structure is illustrated in Fig. 2.

Figure 2. FNN structure



The state of the output neuron is determined by the following formula :

$$y_k = f_2 \left\{ \sum_{j-1}^{J} w_2(j,k)\, f_1 \left[\sum_{i=1}^{I} w_1(i,j) x_i + b_1(j) \right] + b_2(k) \right\} \tag{7}$$

Where, x_i are the input variables of FNN; I is the number of input variables; J is the number of neurons in the hidden layer; K is the number of nodes in the output layer; f_1 and f_2 are, respectively, the transfer function of the first and second layer; w_1 is the weight matrix of the hidden layer; w_2 is the weight vector of the output layer; b_1 and b_2 are the bias vectors of the hidden layer and output layer, respectively.

2.3.2. Optimal FNN Design

A lot of expert knowledge and also several experiments are required to determine the optimal architecture of FNN because there are no scientific rules to define the optimal network design

(Lackes et al., 2009). Therefore, several parameters must be adjusted to select the best network topology:

- The number of hidden layers

According to Zhang et al. (1998), the ideal number of hidden layers in a backpropagation FNN is generally one or two layers. Furthermore, Yu et al. (2008) suggested that the single layer FNN can model any nonlinear time series.

- The number of hidden nodes

There are no universal standards to define the number of hidden neurons (Ögüt et al., 2009). The best procedure is to use the least amount of units which allow to achieve significant results, as too many nodes could deduce an overfitting problem and too few could cause an underfitting problem (Kaastra and Boyd, 1996). Therefore, the number of nodes in hidden layer is defined as 13 in this analysis. This number is determined by using trial and error.

- The choice of activation function

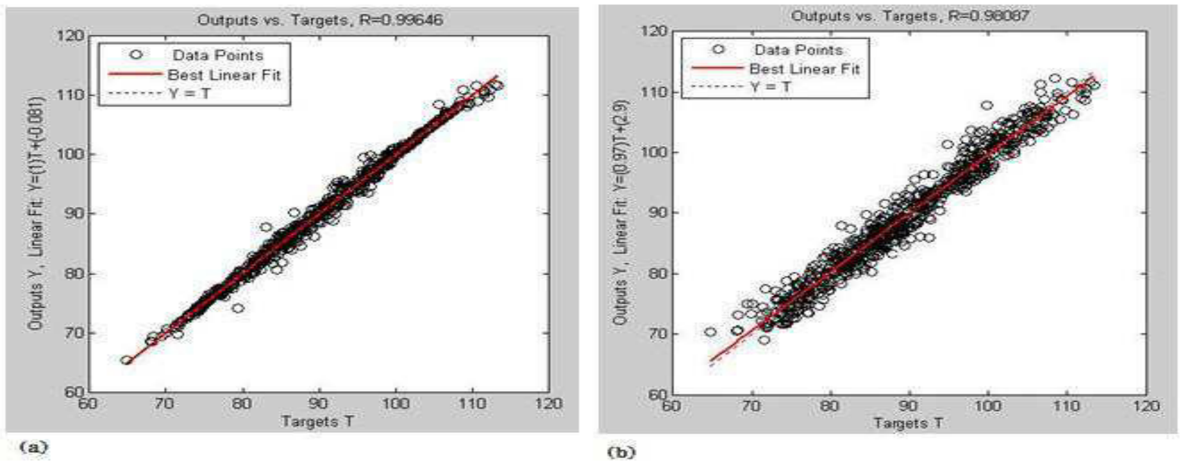
In the use of ANN, there are different activation functions; however, the sigmoid and hyperbolic tangent functions are the most used in financial applications (Haykin, 1999). In our study, we use the hyperbolic tangent function and the linear function, respectively for the hidden and output layer since they are the most commonly adopted (Yonaba et al, 2010 ; Caner et al., 2011 ; Jammazi and Aloui, 2012).

Thus in our analysis, we select a one hidden layer FNN trained with gradient descent backpropagation algorithm. As summary, a backpropagation FNN with the node numbers (5,13,1) is configured in this study.

2.4. Expriment Results and Discussion

Before checking the forecasting power of the two proposed networks, we should verify the quality of training process given that ‘‘*a well-trained network is expected to provide robust predictions.*’’ (Mirmirani and Li, 2004, p.6). Therefore, in our study, the training phase was evaluated based on regression analysis depicted in Fig. 3.

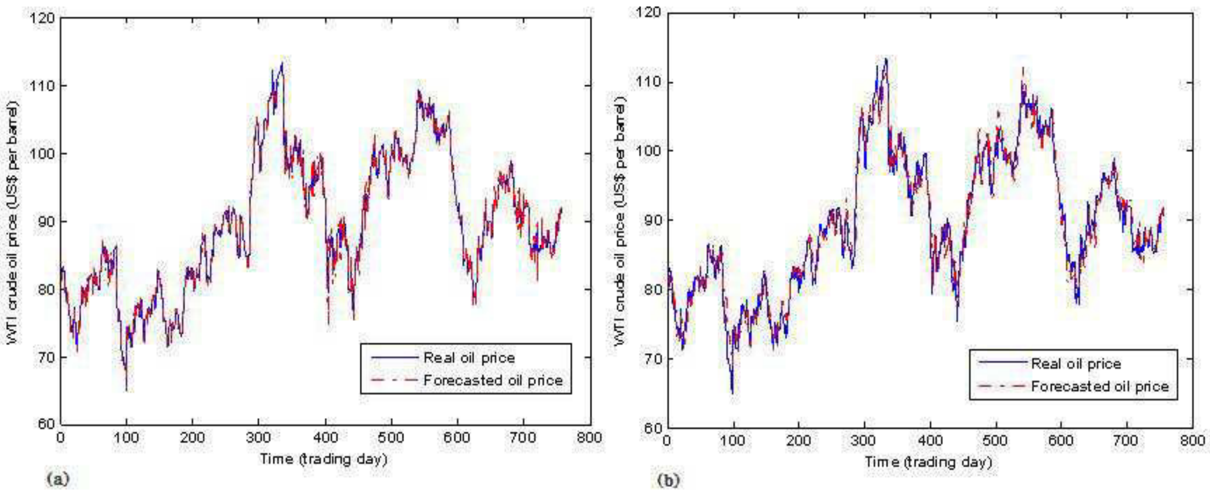
Figure 3. Comparison of target and ouput values of WTI crude oil price : in training process of FLANN (a) and FNN (b)



These plots illustrate the linear regression of targets relative to network predictions. In the afromentioned figures, the circles represent the data points and the red line indicates the perfect adjust line or the best fit between observed and estimated values. By comparing the sacatter plots, it's clear that FLANN is less scattered.

Furthermore, the R-value is a vital criterion derived from regression plots. This measure indicates the degree of correlation between the estimated and actual values. In fact, more the correlation coefficient (R) is close to 1 more there is a perfect correlation between targets and outputs. This regression analysis indicates that the R-value of FLANN is equal to 0.99646 which is very close to 1 and superior to the R-value of FNN (0.98087). According to these findings, the FLANN fits much better and therefore we can deduce that the latter model can better predict the oil price compared to the FNN model. Figure 4 illustrates the actual and estimated WTI crude oil prices for the two proposed models in the training phase.

Figure 4. Comparison of target and ouput values of WTI crude oil price : in training process of FLANN (a) and FNN (b)



Thereafter, the predictive power of the models under study must be verified on the basis of the test samples. Therefore, the forecasting ability of FLANN and FNN models are compared based on three performance metrics such as the RMSE, MAE and R^2 (see Table I). These statistics which are the most commonly used to judge ANN performance are defined as :

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(d_i - y_i)^2} \quad (8)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|d_i - y_i| \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(d_i - y_i)^2}{\sum_{i=1}^{n}(d_i - \bar{d}_i)^2} \quad (10)$$

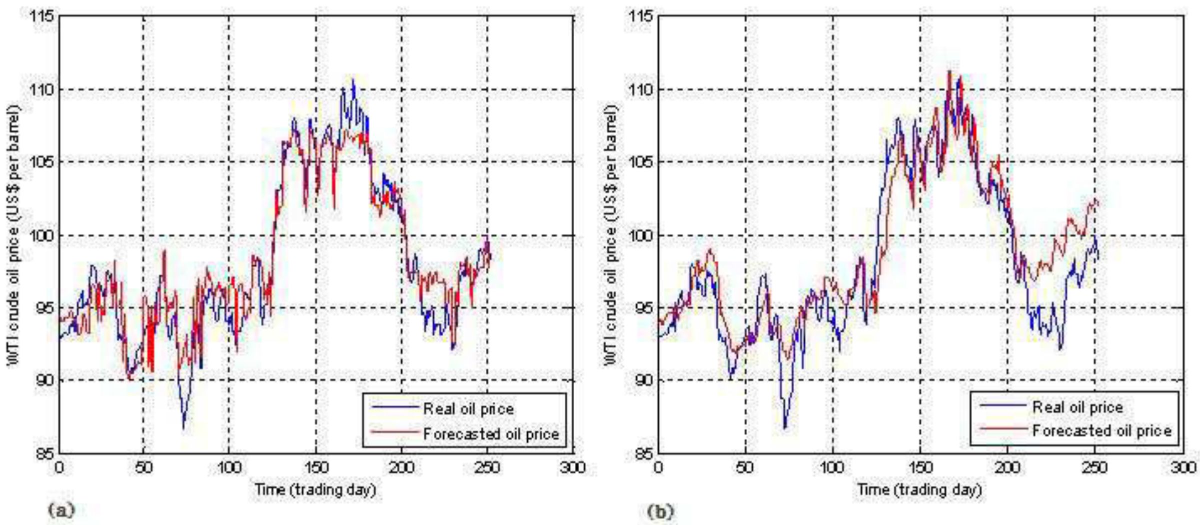
Where *d* is the desired oil price and *y* is the predicted one. N is the size of test sample.

Table I. Comparison of networks performance

Models	*Evaluation metrics*		
	RMSE	MAE	R^2
FNN	2.3279	1.8247	84.29%
FLANN	1.7240	1.3606	92.71%

Focusing on the above Table, we can conclude that FLANN model outperforms the FNN model for the daily forecast of WTI crude oil prices. In fact, the values of RMSE and MAE indicators of FNN model are higher than those of FLANN model. Moreover, the R^2 performance measure indicates the significant superiority of FLANN technique compared to FNN as $R^2_{of\ FLANN}=0.9271 > R^2_{of\ FNN}=0.8429$. The observed values of the WTI crude oil prices and the predicted values in testing part of FLANN and FNN models are shown in Fig. 5.

Figure 5. Comparison of target and ouput values of WTI crude oil price : in testing process of FLANN (a) and FNN (b)



In order to achieve more credible conclusions, we have computed another measure called hit rate or success ratio for direction prediction which is defined as follows (McNeils, 2005):

$$Hit\ rate = \frac{1}{N}\sum_{i=1}^{n} A\ ;\ A = 1\ if\ d_{t+1}.y_{t+1} \succ 0\ and\ 0\ otherwise. \qquad (11)$$

Where d_{t+1} is the value of the desired price and y_{t+1} is the predicted price, at time t+1. This metric indicates the % of deviation between the observed and forecasted prices, therefore, can reflect the percentage of good forecast (Wang et al., 2005 ; Kulkarni and Haider, 2009 ; Lackes et al., 2009 ; Jammazi and Aloui, 2012). By applying the FNN model, the hit rate is equal to 49.03% while he is much better by using FLANN model (72.82%).

For mid-term prediction, other variables which are the basis of the recent drop in oil prices such as the US crude oil and biofuels production who increase supply of oil, are also taken into account in our analysis. Thereafter, simulations on the latest trends in oil prices (2014 and 2015) are also required to better validate the model. To do this, the monthly data of the previous input variables as well as the two new factors (which are retrieved from the US Energy Information administration website), covering the period between January 2010 and December 2015, were used as new inputs of the models. Moreover, to more explain and understand our forecasts, we should distinguish between cyclical and structural factors used in our analysis. These factors affect and influence the price of crude oil in short-term (cyclical factors) and also in mid and long-term (structural factors). Therefore we can say that prices (gold spot price, heating oil spot price and US crude oil spot price) and also the US dollar and S&P 500 stock price indexes should be considered as cyclical factors while variables such as oil production, biofuels are structural in nature.

To note, the networks were trained based on (2010-2014) data set and the year 2015 was used as the test period. The quality of the training process was evaluated based on the R^2 performance criterion. As results, the FLANN model outperforms the standard FNN ($R^2_{\text{of FLANN}}=0.9879 > R^2_{\text{of FNN}}=0.9751$). For the testing process, the empirical results of the mid-term forecasting analysis are presented in the following table :

Table II. The evaluation of networks performance for mid-term forecast

Models	***Evaluation Criteria***			
	RMSE	MAE	R^2	Hit rate
FNN[2]	3.9960	2.9888	75.46%	66.66%
FLANN	2.8034	1.8002	81.62%	75%

As can be clearly revealed from the above table, the FLANN model produces the most accurate forecasting results compared to FNN model. The level of prediction accuracy of FLANN is higher compared to FNN model in which the calculated errors (RMSE and MAE) are explicitly superior than those of FLANN. Also, the FLANN model presents the highest R^2 and hit rate compared to the standard FNN.

Comparatively, the empirical results of the short and mid-term prediction of the WTI crude oil prices showed that FLANN model performs much better than the standard FNN in terms of all performance evaluation measures, used in our study.

3. Conclusion

In this paper, the FLANN model is introduced to predict the next day's price of WTI crude oil. The proposed model is structurally most simple than the other networks, therefore, it involves lesser computational load. In fact, the most critical issue is the definition of the optimal architecture of an ANN. FLANN is only composed of single layer representing the output layer and hence there is no need to determine the optimal number of hidden

[2] A single layer FNN with 19 hidden units is employed in this analysis.

layer/neurons. Our empirical study proves the superiority of FLANN model, in terms of all the selected evaluation criteria compared to the standard FNN. Then, FLANN is a reliable forecasting approach (for both short and mid-term) no only in terms of accuracy, but also in terms of ability to reduce computational load. However, this model could not detect some points especially the high rise / fall of oil price (see Figure 5) which can be explained by the occurrence of unexpected events mainly related to political aspects, the impact of the revolution in North Africa and Middle East zone and also to the psychological expectations of investors. Therefore, we should focus in future research on the introduction of qualitative factors that can enhance the performance of the oil market prediction.

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