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Prediction Model for Crude Oil Price Using Artificial Neural Networks

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Abstract

This paper presents a prediction model for crude oil price spot price direction in the short-term. The prediction model based on artificial neural network (ANN) to forecast and compared with least square method (LSM). The results show that on the short-term, the best prediction model for ANN of four, three, two and one hidden layers, respectively. The ANN of one - four hidden layers is found to be able to forecast better than the LSM.

Keywords: Crude Oil Price, Prediction Model, Artificial Neural Networks, Least Square Method

1. Introduction

Crude oil is the significance of global economic variable. It is a vital component for the economic development and growth for industrialized. However, extreme weather, speculation in financial market, amongst others is major characteristics of crude oil market which increase the level of price volatility in the oil markets. The effect of oil price fluctuation extends to reach large number of goods and services which have direct impact on the economy as well as the communities. Therefore, to reduce the negative impact of the price fluctuations, it is very important to predicate the price direction.

Artificial Neural Network (ANN) is the science of Artificial Intelligence (AI) that being applied in various fields effectively, for example, pattern recognition, prediction, control, optimization and clustering. The concept is that it simulates the working of the human brain neurons. Generally, it can be seen from the nodes of neural network which are simulated from synapse. Also, the signal transmission of nodes is simulated from dendrite and axon. Finally, activation function or transfer functions are simulated from the human neuron. The mathematical model of ANN is a dynamic weighted sum, a general possibly convergent function, which is far different from any of the basic neural models or their compositions. It is perhaps a good instance which indicates that artificial intelligent not be rigorously studied before the natural intelligence [1-3]. Least Square Method (LSM) is probably the most popular technique in statistics. LSM arise when fitting a parameterized linear or nonlinear function to a set of measured data points by minimizing the sum of the squares of the errors between the data points and the linear or nonlinear function [4-6].

This paper presents a very brief review of the related and recent studies. Wang et al [7] present a hybrid methodology to forecast crude oil monthly prices. The model consists of combination of three separate components that they extract rule based system. These three components work disjointedly, and then intergraded together to get the final results. They claimed that nonlinear integration of these three models has outperformed any single one. However, there are several issues in this system. For example, the rule base system of the text mining model 3 depends on the knowledge base which developed by human experts. This process is not only controversial, but also unreliable, experts opinions vary on the same problem. Moreover, neither the rules nor the knowledge base was made available to the public.

Bopp and Sitzer tested [8] whether futures prices are good predictors for cash price in the future for 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.

Abosedra and Baghestani tested [9] monthly future prices for long term-forecast. The results showed that only future 1 and 12 months ahead produced significant forecast and could be useful for policy making purposes.

In this study, we presented the ANN for crude oil price prediction for the short-term. Next, we test whether crude oil future prices contain information about spot price direction on the short-term. The prediction model based on ANN of four layers feedforward network with backpropagation algorithm to forecast and compared with LSM. First, section 2 presents model and calculations, and preprocessing along with our methodology. Second, section 3 presents results and discussion. Finally the paper is concluded in Section 4.

2. Model and calculations

ANN architecture is divided into 2 types: a single neural network layer and a multi neural network layer. The single layer has only input and output level (see Figure 1). However, the multi neural network layer has one or more than one hidden levels which are in the middle of the input and output level (see Figure 2).

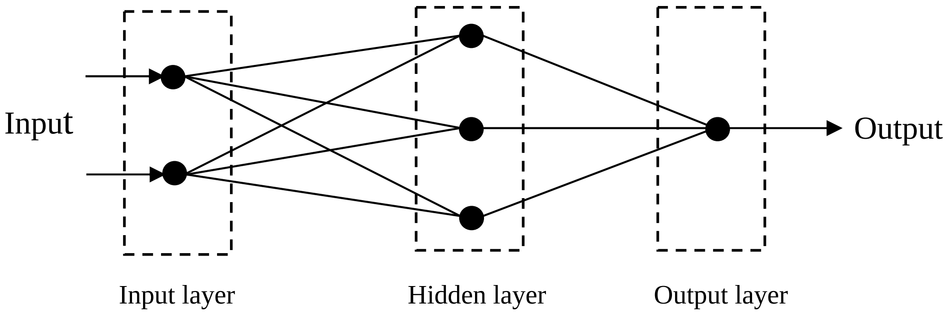


Figure 1 The model of single neural network layer.

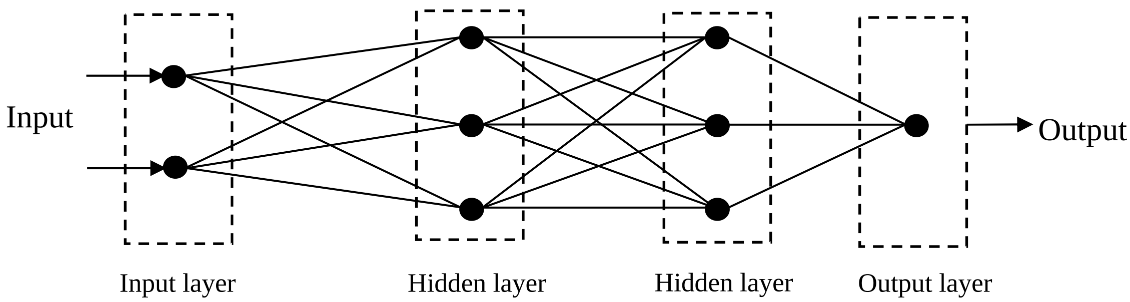


Figure 2 The model of multi neural network layer.

LSM is probably the most popular technique in statistics. LSM arise when fitting a parameterized function to a set of measured data points by minimizing the sum of the squares of the errors between the data points and the function. LSM based methods have received considerable attention for crude oil price forecasting. These models have been used to deal with the nonlinearity of crude oil price. The methodology of this study is based on four layers feedforward network with backpropagation algorithm. The goal is to forecast crude oil prices. Convergence, the ability of the model to perform with new data and Satiability, consistency of the network output are main requirements for any successful ANN [10]. The points are successfully, a large number of considerations need to be taken into account, the size and frequency of the data, network architect, the number of hidden neurons, and activation function.

The residuals mean squared error (RMSE) used metric for ANN performance regardless of the network goal. The measure of linear correlation between the forecasted and value [10]. In this study, we used mean squared error (MSE) for ANN. Finally, the information coefficient given by equation 2.1 was used.

$$MSE = \sum_{i=1}^{n} \left(\frac{\left(y(x_i) - \hat{y}(w, x_i) \right)^2}{2} \right) \tag{2.1}$$

Where $y(x_i)$ is the observation data, $\hat{y}(w, x_i)$ is the predicted value that ensconced activation function and weight, x_i is the original time series, and w is weight.

The observation data is daily closing price; from Sep 2002 to Aug 2013, it includes 3057 data points for each time series. All data sets retrieved from Energy Information Administration web site: http://www.eia.doe.gov/ [11]. We used 85 % of the data for training and 15 % for out of sample testing.

The network normalization is transferred the data to fit within the limit of transfer function. A linear normalization method is given by equation 2.2 to transfer the data to fit between [-1, 1].

$$y_i = 2 \times \frac{\left(x_i - \min(x_i) \right)}{\left(\max(x_i) - \min(x_i) \right)} - 1 \tag{2.2}$$

The most widely used activation functions for ANN in the hidden layer are the sigmoid functions and the hyperbolic tangent. We used sigmoid function in Figure 3 for activation function.

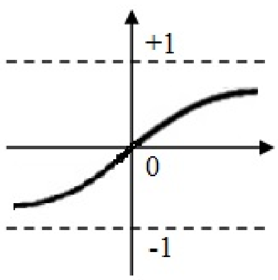


Figure 3 The sigmoid function and normalization method.

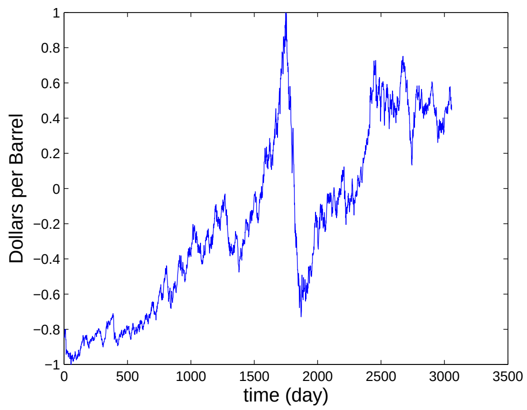
The sigmoid function is given by equation 2.3

$$g(x_i) = \frac{1}{1 + e^{-x_i}} \tag{2.3}$$

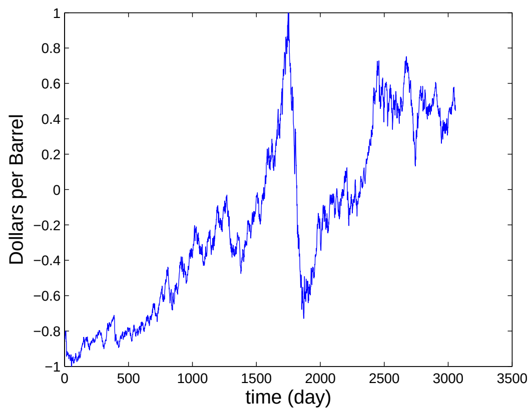
Finally, parameters are used learning rate, training time, optimization algorithm that selected base on experiments.

3. Results and discussion

The methodology of this study was compared a fully connected feedforward for backpropagation algorithm networks of one to four hidden layers with LSM. Hence, we focus our interest on modeling with feedforward network. The Choice of activation function, learning rate, were determined by experiments. The optimization algorithms was chosen Leveberg-Maquardt [12-13] that was approximated the second order. A linear normalization method is given by Figure 3 for the data to fit between [-1, 1].



(a)



(b)

Figure 4 The observations data (a) and the normalization of observations data (b).

The network architecture is 4 layers feedforward with 9 neurons in the hidden layer. The network was trained for 1000 iterations or until one of the stopping criteria is met. The learning rate is 0.01 and training algorithm is Levenberg-

Marquardt.

The results of the prediction model for ANN show that on Table I-III, ANN (one, two, three and four hidden layer) are found to be able to forecast better than the LSM. This makes sense, the targets of ANN shown in Table I-II and the output of the prediction model based on ANN shown the best solution in four, three, two and one hidden layer, respectively. The outputs of ANN are found to be able to forecast better than the LSM.

TABLE I. The prediction model for crude oil price of normalization data used ANN in one and two hidden layer for target and output.

Time Series	One hidden layer		Two hidden layer	
	Target	**Output**	**Target**	**Output**
1	-0.841494	-0.854032	-0.841494	-0.821653
2	-0.826899	-0.850917	-0.826899	-0.819214
3	-0.826114	-0.840760	-0.826114	-0.812024
4	-0.802103	-0.837337	-0.802103	-0.809363
5	-0.815913	-0.820602	-0.815913	-0.799180
6	-0.816541	-0.825366	-0.816541	-0.801096
7	-0.800534	-0.827686	-0.800534	-0.805170
8	-0.814658	-0.817290	-0.814658	-0.797250
9	-0.826899	-0.823919	-0.826899	-0.800737
10	-0.859856	-0.834241	-0.859856	-0.809646
11	-0.857815	-0.857368	-0.857815	-0.825137
12	-0.864093	-0.862249	-0.864093	-0.829133
13	-0.935342	-0.866728	-0.935342	-0.829747
14	-0.943189	-0.903946	-0.943189	-0.857630
15	-0.934714	-0.916929	-0.934714	-0.869641

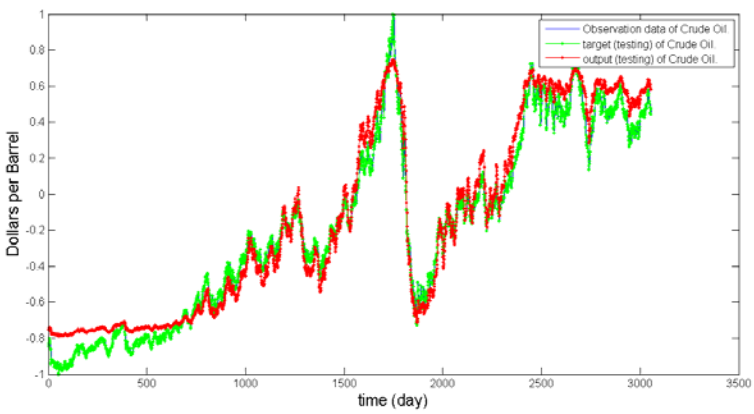
TABLE II. The prediction model for crude oil price of normalization data used ANN in three and four hidden layer for target and output.

Time Series	Three hidden layer		Four hidden layer	
	Target	**Output**	**Target**	**Output**
1	-0.841494	-0.862796	-0.841494	-0.830432
2	-0.826899	-0.859872	-0.826899	-0.827379
3	-0.826114	-0.847411	-0.826114	-0.818852
4	-0.802103	-0.841271	-0.802103	-0.818438
5	-0.815913	-0.817085	-0.815913	-0.803688
6	-0.816541	-0.821629	-0.816541	-0.812378
7	-0.800534	-0.821937	-0.800534	-0.812816
8	-0.814658	-0.810136	-0.814658	-0.802755
9	-0.826899	-0.818080	-0.826899	-0.811645
10	-0.859856	-0.829918	-0.859856	-0.819081
11	-0.857815	-0.860061	-0.857815	-0.837806
12	-0.864093	-0.870408	-0.864093	-0.836577
13	-0.935342	-0.879890	-0.935342	-0.839891
14	-0.943189	-0.915614	-0.943189	-0.874719
15	-0.934714	-0.933299	-0.934714	-0.877994

TABLE III. Structure of LSM and mean squared error.

Time Series	LSM	
	Observations data	**Output**
1	-0.841494	-0.993395
2	-0.826899	-0.993391
3	-0.826114	-0.993215
4	-0.802103	-0.993009
5	-0.815913	-0.992582
6	-0.816541	-0.992457
7	-0.800534	-0.992294
8	-0.814658	-0.992313
9	-0.826899	-0.992296
10	-0.859856	-0.992373
11	-0.857815	-0.993013
12	-0.864093	-0.993433
13	-0.935342	-0.993794
14	-0.943189	-0.994315
15	-0.934714	-0.994835

The MSE is by far the most used metric for ANN performance regardless of the network goal and LSM used MSE for measure information. The results of the prediction model between ANN of one to four hidden layers with LSM. This makes sense, the a measure of the predictions model shown in Figure 5 - 9 and the MSE of the prediction model based on ANN shown the error of information coefficient in four, three, two and one hidden layer, respectively. The error between observations data with predicted value of ANN are found to be able to forecast better than the LSM.



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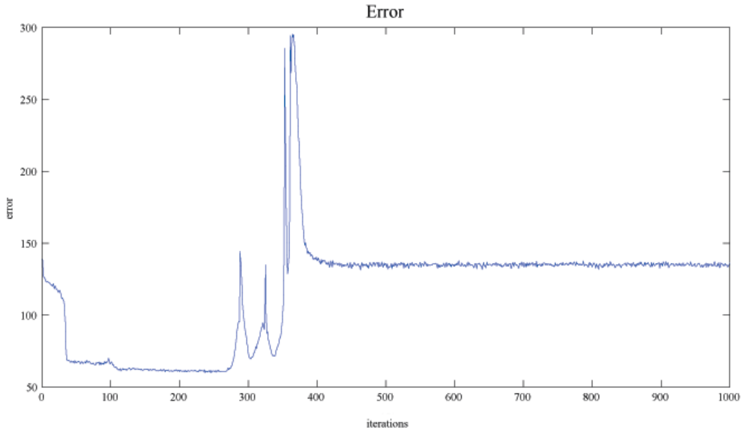
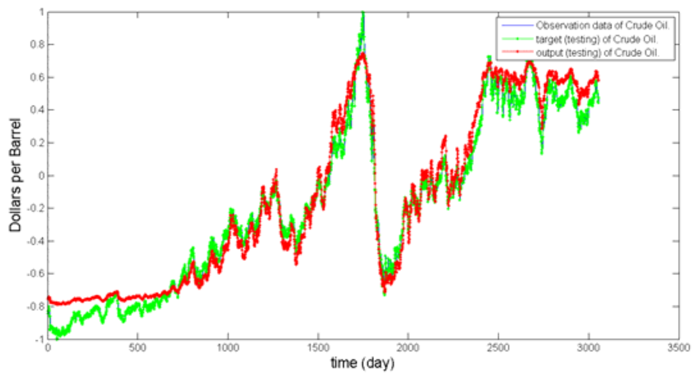
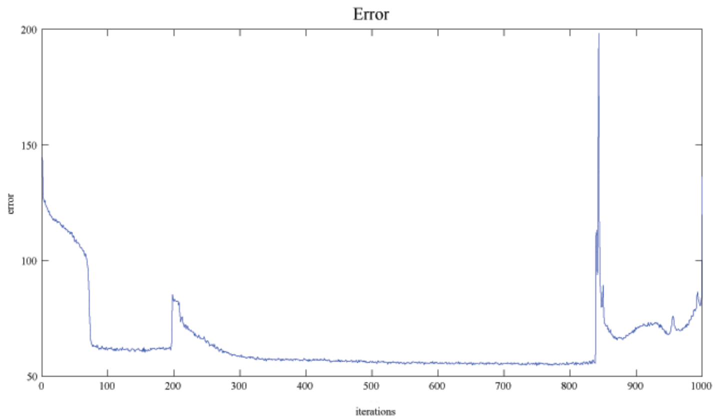


(b)

Figure 5 The result of ANN with one hidden layer (a) and the error of training and testing with the network (b).

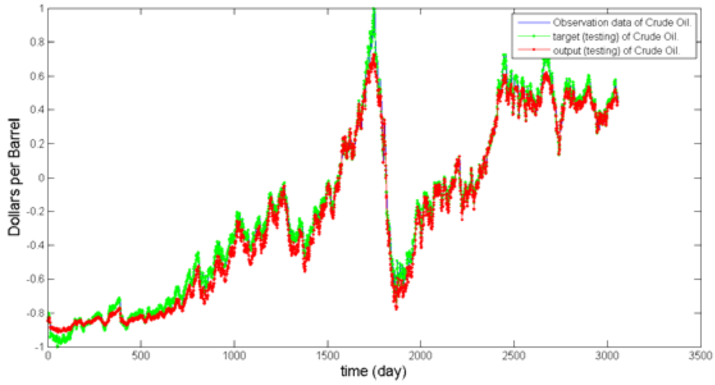


(a)

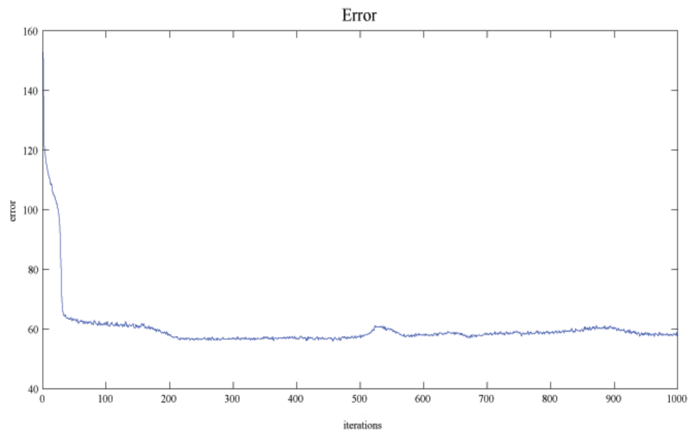


(b)

Figure 6 The result of ANN with two hidden layer (a) and the error of training and testing with the network (b).

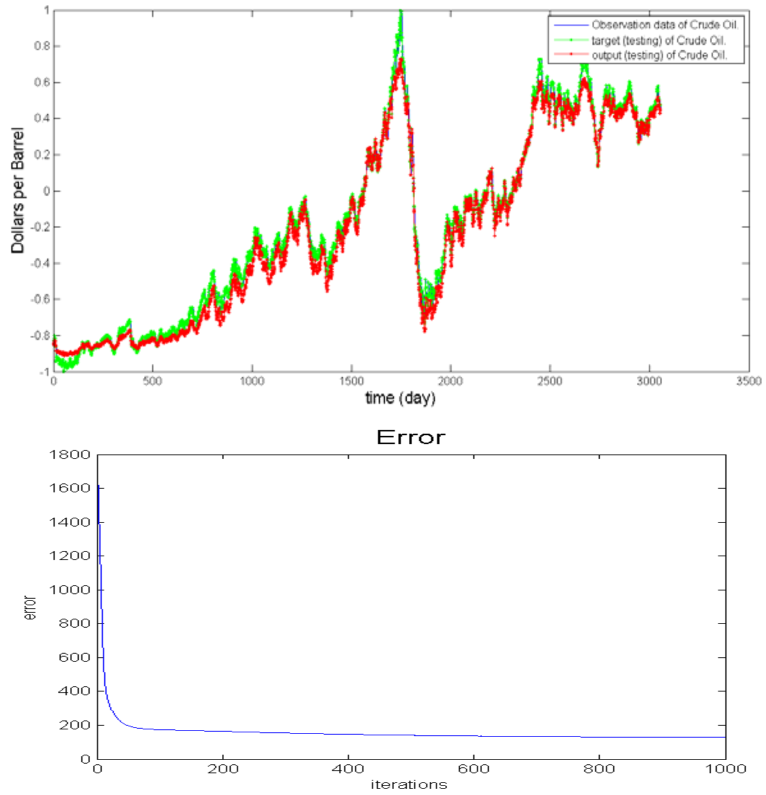


(a)



(b)

Figure 7 The result of ANN with three hidden layer (a) and the error of training and testing with the network (b).



(a)

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Figure 8 The result of ANN with four hidden layer (a) and the error of training and testing with the network (b).

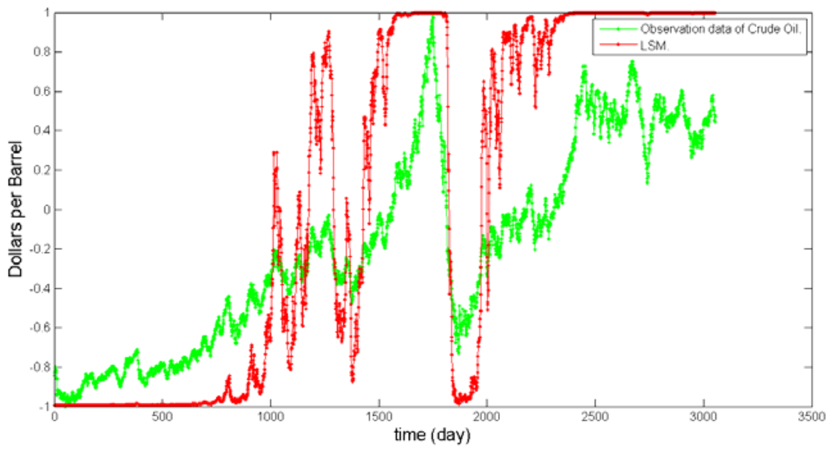

Figure 9 The result of LSM.

4. Conclusion

In this paper we presented a prediction model for crude oil price spot price direction in the short-term. Data was obtained from Energy Information Administration covering from 2002 to 2013. In addition, we tested the relation crude oil prices and the prediction model based on ANN to forecast and compared with LSM. The results shown that on the short-term, the best prediction model for ANN of four, three, two and one hidden layers, respectively. The ANN of one to four hidden layers is found to be able to forecast better than the LSM in Figure 5 - 9. Finally, our future research continue to investigate other variable which could lead to improving the short-term forecast, such as heating oil prices, share of stock, share of business, interest rate, and gold prices.

References

[1] M. Azoff, Neural network time series forecasting of financial markets, John Wiley, New York, 1994.

[2] R. Neuneier and H. Zimmermann, How to train neural networks Neural networks, Spring, 1 (1998), 273-423.

[3] S. Haykin, Neural networks a comprehensive foundation, Wiley, New Jersey, 1999.

[4] D. M. Batesand and D. G. Watts, Nonlinear regression and its applications, Wiley, New York, 1988.

[5] G. Philip and M. Walter, Algorithms for the solution of the nonlinear least-squares problem, SIAM Journal, 4 (1978), 977-992.

[6] I. Griva, S. Nash and A. Sofer, Linear and nonlinear optimization, Springer Science, 2009.

[7] S.Wang, L. Yu and K. Lai, Crude oil price forecasting with TEI@Imethodology, Journal of Systems Science and Complexity, 18 (2005), 145-166.

[8] E. Bopp and S. Sitzer, Are petroleum futures prices good predictors of cash value, The Journal of Futures Market, 7 (1987), 705-719.

[9] S. Abosedra and H. Baghestani, On the predictive accuracy of crude oil futures prices, Energy Policy, 1 (2004), 1389-1393.

[10] A. Refenes, Neural networks in the capital markets, Wiley, New York, 1995.

[11] A. Coppola, Forecasting oil price movements: Exploiting the information in futures market ,The Journal of Futures Markets, 28 (2008), 34-56.
http://papers.ssrn.com/paper.taf?abstract_id=967408

[12] H. Gavin, The Levenberg-Marquardt method for nonlinear least squares curve fitting problems, Journal of Computational Physic, 2 (2011), 164-168.

[13] D.W. Marquardt, An algorithm for least-squares estimation of nonlinear parameters, Journal of the Society for Industrial and Applied Mathematics, 11 (1963), 431-441.
http://www.brnt.eu/ phd/node10.html

[14] B. Vanstone, Trading in the Australian stock market using artificial neural networks, Bond University in fulfillment of the requirements for the degree Doctor of Philosophy, 2005.

[15] C. Brooks, Introductory econometrics for finance, Cambridge University press, Cambridge, 2002.

[16] R. Grothmann, Multi-agent market modeling based on neural networks, University of Bremen, Germany, 2005.

[17] G. Bowden and K. James, Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications, Journal Environmental Modelling and Software, 15 (2001), 101-124.

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