

Oil Forecasting Using Artificial Intelligence

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Abstract

The motivation for this research paper is the application of two novel models in the prediction of crude oil index. The first model is a generic deep belief network and the second model is an adaptive neural fuzzy inference system. Furthermore we have to emphasize on the second contribution in this paper which is the use of an extensive number of inputs including mixed and autoregressive inputs. Both proposed methodologies have been used in the past in different problems such as face recognition, prediction of chromosome anomalies etc, providing higher outputs than usual. For comparison purposes, the forecasting statistical and empirical accuracy of models is benchmarked with traditional strategies such as a naïve strategy, a moving average convergence divergence model and an autoregressive moving average model. As it turns out, the proposed novel techniques produce higher statistical and empirical results outperforming the other linear models. Concluding first time such research work brings such outstanding outputs in terms of forecasting oil markets.

Keywords

Future Contract, Crude Oil, Deep Beliefs, ANFIS Model

1. Introduction

Numerous studies have documented that forecasting oil is not an easy task. Researchers have used a massive amount of linear and nonlinear models to capture the correct direction of oil contracts but this seems to hide an error which is quite high. Most probably this is coming from the market volatility or from non-linearity that models cannot catch. For overpassing the previous obstacles we decide to take in consideration two hi-tech tools named Deep Beliefs networks and adaptive neural fuzzy inference system in terms of forecasting crude oil closing prices. From literature aspect these models are giving better forecast accuracy and at the same time are easier and extremely fast to process. Karatha-

nasopoulos, [1] was the first that used this method in terms of forecasting the crack spread. He was convinced that this new methodology is promising and outperforms all the traditional linear and non-linear models.

Theoretical Basis: Deep Belief Networks and adaptive Neurofuzzy Inference system.

Deep belief networks, (DBNs) have been presented for the first time by Hinton *et al.* [2]. The DBN model is based on multiple layers. The bottom layer is observable, while the remaining hidden layers are formed by stacking many restricted Boltzmann machines (RBMs), introduced by Ackley *et al.* [3] and Hinton and Sejnowski [4], on the top of each other. When the system is fed with a large quantity of data, it is first processed through the visible layer units, and, subsequently, the hidden layers help to detect data features according to the connection weights. Importantly, there are no connections between the units of a single layer—all the connections of the RBM's units are restricted to different layers. The procedures for data are the same for all the RBMs, constructing the DBN. Both DBNs and RBMs have been frequently employed as a forecasting tool in time-series analysis (Chao *et al.* [5], Fagiani *et al.* [6], He [7], Hinton and Salakhutdinov [8], Kang and Choi [9], Kuremoto *et al.* [10], Shen *et al.* [11], and Karathanasopoulos and Osman [12]). To sum up, as far as we are concerned, this is the first study to utilize the DBNs for oil market predictions. From the other side ANFIS was first introduced from Jang [13]. ANFIS is putting together the advantages of neural networks (NN) and Fuzzy Inference Systems (FIS) in terms of improving the accuracy of forecasts. ANFIS has the capability of learning fast, the capability of seizing the nonlinear structure and the capability of adaptation, making itself easy to use. The ANFIS has been successfully implemented to a broad range of problems in a variety of fields including economics [14], energy [15], health [16] and the environment [17] for different purposes including diagnosis [18], evaluation [19], prediction [20], and forecasting [21].

2. Data Analysis for Dubai Crude Oil

We start our forecast research analysis on crude oil by downloading 18 years daily closing prices data from Thomson Reuter's database. Moreover by using the log return equation we convert our data to daily returns. Instead of being confident with our data we are checking for stationarity. The stationarity test used this time is the Augmented Dickey-Fuller (ADF) test. The output proves that daily oil prices are stationary and indicates that further analysis can be done. In the next step we divide the data through optimizing the dataset in the below segmentation (Table 1).

Table 1. Total dataset divided in training and validation periods.

Name of Period	Trading Days	Beginning	End
<i>Total Dataset</i>	4500	1/1/2000	30/12/2018
<i>Training Dataset</i>	3550	1/1/2000	30/12/2015
<i>Validation Set</i>	950	1/1/2015	30/12/2018

3. Models in Study

By using the below models we can compare their predictive ability and their statistical accuracy.

Naive strategy. The simplest strategy assumes that the return on day $t + 1$ is equal to the return on day t (yesterday closing price is the today forecast)

$$\hat{Y}_{t+1} = Y_t \quad (1)$$

where Y_t is the actual return on day t , and \hat{Y}_{t+1} denotes the predicted return for day $t + 1$.

Moving Average Convergence Divergence (MACD). The MACD model reports that the return on day $t + 1$ equals the average return through a certain trailing window:

$$M_t = \frac{(Y_t + Y_{t-1} + Y_{t-2} + \dots + Y_{t-n+1})}{n} \quad (2)$$

where M_t represents is the moving average on day t , and n denotes the length of the moving average window (the number of days).

Autoregressive moving average models (ARMA). The ARMA model predicts returns based on their previous values Koreisha and Fang, (the autoregressive part) and on their residuals (the moving average parts). The ARMA model can take the below form:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t - w_1 \varepsilon_{t-1} - w_2 \varepsilon_{t-2} - \dots - w_q \varepsilon_{t-q} \quad (3)$$

where Y_t is the return on day t and Y_{t-1} , Y_{t-2} , and Y_{t-p} are the lagged returns, ϕ_0 , ϕ_1 , ϕ_2 , and ϕ_p denote the regression coefficients, ε_t indicates the residual term and ε_{t-1} , ε_{t-2} , and ε_{t-q} are its lagged values. Finally, w_1 , w_2 , and w_q denotes the weights.

4. Deep Beliefs Networks

Karathanasopoulos and Osman [12] have used the Deep Belief Network with the below description to forecast successfully the Dubai financial market. Deep belief network is a very new probabilistic feed-forward forecasting tool with input layer, hidden and output layer (see **Figure 1**).

Karathanasopoulos and Osman [12] mentioned that the basic idea behind this new model is the use of a layer-by-layer unsupervised learning method in order to pre-train the initial values of the weights in the neural network. A layer-by-layer unsupervised training procedure implies that each layer captures the features of the previous one, and transferring them to next one. In this research paper each pair of layers is pre-trained by using the restricted Boltzmann machines. Restricted Boltzmann machines are composed from 2 different layers connected together. One layer has visible nodes/neurons and the other hidden nodes/neurons (see **Figure 2**).

The nodes on each layer have no connections between them only with units of

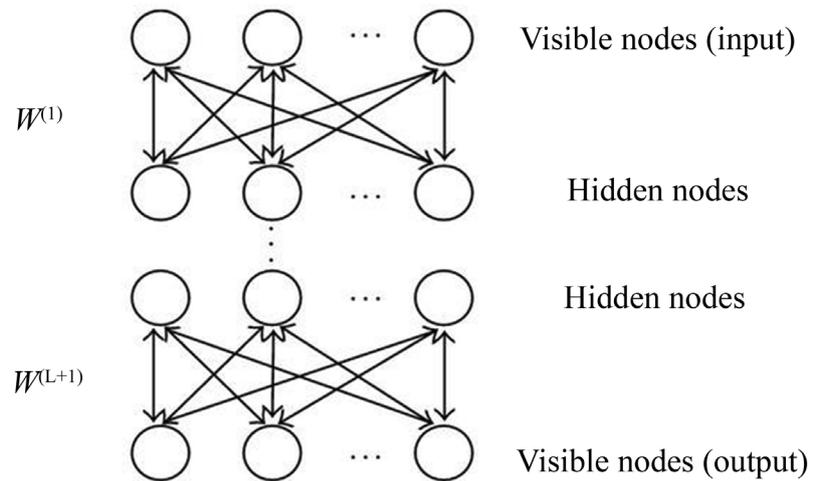


Figure 1. Deep belief network structure.

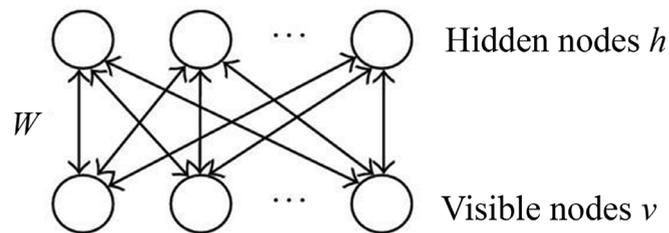


Figure 2. Restricted Boltzmann machine structure.

other layers. All these connections are symmetric and bidirectional. As Karathanasopoulos and Osman [12] mentioned, that restricted Boltzmann machines can be used in numerous tasks but in forecasting experiments are providing the learning training for the structure of the deep belief network. In few words restricted Boltzmann machines are a special type of generative energy based models that can learn a probability distribution over its set of inputs. Except from that the standard type of restricted Boltzmann machine has binary valued hidden and visible nodes.

5. Neural Fuzzy Inference System

The Adaptive neural fuzzy inference system ANFIS is a very common and widely used artificial intelligence technique in literature. This method covers advantages of Fuzzy Logic and Artificial Neural Networks in the same structure. Although Neural Networks have powerful learning ability, Fuzzy structures have strong inference systems and no learning ability. In contrary, ANFIS combines these both desirable characteristics in the same topology. ANFIS was presented by R. Yang in 1993 [22]. From the three type of ANFIS structure we chose the Sugeno ANFIS structure which is explained in the next five stages.

Stage 1: This layer can be called as fuzzification layer. In this stage the parameters are called premise parameters and can be re-arranged according to the output error in every loop. These parameters are the input parameters which

show the membership grades on the fuzzy.

Stage 2: In the second stage is computed the fixed node which is the output of all the incoming signals. Every output of the second stage can affect the triggering level of rules in the next stage. The trigger level is called the firing strength of the fuzzy system.

Stage 3: In the third stage we have the layer which is called normalization layer. For this layer, all firing strengths are re-arranged again by considering their own weights.

Stage 4: In the fourth stage the Defuzzification layer reports the preliminary calculation of the output, this layer has adaptive nodes and is expressed in functions. Because are ANFIS model is Sugeno type if then calculation turns to linear approach [23].

Stage 5: In the last stage we have the Summation neuro which is a fixed node that computes the overall output of all the incoming signals. ANFIS has Backwards and forward Learning Ability in one loop. This correction is processed though Least square estimator which arranges the parameters and minimize the squared error (Table 2).

Table 2. ANFIS parameters.

ANFIS Characteristics:	
<i>Range of influence</i>	0.9
<i>Squash factor</i>	5
<i>Reject ratio</i>	0.25
<i>Accept ratio</i>	0.6

6. Trading Signals and Strategy

The trading strategy we follow is based on the directional price of the forecasts, Karathanasopoulos *et al.* [24] and Karathanasopoulos [25] [26]. We hypothetically assuming a long (buy) or short (sell) position in the crude oil if the given models predict positive or negative return for the next day. Further to that, when the forecast indicates consecutive positive or negative price changes, the short/long positions, are maintained, focusing on the decrease of the trading costs.

7. Statistical performance and Empirical Performance (Table 3 & Table 4)

Table 3. Out of sample statistical performance for the Dubai Crude Oil (excluding cost).

Forecast	Naïve Strategy	MACD	ARMA	Deep Belief Network	ANFIS model
MAE	0.0231	0.2110	0.0190	0.0132	0.0120
MAPE	148.21%	192.72%	156.66%	98.91%	86.21%
RMSE	0.0446	0.0456	0.0342	0.0187	0.0200

Table 4. Out of sample empirical performance for the Dubai Crude Oil (excluding cost).

Forecast	Naïve Strategy	MACD	ARMA	Deep Belief Network	ANFIS model
Annualized Returns	10.13%	11.12%	12.87%	18.87%	19.67%
Annualized Volatility	13.78%	14.89%	15.87%	18.12%	16.67%
Maximum drawdown	-14.67%	-12.87%	-14.67%	-15.77%	-12.12%
Sharpe ratio	0.73	0.74	0.81	1.04	1.17

8. Concluding Remarks

In this research paper, we propose a deep belief network and an adaptive neural fuzzy inference system for forecasting the Crude oil closing prices. More specifically we have used these novel methodologies for the first time in terms of forecasting one day ahead of the crude oil prices. In terms of feeding both networks we have used a pool of 5000 most correlated indices to the main oil index. In terms of benchmarking our forecasted returns we use three linear models such as naïve strategy MACD and ARMA model. Furthermore, evaluating the forecast with statistical and empirical measures we came to the conclusion that both new models outperform significantly all the other models and give promising results for further use in financial forecasting.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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