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Analysis of the Relation Between Crude Oil Futures Prices and Spot Price Using Nonlinear Artificial Neural Networks

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Abstract

As the oil demand continues to surge ahead and production continues to decline, it is believed that oil prices will continue to rise to unprecedented levels. As a reference, in 2004, the crude oil price was averaging \$41 per barrel while it is above \$130 in today's market. This oil price increase is affecting the economy from both developing and developed countries. This paper investigates the possibility of using oil futures price to forecast spot price direction for short term, one day ahead using multilayer feedforward neural networks. The data was pre-processed to reflect the direction and the turning point of the price. Our approach is to create a benchmark based on lagged value of pre-processed spot price, then add pre-processed futures prices 1, 2, 3, and 4 months for maturity one by one and also altogether. For all the experiments, that include futures data as an input, the results show that on the short term, one day ahead, there is weak evidence to support futures price do hold new information on the spot price direction. This evidence is stronger for futures 1, 2 months to maturity.

Key words: Crude oil, futures price, nonlinear prediction models, ANN

JEL classification: C22**,** C45, C53

1. Introduction:

Crude oil is a vital commodity for economy developments. Unfortunately, crude oil price has proven to be one of the most volatile markets in the world. In addition to daily price fluctuations, oil prices have risen substantially in last few years. As an example, in 2004, the West Texas Intermediate (WTI) light sweet crude oil price was averaging around $41 per barrel, while it is above $130 in today's market. The International Energy Agency (IEA), in their report (2004), claims the variation in oil prices have a direct effect on the global economy. Moreover, they found that, higher oil prices have a negative impact not only on the economy of oil importing countries, but also on the global economy, international trade, and finance. The importance of crude oil to the economy is reflected by the number of studies in this area. There are large and rich literature related to every aspect of crude oil.

Some studies deal with the fundamental variables in the energy market which are believed to play an important role in driving oil prices, such as supply, demand, and inventory, while other research concentrates on oil shock and its effect on the market. This paper reinvestigates the relation between crude oil futures price and spot price, using multilayer feedforward neural networks. The aim of this paper is to find whether crude oil futures prices are able to predict spot price direction on the short term.

This paper proceeds as follows, Section 2 represents short literature review, Section 3 presents data description, and pre-processing along with our methodology. Section 4 details the results and discussion, and finally the paper is concluded in Section 5.

2. Literature review:

Futures contracts serve several purposes in the market, the most important one, however, is providing risk management tool to protect agents price volatility for the underling commodity (Bopp, and Sitzer 1987 p.706).

Crude oil futures contract was introduced to NYMEX in 1983, however, trading in these particular contracts were relatively shallow until 1985, whereas, each of the 161 type of oil contracts are considered as an important tool in the energy market (Haubrich, Higgins, & Miller 2004).

The relation between futures prices and spot price has been the centre of attention for a large number of scholars, and the literature is rich with several studies covering a range of aspects with respect to this relationship. Lead-lag, efficiency, prediction amongst other factors, are the most studied areas in futures-spot literature.

It is important to note, however, that some economists believe that futures price is not a predictor for spot price, for example, Haubrich, Higgins, & Miller (2004), argue that crude oil futures prices is not a suitable vehicle to forecast spot price. Therefore, futures prices do not hold any new information, not even in the short term. However, the idea of using commodity futures price to predict spot price is based on the assumption that the futures price react faster to the new information entering the market than spot price. According to Silvapulle, and Moosa (1999) trading in the futures market has many advantages, such as low transaction cost, high liquidity, and low cash in up-front, amongst others. This makes it much more attractive for investors to react for new information, than taking position in the spot market. This argument applies for most of the commodity listed in the financial markets; however, it is more relevant to the energy markets. The reason for this is, when new information related to the oil market is introduced, investors have two options, either to take a position (buy or sell) in spot or in futures market. In most of the cases, taking a position in spot market is not the best way for reacting to the new information. Because it requires high transaction costs, storage costs, and delivery costs etc. Especially, if investors are not interested in the commodity itself rather they are hedging for another commodity, or simply just investing in the market in hope of arbitrage opportunity i.e. speculation. In this context, futures market is much more attractive place for an investor to react to new information for the reasons discussed above (Silvapulle, and Moosa 1999).

An early study by Bopp and Sitzer (1987) tested whether futures prices are good predictors for cash price in the futures in the heating oil market. In attempt to answer if futures prices has the capacity to improve forecasting ability of econometrical models. The results showed that only futures contract 1 and 2 months to maturity are statistically significant for cash price forecast, in other words contain new information.

Chan (1992) studied the lead-lag relationship between S&P 500 futures and cash price intraday data for both, spot and futures were tested. Both assumptions, futures lead cash, and vice versa, was investigated. According to the author strong empirical evidence was found in support of futures price lead the cash price while only weak one in support of the opposite. Furthermore, the author claimed that cash and futures markets do not have the same access to information, this can be attributed to the difference in transaction cost and expected profits. Therefore, futures price is faster in reacting to new information than cash price, which led him to conclude that, futures market is the main source of information on market wide level while cash market is the main source of firm specific information.

In order to thoroughly understand the issue, it is useful to examine the finding of Silvapulle, and Moosa (1999) about the lead-lag relationship between crude oil futures and spot price. Their goal was to find whether the change in crude oil futures price causes the change in crude oil spot price i.e. causality, using linear and nonlinear tests. The dataset was composed of daily spot price, as well as futures contracts of 1, 3, 6 months of maturity, from 1985 to 1996. Their results showed that both futures and spot price react to new information at the same time. Moreover, the authors also concluded that, there is some evidence in support feedback between futures price and spot. However, this feedback runs in one direction only; from futures spot, and not vice versa. Finally, their results showed that the pattern of lead lags is not constant and changeable over time. One point is worth in mentioning, that the authors reported at the end of the article several cavities in their study, which might have an effect on the conclusion.

Moshiri and Foroutan (2005) began their study by testing for the chaos and nonlinearity in crude oil futures prices. Performing several statistical and econometrical tests led them to conclude that futures prices time series is stochastic, and non-linear. Moreover, the authors compared linear and non-linear models for forecasting crude oil futures prices. Namely, they compared ARMA and GARCH, to ANN, and found that ANN is superior and produces a statistically significant forecast. However, in our opinion the results obtained using ANN could be limited by the use of the entire dataset as an input. (1983 to 2000). Generally, when dealing with ANN the more data points, the better the network generalization. Nonetheless this is not necessarily the case when dealing with financial or economical time series. As economic conditions change over time, non-current (old information) could affect prediction results negatively. Because training the network with irrelevant information to the current conditions could result in a poor model generalization.

Coppola (2007) studied the relationship between crude oil spot price and futures price using the cost of carry model. The aim was to forecast the out of sample and price movements in the futures. The author used Vector Error Correction model (VECM) for the forecast, comparing the results to random walk model. Evidence of co-integration was recorded between spot and futures weekly prices. The author also found that futures contracts are able to reflect the information in the futures, however, these results stands only for in sample forecast. For out of sample forecast the author claims that VECM outperform random walk model in both accuracy of forecast and timing the market.

The activity of investors and hedgers and its effect on the market was also studied widely. Milunovich and Ripple (2006) present a new model to estimate the magnitude of hedging activity on crude oil futures volatility, using a combination of Dynamic conditional coloration and augmented EGARCH. They found that hedging activity has a significant influence on the conditional volatility of crude oil futures returns.

Although the body of oil literature is substantial, there is still a great deal of inconsistency in the findings. This is particularly the case in the relation between spot prices and futures price. While most of studies agree on the importance of futures prices for financial markets, only a few studies, if any, agree on how, and why it is important. Furthermore, the vast majority of the literature is based on econometrical models. A major shortfall of econometrical model is making strong assumption about the problem. This means if the assumptions are not correct; the model could generate misleading results. Furthermore, a recent servery by Labonte (2004) for, conclude that one of the most common cavities of econometrical models is omitted variable and in some cases structural misspecification. In these contexts artificial neural networks (ANN) are viewed as nonparametric, nonlinear, assumption free model (Azoff 1994). This means it does not make *a priori* assumption about the problem; rather it let the data speak for itself (Refenes 1995). Furthermore, ANN is considered as general approximate method (Hornik, *et al* 1989), and has been around for a while now and successfully used in several studies for variety of problems including crude oil price forecast.

Although, some study of crude oil forecasting has used ANN model, nonetheless, to our best of knowledge, no study of the relation of futures prices as spot predictor is based in ANN model. Finally, reader should bear in mind that we are not testing for causality, whether futures price cause spot price or other variables affect the relationship. We are simply testing if futures aggregate useful information on spot price futures direction. This aggregation of information could be results of the activity of market participant, who often take a position in futures market not only based on expectation of price raise or fall but also, to hedge from the conscience of such event (Bopp and Sitzer 1987).

3. Methodology:

The methodology is based on three layers neural network model with backpropagation algorithm. The goal of this study is to test whether oil futures price contain newer information about the direction of spot price in the near futures, one day ahead, also if information in futures price integrated with spot price will lead to better forecast accuracy. The overall methodology is creating a benchmark based on the current and past information embedded in crude oil spot price solely, using three layer feedforward network. In able to do so effectively, attention was paid to the finding optimal ANN model. This involves several steps to find, the best transformation method of the data the temporal structure of the spot price time series the optimal number of hidden neurons, training algorithm, training time, learning rate amongst other. Once this benchmark is ready, futures prices are added on top of the lagged spot price one day in the past In other words, if the forecast goal is spot price at time $t+1$ then, futures contracts closing prices are added up to time t one by one, and altogether. In addition to this, futures data was introduced to the network as input solely, while the target is spot data to measure the amount of information each contracts contain on the diraction of spot price.

Figure 3.1 summarize the steps involve in applying neural network to most of forecasting problems.

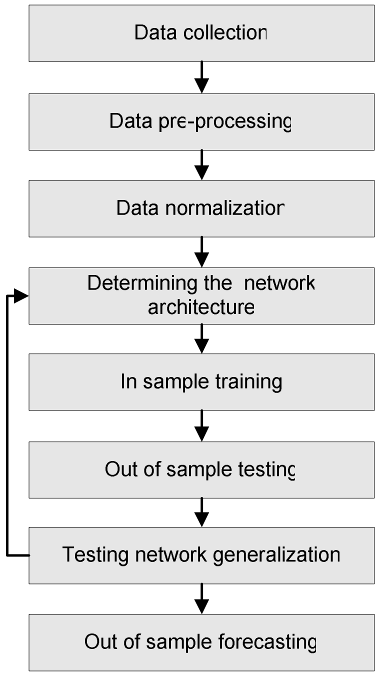

Figure 3.1: *A flow chart of ANN based model for forecasting*

3.1. Data collection and pre-processing:

Five time series are used in this study, West Texas Intermediate (WTI) light sweet crude oil spot price and futures contracts traded at NYMEX. Futures data include four contracts 1, 2, 3, 4 months of maturity. The data frequency is daily closing price; from Sep 1996 to Aug 2007, it includes 2705 data points for each time series. All data sets retrieved from US Department of energy: Energy Information Administration Web site: http://www.eia.doe.gov/ .

Each contract expires on the third business day prior the 25^{th} calendar day of the month preceding delivery. If the 25^{th} was not a business day then the contract expire at the third business day before the business day prior the 25th calendar day. As soon as the contract expire contract 1 for the reminder of the calendar month is the second following month. This also applies for Contract 2, 3, 4 which represent successive delivery months following Contract 1. (Energy Information Administration Web site: http://www.eia.doe.gov/). The data was divided into training and testing sets, we use 90% of the data for training and 10% for out of sample testing.

3.2. Data pre-processing:

Financial and economical time series often are affected by excess kurtosis, outliers, unit root, amongst other. Although, in one hand it is desirable to use the raw data when applying ANN to financial and economic time series; since pre-processing the data could destroy the structure inbuilt only in the original time series (Azoff 1994, Venstone 2005). However, in the other hand, time series should be stationary, because constant mean, variance and covariance is assumed by statistical deduction (McNelis 2005). Therefore, in most of the cases, pre-processing is necessary to insure model stability and avoided misleading results. Thus it is essential to transform any non-stationary time series into a stationary form. A common practice is to apply logarithmic first differencing. Let x a time series, then the logarithmic first differencing of x is:

$$y_t = \ln(x_t) - \ln(x_{t-1}) \tag{3.1}$$

Alternately relative difference could be used, however, Neuneier & Zimmermann (1998) and Gorthmann (2005) suggested the use of the combination of first order relative change (equation 3.2) to represent the change in direction *momentum* and the second order relative change *force* (equation 3.3) to represent turning point of the tie series.

$$y_t = \left(\frac{x_t - x_{t-n}}{x_{t-n}} \right) \tag{3.2}$$

$$y_t = \left(\frac{x_t - 2x_{t-n} + x_{t-2n}}{x_{t-n}} \right) \tag{3.3}$$

where: x is the original time series and y is the transformed of x and n is the forecast horizon.

3.3. Data normalization:

Data normalization is important in ANN applications for two reasons. First and foremost, the activation function used in the hidden layer of the network can process data within limited range (usually [0, 1] for logsig and [-1, 1] for tansig). If the data does not fit within this range, or it does fit within the range but it is not well diversified, then data should be normalized to fit within the rang of the activation function. Otherwise, any value of the data which does not fit within the range of the function will simply be lost hence affecting the network ability to learn (McNelis 2005). Second, normalization prevents the network from adjusting for a range of data in the input and target (Refenes 1995). This also could affect the network ability to learn.

The data was normalized to fit between -1 and 1 since we are using hyperbolic tangent function, also known as tansig.

Equation 3.4 presents liner method for data normalization [-1, 1] to scale a variable x_z to $y_{z,t}$

$$y_{z,t} = 2.\frac{x_{z,t} - \min(x_z)}{\max(x_z) - \min(x_z)} - 1 \qquad (3.4)$$

An alternative to equation 3.4, are non-linear methods for data normalization[1].

3.4. Creating Benchmark:

Creating a benchmark using crude oil spot price alone should serve two roles in this study. First of all, it shows to what extent information embedded within oil spot price is useful for one day ahead forecast. In other words, is spot price direction predictable in the first place? Second, this benchmark is used as comparison criteria when we later test futures price. Therefore it is crucial to build efficient model for the benchmark. We start investigating for the temporal structure of the data how many lagged value is improving the forecast price. In addition to the conventional autocorrelation and partial-autocorrelation, we apply the non-linear ANN model. To avoid complexity and make easy comparison, momentum and force from equations 3.2, 3.3 consecutively were used as input-output each separately. Starting from one lag up to 20 lags were considered. Each lag in each time series was treated in separate feedforward network. For this kind of experiment finding the optimal model (number of hidden layers, number of hidden neurons, learning rate, training algorithm and time) is a challenging task. Moreover, there are no formal rules only general guidelines. Only one

[1] See MacNelis 2005 p.64

hidden layer was considered for this study. This comes in line with the approximation theorem which assumes that adequately sized three layers network should be able to approximate any function (Hornik, *et al* 1989).

The most critical issue when dealing with neural network is to determine the number of hidden neurons. As too many hidden neurons will result in over fitting, and too few could result of under fitting. There are no formal rules to solve this dilemma. Despite the fact that some rules of thump do exist in ANN literature, however, there are no formal evidence to support whether any of these rules will work for any single problem. Therefore, the number of hidden neurons for each network in this study was determined by experiments. For each network, we start with 1 hidden neuron and add one each time up to 10. Each network for each number of neuron is test for three times with different sets of weights to insure stability. Obviously, this a very time consuming exercise, but proves to be much more accurate than depending on guess or applying any of the rules of thump on this problem.

In addition to test of equation 3.2 and 3.3 are tested separately each as input-output. According to Neuneier & Zimmermann (1998) and Gorthmann (2005) a model based on data transformed by eq 3.2 could generate misleading results. Furthers, they suggested a combination of eq 3.2 and 3.3 for network input, could advantage the model. Therefore, the next step is to test whether combining these time series together will improve forecasting accuracy. Hence, five different combinations were tested. Table 3.1 summarize the combination of input-output tested.

Table 3.1: *Input- output combinations*

Option	Input	Output
1	Momentum	Momentum
2	Force	Force
3	Momentum+ Force	Momentum
4	Momentum+ Force	Force
5	Momentum+ Force	Momentum+ Force

Other parameters such as training algorithm, learning rate, training time was determined by experimenting a number of combinations of parameters using one lag of data as input.

The performance measure for these experiments is Root Mean Square Error (RMES) equation 3.5:

$$RMSE = \sqrt{\frac{\sum_{n=1}^{n}(x-o)^2}{n}} \tag{3.5}$$

Where: x is the network target, o is the network output and n is the sample size.

The other metric we used is the success ratio for sign prediction (the hit rate) equation (3.6), which is practical type of measure, since predicting the direction of the market, is the ultimate goal of this study.

$$h = \frac{1}{n}\sum_{n=1}^{n} z \tag{3.6}$$

$z = 1$ if $x_{t+1}.o_{t+1} > 0$, and 0 otherwise.

where: n is the sample size x_{t+1}, o_{t+1} are the value of the target and the out put at time $t+1$ consecutively.

The hit rate and RMSE are the main performance measures; however, in addition other metrics were also calculated.

R square, which represents the square of equation 3.7, is also used as goodness of fit measure.

$$R = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{3.7}$$

Ljung-Box Q-test equation 3.8 test used as autocorrelation tests for input data.

$$LQ = m(m+2)\sum_{i=1}^{n}\frac{\hat{\rho}_k^{\,2}}{m-i} \tag{3.8}$$

where m is the sample size, n is the number of lags tested for autocorrelation ,while $\hat{\rho}_k$ is the sample autocorrelation at lag k This model under the null hypothesis there is no significant correlation, when applied on the input data it show if there is significant autocorrelation at a given lag. Also when applied on the residual it show if there is a significant autocorrelation in the residual of the model which indicate poor fit.

In addition to this Mean Square Error (MSE), Mean Absolute Error (MAE), and Sum Square Error (SSE) were also calculated.

4. Results and dissection:

Table 4.1 presents the results of the Ljung-Box Q-test for the relative change, which shows significant correlation for all lags tested (5, 10, 15, and 20) at 5% significant level.

Table 4.1: *Ljung-Box Q-test for the relative first difference*

Lag	P Value	Stat	Critical value
5	0.0241	12.9276	11.0705
10	0.0090	23.5131	18.3070
15	0.0051	32.7394	24.9958
20	0.0042	40.6091	31.4104

The interpretation of these results is that present and past information could be useful to price the futures direction. Following this further, we tested the autocorrelation in the spot relative change time series using ANN model at several lags. This model is superior to the liner autocorrelations methods. Spot data from eq. 3.2, and 3.3, was used separately. Figure 4.1 show an example of input output data for 20 lag.

$$\text{Input for 20 lags}\begin{bmatrix} x_{t-1} & x_{t-2} & \cdots & x_{t-n} \\ x_{t-2} & x_{t-3} & \cdots & x_{t-n-1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{t-20} & x_{t-19} & \cdots & x_{t-n-20} \end{bmatrix}$$

$$\downarrow$$

$$\text{Target}\begin{bmatrix} x_t & x_{t-1} & \cdots & x_{t-n-1} \end{bmatrix}$$

Figure 4.1: *input target pairs*

Table 4.2: *Hit rate and RMSE input eq.3.2 in and out of sample*

Lag	Hit Rate (%)		RMSE	
	In sample	Out of Sample	In sample	Out of sample
1	52.65	53.39	0.0251	0.0194
2	52.8	52.5	0.0248	0.0277
3	51	52.8	0.0251	0.0209
4	51.3	52.5	0.0248	0.0276
5	51.4	51.1	0.0246	0.0326
6	51.7	52	0.024	0.6823
7	54.1	53.3	0.0239	0.2197
8	52.57	51.62	0.024	0.04
9	51.35	52.35	0.0242	0.8021
10	50.39	53.2	0.0246	0.6232
12	58	52.8	0.02	0.9764
13	54	51	0.0231	0.0417
14	58	51	0.0231	0.6126
18*	60.71	53.68	0.0227	0.0311
20*	72	50	0.022	0.0919

Table 4.3: *Hit rate and RMSE input eq 3.3 in and out of sample*= model is not stable anymore*

Lag	Hit Rate (%)		RMSE	
	In sample	Out of sample	In sample	Out of sample
1	65.89	64.44	0.0313	0.0637
2	67.79	71.11	0.0292	0.0209
3	69.97	69.77	0.0276	0.0204
4	70.09	70.22	0.0273	0.0201
5	70.98	71.55	0.0266	0.0199
6	71.10	70.66	0.0264	0.0203
7	71.30	70.66	0.0260	0.0202
8	72.47	71.55	0.0256	0.0203
9	72.27	73.77	0.0254	0.0199
10	72.80	72.88	0.0248	0.0206
12	72.92	72.88	0.0244	0.0206
14	73.80	73.77	0.0233	0.0208
16*	73.89	72	0.0233	0.0204
18*	75.42	72.44	0.0229	0.0202
20*	74.89	72	0.0242	0.0210

4.1. Input output combination:

In general, as can be seen from Table 4.5 data transformed by eq 3.2 relative change produced unsatisfactory results regardless to any change in the model parameters or number of lags regressed. Clearly the network has failed to approximate the function, even for in sample, which could be attributed to the noise in the data[2]; therefore, noise filter such as moving average could be useful to improve results.

On the other hand, data transformation using eq. 3.3 has generated better results for in and out of sample, as eq. 3.3 contain two step differencing. Nonetheless, three other combinations listed in Table 3.1 were tested as well using one lage each. The best combination which outperformed all other option in Table 3.1 is momentum eq. 3.2 and force eq. 3.3 as input, and force solely as target. Following this further, only this combination was tested for multiple lags (up to 12 lag form each equation). The hit rate performance was improved about 8% compared to transformation by eq 3.3 as input and target alone, while comparing to eq 3.2 the improvement was substantial.

Finally, the best performance which is considered as candidate for the benchmark is combination of 7 lags of momentum and 7 lags of force (eq 3.2, 3.3) in the input, and 1 lag of force as target. Furthermore, the network architecture is three layers feedforward with 8 neurons in the hidden layer. The network was trained for 1000 iterations or until one of the stoping criteria is met. The learning rate is 0.01 and training algorithm is Levenberg-Marquardt. Table 4.7 summarize the benchmark performance averaged over 5 trials.

Table 4.4: *Summary of performance masers of the candidate benchmark*

Metric	**Hit rate %**	**RMSE**	**R^2**	**MSE**	**MAE**	**SSE**
In sample	74.93	0.02312	0.5875	0.00052	0.01724	1.32592
Out of sample	76	0.01922	0.5006	0.00038	0.01502	0.0832

On the other hand, 3 day moving average was applied on the raw data then equation 3.2 was applied. Table 4.5 present the results at different lags after applying the moving average filter.

[2] For more information on the effect of noisy data on neural network performance, see Refenes 1995 p.60.

Table 4.5: *Hit rate and RMSE input 3 day MA then eq.3 2 in and out of sample*

Lag	Hit Rate (%)		RMSE	
	In sample	Out of sample	In sample	Out of sample
1	72.77	73.75	0.0108	0.0079
2	72.88	74.01	0.0107	0.0080
3	73.74	74.54	0.0104	0.0077
4	75.42	76.37	0.0099	0.0073
5	76.02	76.90	0.0096	0.0074
6	76.16	77.16	0.0095	0.0072
7	77.25	77.11	0.0085	0.0077
8	78.01	75.59	0.0091	0.0070
9	78.23	76.77	0.0088	0.0070
10	77.78	78.08	0.0089	0.0069
11	78.03	76.37	0.0086	0.0071
12	77.97	77.95	0.0087	0.0070
13	79.45	79.79	0.0083	0.0068
14	79.39	77.42	0.0083	0.0072
15	79.75	79.11	0.0078	0.0073
16	79.77	79	0.0081	0.0071
17	79.45	78.34	0.0080	0.0069
18	80.40	78.87	0.0076	0.0133
19	80.95	77.16	0.0076	0.0075
20	81.38	77.55	0.0074	0.0074

As can be seen the 3 day simple moving average has improved the results significantly, for in and out of sample. Therefore the same approach will be used for the futures data as well. Table 4.5 also show that the performance has improved as the number of lags increased; however, it is important to choose the best performance with least number of lags, and hidden neurons to keep the model stable. 13 lags seem to produce reasonably high hit rate and the results for in and out of sample are very close. Furthermore, the R^2 is 0.67, meaning the model was able to explain 67% of the variation of the data. Table 4.6 summarize the performance of the benchmark.

Table 4.6: *Summary of the benchmark performance*

Metric	**Hit rate %**	**RMSE**	**R^2**	**MSE**	**MAE**	**SSE**
In sample	79.45	0.0083	0.6701	0.0001	0.0062	0.1486
Out of sample	79.79	0.0068	0.5762	0.0000	0.0053	0.0119

Another advantage of this transformation is less hidden neurons were required. We used only 6 hidden neurons to get the performance listed in table 4.6. In addition to this the Ic ratio (the information coefficient) was calculated.

$$Ic = \frac{\sqrt{\sum_{t=1}^{n}(y_t - x_t)^2}}{\sqrt{\sum_{t=1}^{n}(x_t - x_{t-1})^2}} \quad (3.9)$$

where: y is the predicted value, and x is the actual value. This ratio provides an indication of the prediction compared to the trivial predictor based on the random walk (Refenes 1995). Where $Ic \geq 1$ indicate poor prediction, and $Ic < 1$ means the prediction is better prediction than the random walk.

For the benchmark the Ic is 0.58 for in sample and 0.69 for out of sample which means the network is outperforming the trivial predictor.

4.2. Futures contracts:

In order for futures contracts to predict spot price directions, information embedded in futures data should improve the overall results. Otherwise, the assumption that futures prices contain newer information about of spot price direction cannot be accepted.

We start measuring how much information could be extracted from each futures contract about the direction of spot price next day. The moving average and relative change transformation was applied to all futures contracts and each contract was presented to the network as input while the spot price in the same transformation.

Table 4.7: *Futures 1 performance at different lags*

Lag	Hit Rate (%)		RMSE	
	In sample	Out of sample	In sample	Out of sample
1	71.72	73.55	0.0112	0.0079
2	71.92	73.80	0.0109	0.0081
3	71.42	71.96	0.0108	0.0079
4	73.65	75.15	0.0104	0.0075
5	74.37	74.91	0.0094	0.0085
6	74	76.51	0.0102	0.0074
7	75.23	77.61	0.0099	0.0073
8	74.99	75.26	0.0090	0.0081
9	75.40	75.52	0.0096	0.0085
10	75.64	77.49	0.0095	0.0072
11	76	76.51	0.0095	0.0073
12	75.82	77.24	0.0095	0.0070
13	76.35	76.01	0.0093	0.0073
14	76.91	75.89	0.0092	0.0074
15	76.78	75.52	0.0092	0.0074
16	76.84	78.11	0.0091	0.0072
17	77.94	75.52	0.0088	0.0076
18	78.09	76.63	0.0087	0.0079
19	77.66	77.24	0.0087	0.0078
20	78.87	76.14	0.0086	0.0078

Table 4.8: *Futures 2 performance at different lags*

Lag	Hit Rate (%)		RMSE	
	In sample	Out of sample	In sample	Out of sample
1	70.98	72.45	0.0114	0.0082
2	71.51	73.31	0.0111	0.0084
3	71.53	74.05	0.0110	0.0081
4	73.17	73.43	0.0106	0.0077
5	73.24	73.58	0.0096	0.0088
6	73.79	73.80	0.0104	0.0077
7	75.10	75.03	0.0102	0.0075
8	75.43	72.69	0.0101	0.0077
9	74.73	74.29	0.0099	0.0076
10	75.27	75.28	0.0097	0.0083
11	75.87	76.51	0.0098	0.0075
12	76.72	73.80	0.0094	0.0079
13	76.51	75.15	0.0094	0.0096
14	76.96	75.40	0.0094	0.0077
15	77.22	74.05	0.0094	0.0079
16	77.54	73.68	0.0091	0.0103
17	77.96	74.42	0.0090	0.0077
18	77.08	74.17	0.0089	0.0080
19	77.68	75.77	0.0088	0.0081
20	77.67	72.82	0.0088	0.0085

Table 4.9: *Futures 3 performance at different lags*

Lag	Hit Rate (%)		RMSE	
	In sample	Out of sample	In sample	Out of sample
1	70.96	71.46	0.0115	0.0083
2	70.80	72.32	0.0112	0.0086
3	70.93	74.29	0.0111	0.0083
4	72.87	74.54	0.0107	0.0080
5	73.20	74.54	0.0106	0.0080
6	73.13	74.54	0.0105	0.0079
7	74.44	74.29	0.0103	0.0077
8	75.22	74.17	0.0100	0.0078
9	74.84	72.94	0.0101	0.0079
10	75.12	75.52	0.0098	0.1078
11	75.71	75.28	0.0097	0.0077
12	76.21	76.75	0.0097	0.0181
13	76.44	76.63	0.0094	0.0078
14	76.64	75.65	0.0096	0.0083
15	76.74	75.15	0.0094	0.0521
16	76.74	74.78	0.0091	0.0086
17	75.52	73.75	0.0109	0.0085
18	77.64	74.29	0.0091	0.0082
19	77.35	74.42	0.0089	0.0085
20	77.28	73.43	0.0092	0.0084

Table 4.10: *Futures 4 performance at different lags*

Lag	Hit Rate (%)		RMSE	
	In sample	Out of sample	In sample	Out of sample
1	70.11	72.32	0.0116	0.0084
2	70.20	71.71	0.0113	0.0087
3	70.57	72.94	0.0112	0.0083
4	72.42	74.05	0.0108	0.0081
5	73.05	74.29	0.0107	0.0082
6	72.94	74.66	0.0106	0.0079
7	74.42	75.65	0.0104	0.0079
8	74.16	72.94	0.0103	0.0078
9	74.21	73.68	0.0102	0.0137
10	74.47	74.91	0.0100	0.0081
11	75.72	76.26	0.0099	0.0432
12	74.88	74.66	0.0100	0.0080
13	75.42	74.29	0.0097	0.0154
14	75.49	75.65	0.0098	0.0079
15	75.61	74.17	0.0097	0.0126
16	76.07	76.14	0.0097	0.0085
17	76.43	72.69	0.0095	0.0082
18	76.59	73.80	0.0093	0.0086
19	76.90	74.91	0.0090	0.0398
20	77.02	72.82	0.0092	0.0083

Tables 4.7 to 4.10 show that none of the futures contracts alone as input was able to outperform the benchmark. For contract 1, even with 20 lags, the forecast was less accurate than what we obtained from spot price solely. Nonetheless, it is fair to say that the performance of futures as input is not poor either. However, the real test is whether any of these contracts (or a combination of them) will improve the results if added to the benchmark.

Table 4.11: *Futures1 added to the Benchmark*

Metric	**Hit rate %**	**RMSE**	**R^2**	**IC**	**MSE**	**MAE**	**SSE**
In sample	79.18	0.0084	0.6520	0.5883	0.0001	0.0063	0.1608
Out of sample	80.44	0.0059	0.6806	0.6358	0.0000	0.0046	0.0096

Table 4.12: *Futures2 added to the Benchmark*

Metric	**Hit rate %**	**RMSE**	**R^2**	**IC**	**MSE**	**MAE**	**SSE**
In sample	79.25	0.0084	0.6485	0.5896	0.0001	0.0064	0.1624
Out of sample	80	0.0060	0.6702	0.6285	0.0000	0.0047	0.0098

Table 4.13: *Futures3 added to the Benchmark*

Metric	**Hit rate %**	**RMSE**	**R^2**	**IC**	**MSE**	**MAE**	**SSE**
In sample	78.84	0.0084	0.6461	0.5897	0.0001	0.0064	0.1635
Out of sample	79.55	0.0063	0.6383	0.6530	0.0000	0.0049	0.0107

Table 4.14: *Futures4 added to the Benchmark*

Metric	Hit rate %	RMSE	R^2	IC	MSE	MAE	SSE
In sample	79.16	0.0084	0.6496	0.5876	0.0001	0.0063	0.1619
Out of sample	79.77	0.0063	0.6346	0.6539	0.0000	0.0049	0.0108

Table 4.15: *Futures1, 2, 3, and 4 added to the Benchmark*

Metric	Hit rate %	RMSE	R^2	IC	MSE	MAE	SSE
In sample	79.0398	0.0083	0.6510	0.8068	0.5870	0.0001	0.0064
Out of sample	78.1550	0.0070	0.5459	0.7384	0.7019	0.0000	0.0055

As can bee seen form tables 4.11 to 4.15, adding futures to the benchmark (13 lag of transformed spot) did not outperformed the benchmark in term of hit rate in sample. While for out of sample network contain futures 1 and network contain futures 2 has slightly outperformed the benchmark[3]. Further, there is no significant improvement for RMSE for in sample, however, it did improve for out of sample for each of the futures compared to the benchmark, and futures 1 preformed the best. The R^2 was noticeable better for out of sample futures contract 1 compared to the benchmark indicating better fit, while for in sample was less than the benchmark. The information coefficient ratio Ic did not change for in sample for all of the contracts, however, it was improved for out of sample for all futures contracts especially contract 1 and 2. Overall the performance was improved for out of sample and did not change for in sample.

Finally, adding all the contracts 1, 2, 3, 4 together to the benchmark has disadvantaged the model. It is safe to conclude that futures contracts 1 and 2 months to maturity have slightly improved the out of sample prediction, however, this improvement is not significant enough to make concrete conclusion.

5. Conclusion

In this paper we tested the relation between crude oil futures prices and spot price and if futures are good predictors to the spot applying nonlinear ANN model. Namely, Daily spot price for WTI and futures prices for 1, 2, 3, and 4, months to maturity was considered. Data was obtained from Energy Information Administration covering the period from 1996 to 2007. Several transformation methods was tested, we find that applying 3 days simple moving average to the original data then transform it into relative change is the best methods amongst the other means tested. Moreover, attentions was paid for finding ANN model

[3] The reader should bear in mind that all the results represent average of serval trail with different set of weight to insure model stability therefore slight differences in the performance should be ignored.

structure, as well as discovering the optimal number of lags based on spot price solely as input, and use it for benchmark purposes. Then futures price was added to the benchmark and the performance was compared. Weak evidence was found in support that futures prices of crude oil WTI contain new information about oil spot price. Futures contracts 1, 2 have preformed better than contracts 3, 4 but the overall improvement was insignificant. Finally, it is worth mentioning that the frequency of the data in this study (daily) makes the results not conclusive to reject the hypothesis that futures price could contain new information and therefore it could predict the spot price. The relation between spot and futures could be different during the day. In other words, testing with intraday data could produce different results.

References

Analysis of the impact of high oil prices on the global economy. (2004). The International Energy Agency.

Andrea Coppola. (2007). *Forecasting oil price movements: Exploiting the information in futures market.* Unpublished manuscript. Retrieved June 6th 2007, from http://papers.ssrn.com/paper.taf?abstract_id=967408

Anthony E. Bopp. (1987). Are petroleum futures prices good predictors of cash value? *The Journal of Futures Market, 7*(6), 705-719.

Apostolos-Paul Refenes (Ed.). (1995). *Neural networks in the capital markets*. Chichester: John Wiley & Sons, Inc.

Bruce Vanstone. (2005). *Trading in the Australian stock market using artificial neural networks.* Unpublished PhD, Bond University, Australia.

Energy information administration., 2007, from http://www.eia.doe.gov/

George Milunovich, & Ronald D. Ripple. (2006). *Hedgers, investors and futures return volatility: The case of NYMEX crude oil.* Unpublished manuscript.

Joseph G. Haubrich, Patrick Higgins, & Janet Miller. (2004). *Oil prices: Backward to the futures*? *Federal Reserve Bank of Cleveland,*

Kalok Chan. (1992). A further analysis of the lead-lag relationship between the cash market and stock index futures market. *The Review of Financial Studies, 5*(1), 123-152.

Kur Hornik, & Maxwell Stinchcombe. (1989). Multilayer feedforwards are universal approximators. *Neural Networks, 2*, 359-366.

Marc Labonte. (2004). *the effect of oil shocks on the economy: A review of the empirical evidence.* No. RL31608 Congress Research Reports CRS.

Michael E. Azoff. (1994). *Neural network time series forecasting of financial markets*. New York: John Wiley & Sons, Inc.

Parma Silvapulle & Imad A. Mossa. (1999). The relation between spot and futures prices: Evidence from the crude oil market. *The Journal of Futures Markets, 19*(2), 175-193.

Paul D. McNelis. (2005). *Neural networks in finance gaining predictive edge in the market*. Massachusetts: Elsevier Academic Press.

Ralph Grothmann. (2005). *Multi-agent market modeling based on neural networks.* Unpublished PhD, University of Bremen, Germany.

Ralph Neuneier & Hans Georg Zimmermann.(1998). How to train neural networks. In Genevieve B. Orr, Klaus-Robert Müller (Ed.), *Neural networks: Tricks of the trade* (pp. 273-423). Berlin: Spring.

Seed Mohiri, & Faezzeh Foroutan. (2005). Forecasting nonlinear crude oil futures prices. *The Energy Journal*, *27*(4), 81-95.