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Presenting the Feasible Models (ARIMA/ANN) to forecast the Crude Oil Price and Comparison of the predictability models potentials

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ABSTRACT

The significant role assigned to crude oil in global economy has made the price of this commodity a pivotal and influential factor in economic planning and decision making of governments and commercial companies.
In view of the above, forecasting oil price is of great significance for policy makers and other economic entities. Besides previously used methods of forecasting, new methods have recently been adopted. A specimen i.e., neural networks, is a instrument with parallel structure used for processing data and able to execute tasks such as estimation of non-linear functions and classification and recognition of patterns, etc. one of the outstanding features of this instrument is that one can learn to use it through both training and experience.
In this article we first examine previously conducted studies on the ability of both "Auto regressive integrated moving Average" (ARIMA) and "Artificial Neural Networks" (ANN) then set to compare these two methods for the purpose of forecasting the weekly trend of oil price for the period from 06/01/1995 to 18/01/2011.
"Autoregressive integrated moving average" and "Artificial neural networks" are respectively the most meticulous linear and non-linear models of forecasting "time series". The findings show that the latter outdoes the former in forecasting "time series".
In this study we intend to measure the exactitude of the forecasts by applying four criteria including: RMSE, MSE, MAE and U-Theil
KEYWORDS: Forecast, Auto regressive integrated moving average (ARIMA), Artificial neural networks (ANNA)

1. INTRODUCTION

Oil price is regarded as one of the pivotal factors that influence global economy and is used in different ways by different sectors. Overlay an increase in oil price results in movement of funds from importing countries to exporting ones. This is a phenomenon that affects global economy. Furthermore, to achieve the optimal conditions of exporting oil, one must have a perspective of the future trend of oil price. Therefore, an accurate forecast of the price is of substantial significance and has considerable impacts on economic policy making and planning of a country.

On account of the fact that many factors influence oil price and there are also shocks to the price, it undergoes a large number of fluctuations.

Considering the above, single-variable auto regressive models which have time series as a combination of past trends and an accompanying component which is, according to Forutan and Moshiri; (2004) stochastic.

Utilizing neural networks for the purpose of forecasting oil price has recently been on the increase.

The main plus of such networks is their ability to create flexible non-linear models. Theatrically, these networks are able to estimate every continuous function. Such flexibility furnishes a potential instrument for forecasting. However it should be noted that designation of large number of parameters, adds perplexity to the designing process. (Kaastra &Boyd, 1995)

LITERATURE REVIEW

In 2010, weekly price of Iran`s crude oil was forecasted for 10, 20, and 30 percent of the given data by applying the four patterns of neural networks i.e., 1- feed-forward back-propagation network 2- back-propagation cascade network 3- back-propagation Elman network 4- generalized regressive network, along with a pattern of ARIMA. The findings show that by raising the percentage of the data, the exactitude of the forecast diminishes. (Seyed Ebrahim, Dashti Rahmatabadi; Hamid, Mohammadi; Zakariya, Farajzade; 2010)

1- In 2009, oil price was forecasted, dynamically, by applying ANN and oil storage of member countries of Organization for Economic Co-operation and Development (OECD) as a new variable. The findings show that by

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adding this variable, as a new entry, the level of error in two-variable forecast drops. (Mohammad Hossein, Poorkazemi; Mohammad Bagher, Asadi)

2- In 2007, the linear and non-linear models of ARIMA and ANN were combined to forecast the rate of Euro against Iranian Rial. The findings show that the mingled model which consists of ARIMA and multi layer perceptron, yields more precise results. (Mehdi, Khasheie; Mehdi, Bijari)

3- In 2007, the methods of “ARIMA” and “ANN” were compared in respect of forecasting daily price of oil in the period from April, 1983 to June, 2005. Moreover, after the modeling process was done by “ANN”, sensitivity analysis was applied to determine the participation portion of every input parameter. (Iman farjamnia; Mohsen, Naseri; Seyed Mohammad Mahdi, Ahmadi)

4- In 2006,”General Regression Neural Network” was used to present an intelligent model for forecasting short-term price of oil (for the following month). "MATLAB" software was used to replicate new data from the existing ones. (Mohammad Hossein, Shanehchi; Arghavan, Alizadeh)

5- In 2004, a study titled “Testing chaos and forecasting future price of crude oil” evaluated the possibility of existence of chaos in the system that generates (W.T.I) West Texas Intermediate crude oil price in the period from April, 1983 to13/01/2003. The results of Liapanof exponential estimation and correlation aspect substantiate existence of chaos in time series and neural network and BDS estimation indicate that the system which produces daily crude oil price is nonlinear. (Saeed, Moshiri; Faeze, Forutan)

6- In 2002, monthly electricity requirement from 1992-2002 was studied. The data related to the years 2001 and 2002 were selected as evaluation criterion then the two methods of “ARIMA” and “ANN” were applied to forecast. (Reza, Ramezani; Maryam, Ramezani)

7- In 2002, neural networks were used to forecast economic time series. The findings of all the four methods show that “Conjugate gradiant algorithm” yields agreeable results in training the samples of training group (1-30). However, when generalized, the first five samples of the test group (31-35) i.e. the first 40 percent yield agreeable results but the remaining samples have (36-43) disagreeable results. (Asghar, Oskuee)

8- In 2001, structural models, time series, and neural networks were applied to forecast inflation rate in Iran. Both dynamic and static methods were utilized. The results show that neural networks outdo their rivals in the forecasts. (Saeed, Moshiri)

9- In 2010, the efficiency of “Generalized regression neural network” in forecasting inflation rate in Turkey between 2001 and 2006 was studied. The findings show that “Generalized regression neural networks” are superior to “ARIMA” for this purpose. (Recep, Duzgun)

10- In 2009, a model of multilayer feed-forward neural network for forecasting short-term crude oil price (for 3 subsequent days) and several methods for pre-processing the data were tested. The results show that 13-lag dynamic model is optimal for short-term forecasts. (S.Kulkarni; I.Haidar)

11- In 2008, a neural network method, based on “Empirical Mode Decomposition” (EMD) together with a learning pattern was utilized to forecast global crude oil price. The findings show that the proposed method is very appealing. (Lean yu; Shouyang Wang, Kinkeung Lai)

12- In 2007, “wavelet neural network” and data from oil storage of “OECD” countries were used to forecast spot price of crude oil. The results show that “wavelet neural network” can model the non-linear relationship between oil storage and oil prices. (Ye pang, Weix, Lean Yu, Jianma, Kinkeung Lia, Shoyang Wang, Shanying XU)

13- In 2007, linear and non-linear relationships between West Texas Intermediate future daily price and spot price of crude oil were studied in one, two, three and four periods, and apart from Causality Granger Test, a new non-parametric and non-linear test was also applied after controling Co-integration. (Stelios D.Bkiros, Cees G.H Diks)

14- In 2007, an intelligent model for forecasting monthly price of crude oil was designed. (Amin-Naseri,Ghracheh Ahmadi.E)

15- In 2005, the efficiency of neural networks in forecasting inflation rate was evaluated. An out-of-sample test was simulated by using the recent data from the United States of America and the results show that neural networks have a better performance than single-variable auto regressive models for short horizon of ¼ and 2/4. (Emi Nakamura)

16- In 2005, it was proposed that oil price influences output in a complex non-linear approach. The result shows that neural networks are efficient and useful in short-term forecasting of gross domestic product by using oil prices and cascade learning. (Farooq Malik; mahdi, Nasereddin)

17- In 2005, a neural network was designed for forecasting financial and economic time series. In this article designing is divided into eight stages. (Lebeling Kaastra, Milton Boyd)

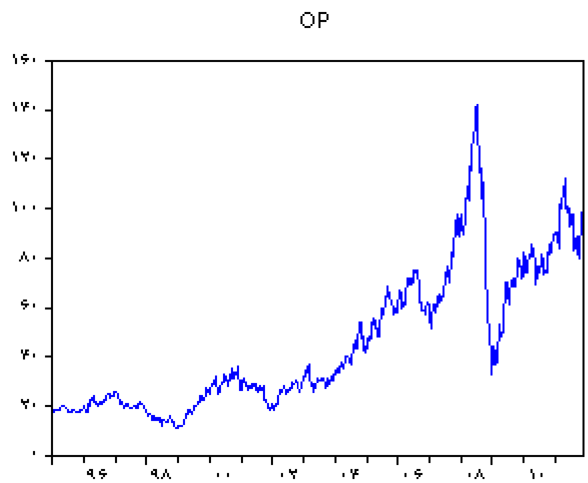
18- In 2000, back-propagation ANN (BPN) was applied to forecast inflation. Then performance of "BPN" was compared with common models of econometrics such as "ARIMA", "vector auto regression", and "Bayesian vector auto regression". (Moshiri,S; Cameron,N)

Auto Regressive Integrated Moving Average (ARIMA)

There are four methods of economic forecasting based on the time series data. They include:

1- Single-Equation regression models
2- Simultaneous-Equation regression models
3- Auto regressive integrated models (ARIMA)
4- Vector auto regressive models

Linear models have extensively and infinitely been applied to forecast economic variables. Among these models "ARIMA" is the most useful and multifunctional one (Duzgun, 2010). The data, in this study, are weekly prices of crude oil, including 881 data within a seventeen-year period. To recap, we can say: within this period the average oil price is approximately 45.56 and the increasing or decreasing trend of the price is irregular. Moreover, the fluctuations are not stable and equal. This shows existence of a non-linear structure and proposes using a non-linear model.



The outstanding time series modeling method i.e. ARIMA is known as "Box Jenkins methodology". In this model, future values of variables are assumed as a function of former observations and stochastic errors. The following equation clarifies the point:

$$y_t = \alpha_t + \alpha_t y_{t-1} + \cdots + \alpha_p y_{t-p} + \varepsilon_t - \beta_1 \varepsilon_t - \cdots \beta_q \varepsilon_{t-q}$$

y_t and ε_t are respectively real values and stochastic errors in the period t, αi (i=1,2,…,p), βj (j=1,2,…,q) are parameters of the model. "q" and "p" are natural numbers and signify the rank of the model. Stochastic errors (ε_t) are assumed independent, equally distributed, having a fixed variance of "σ^2" and average of zero (Gujarati, 2011). "Augmented Dickey-fuller test" is used to determine whether the series is stationary or not. The result of the "ADF test" shows that the data of %1, %5, and %10 are not stationary. To make the data stationary we find first difference equation the results "ADF" are depicted in appendix (1). As shown in the appendix the data of %1, %5, and %10 are stationary. Therefore, if a time series, after "d" times differentiation, becomes stationary after the first differentiation and then we model it by applying "ARIMA(p, q)", the main time series is ARIMA(p, d, q) (Gujarati,2011). An important issue in modeling "ARIMA" is determining the proper rank of the model. There is a practical way, called "Box-Jenkins" to create such models. "Box Jenkins" suggests that "Auto regression function" and "Partial autocorrelation function" be used to distinguish rank of the model (Khasheie, 2009). By choosing an appropriate model of "ARIMA", one can obtain the linear structure existing in time series. Estimation of "ARIMA" shows that "Durbin-Watson" is in a suitable condition (see appendix2). Prior to using the estimated equation for making statistical inferences it is necessary to examine the residuals to determine whether autocorrelation exists or not (Mehregan, 2010). According to the "serial autocorrelation test" developed by Breusch Godfrey, there is no correlation in the residuals of this model (refer to appendix3). With regard to irregular fluctuations of oil price, the homoscedasticity of this model was examined by "Gelejser Test". The result shows that the assumption that hetroscedasticity does not exist is rejected, and it is concluded that the hetroscedasticity of variance is removed by using “White Test”.

The following chart illustrates the performance of “ARIMA”

U-stat	MAE	RMSE	MSE	Criterion
0.0210	2.866	3.707	0.0501	Value

Neural networks

Despite their fifty-year history, neural networks have entered the realm of science in the past 15 years (Kia, 2011). Strong ability to forecast, and to learn the rules, and relations of the data, are the features that make neural networks appealing to economists. In the 1980s, along with the advances in technology, more studies were carried out on neural networks and many new ideas were propounded.

Neural networks learn the trend of the patterns by using the data they get from their inputs and supervisor. Naturally, the structure of networks is determined by the way the parts are joined together. Thus, we can determine the way components are joined by adjusting the value of each joint which is called “joint weight”. Neural networks are utilized to implement elaborate functions in fields such as pattern recognition, identification, classification, image and controlling systems processing and forecasting, etc.(Kia, 2011) In this study neural network is applied for the purpose of forecasting.

A model of “ANN" is made up of three layers, respectively, called (Wang, 2000):

- Input layer
- Hidden layer
- Output layer

It is noteworthy that in some of the previous studies input layer is considered to be more than just one layer. This layer consists of some inputs or explanatory variables of the model. In hidden and output layers some algebraic operations are done on the data and the product enters input layer as a new input. Hidden layers play a pivotal role in the proper learning of the model. No specific rule governs the number of hidden layers and the number of neurons. To evaluate the model accurately, we need enough of these layers and neurons because as the number of neurons increase in the hidden layer, the problem of over fitting occurs. In this case the error is reduced to its lowest level but as new data enter the network, error rate goes extremely up. In this case it is said that the network doesn`t have enough generality*. Researchers have propounded some formulae for determining the optimal number of neurons in the hidden layer. However, the optimum number of neurons is often determined by the method of trier and error. In this article only one layer is used. On the basis of empirical results, it seems that one hidden layer suffices for forecasting (Duzgun, 2010).

A specific response will be received if a particular input enters the neural network after its adjustment. That is, the network matches inputs with the targets to achieve target via outputs.

Many of the input and output pairs are utilized to train the network in a process called “Monitored Learning”.

Generally, monitored methods are used to train neural networks. But networks can be trained through methods that are not monitored and are mostly used in distinguishing data clusters. Some kinds of neural networks, like “Hopfield”, and “linear networks” are directly design by designers. To summarize we can say: there are various methods for designing learning techniques and the user has many options to choose from. Networks that consist of layers of neurons with a non-linear transfer functions, enable the network to learn the linear and non-linear relationship between inputs and outputs. If you need an output in the area of 1 and 0, you can use “logsig” in the output layer. “Back propagation” (BP) is an algorithm with descending slope in which “network weights” move in the direction opposite to the one in which performance function moves. In the simplest “Back propagation” method, weights and biases are updated in the direction in which performance function decreases. A duplication of this algorithm is:

$X_{K+1}=X_K-\alpha_K g_k$

Where “X_K” is the current vector of weights and biases, “g_k” is the current slope, and “α_k” is pace of learning. Considering the error back- propagation algorithm, if error diminishes in each period, learning rate increases. Moreover, if error rate increases, learning rate will be adjusted to thwart this increase. When we have the highest repetition rate, the least error rate, or the least gradiant training is thwarted. (Anvar, Amin Naseri; 2001).

In this study we use a “three-layer feed forward neural network” with “Tansig function” in the hidden layer and a linear function in the output layer.

Broadly speaking, there are three major instruments in every successful “Artificial neural network” : (Kulkarni &Haidar, 2009)

1- Conversion, or inter sample accuracy

2- Generality, ability of the model to run new data
3- Stability, adaptability of the network output.

Designing an Artificial Neural Network (ANN) for forecasting crude oil price

There has been an increase in utilizing “ANN” to forecast time series in recent years. The method of modeling such networks is a non-linear one which is the most complicated of non-linear models. This model, to some extent, resembles the neural network of human beings; thus, it is called “ANN” (Wang, 2009).

This network is a suitable technique for modeling data with elaborate patterns to be used in short-term forecasting. Nonetheless, it is not very economical. However, in case a normal regression model or and “ARIMA” model is on a par with “ANN”, we choose the one that is simpler than the other. But when we have a lot of data with elaborate patterns, “ANN” can be the best of our options (Wang, 2009).

The method for designing a model of neural network used in economic time series is divided into eight stages (Kaastra & Boyd, 1996):

1- Parameter selection 2- Data collection 3- Data pre-processing 4- training, credit –scoring, and test digests 5- Neural Network algorithms 6- Evaluation criteria 7- Training neural network 8- Executing Neural Network

The data used in this study are elicited from “www.eia.deo.gov”. When your model is “ANN”, having more data results in a better generality of the network (Kulkarani & Haidar, 2009). It is a good idea to normalize the data first so that we can confine them to a small area. For this purpose the following formula is used:

$$x_i = (X(i) - Xmin)/(Xmax - Xmin)$$

In the present study, West Texas Intermediate crude oil price time series are first divided into the following 3groups:

1- Training (from 3jan 1986 to 6oct 1995) 2- Credit scoring (from 13oct 1995 to 2jun 2010) 3- Test (from 9jun 2010 to 18nov 2011)

Then the data from training group are utilized to design the network, and those from credit-scoring group to examine the success of inter-sample forecast. The structure used in this network is made up of a three-layer feed-forward network, including 1- an input layer 2- a hidden layer with three neurons 3- an output layer, together with a “Hyperbolic Tangent” non-linear function in the hidden layer, a linear function in the output layer, error back-propagation learning algorithm and “Levernberg-Marguardt” training function.

This is the fastest method to implement and like Quasi-Newton methods, reduces the number of calculations by evading calculation of “Hessian”. Nevertheless, this method is not efficient in distinguishing patterns because its neurons become saturated and it is designed for minimizing the squares (Kia, 2010). Moreover, forecasting is done in a stationary approach and previously obtained values are used for the purpose of forecasting the oil price. Using this structure, we forecasted crude oil price of ten percent of the data by means of software named “Matlab 7.1”, and compared the results with the ones obtained from “ARIMA”.

The criteria applied for evaluation of the results include:

1- Root Mean Squared Error (RMSE) $RMSE = \frac{\sqrt{(\hat{y}_t - y_t)^2}}{n}$

2- Mean Absolute Error (MAE) $MSE = \sum(\hat{y}_t - y_t)^2/n$

3- Mean Squared Error (MSE) $MAE = |\hat{y}_t - y_t|/n$

4- U-Thiel index $U = \frac{RMSE^2}{\left[\frac{(\sum y_t^2)}{n}\right]}$

N= Number of data

Training process requires some examples of the behavior expected by the network including “Input” and “Target”. During the process of training, weights and biases are adjusted to reduce the efficiency function of the model to its minimum.

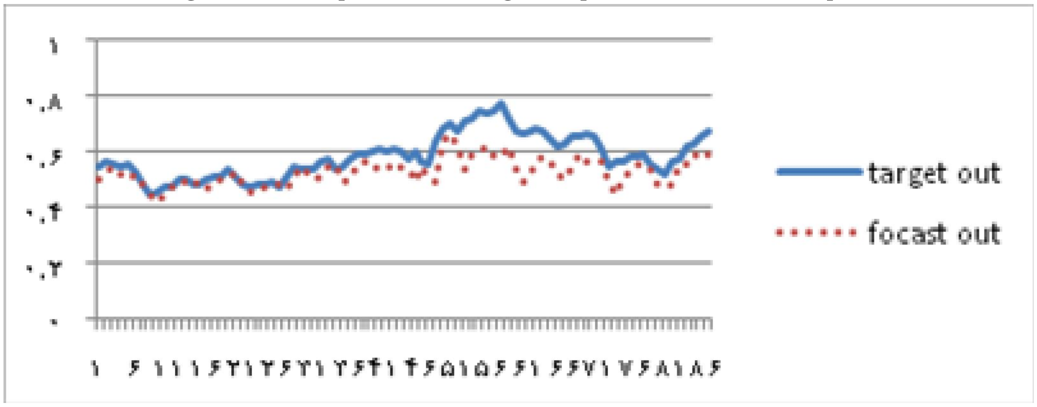
Table (3) illustrates the performance of network in training. It shows that the network has properly been trained.

Table 3: performance of “ANN” in training

U-stat	MAE	RMSE	MSE	criteria
0.0026	0.0072	0.0097	$9.4*10^{-5}$	**performance**

Figure (2) illustrates the results of forecasting the data of testing “ANN”. The dots denote “Target Output” and “Forecast Output”.

Figure 2: A comparison of “Target Output” and “Forecast Output”



To show the superiority of ANN to ARIMA the forecasting results obtained from each models are compared. The performance criteria of the two models are depicted in the following table.

Table 4: A comparison of results ARIMA and ANN crude oil price forecasting

U-stat	MAE	RMSE	MSE	Models
0.015	0.056	0.0053	0.072	**ANN(BPN)**
0.681	2.866	3.707	0.0501	**ARIMA**

As the indices in table 4 show, RMSE, MAE, and U have had better performance in comparison with ARIMA and this is only MSE in ARIMA that renders a better performance. As a result, it is concluded that ANN provide more reliable results than ARIMA; consequently renders more accurate forecast.

RESULTS AND COMMENTS

It is beyond dispute that meticulous forecasting of oil price and modeling its behavior to obtain a perspective of its future trend are of great significance especially for oil-dependent economies and influence future economic policy and decision making of countries.

In the light of the above, it is obvious that oil, as an economic and political commodity, has assumed an internationally significant position. As asserted, this study compares the performance of “ANN” and “ARIMA” in forecasting crude oil price. The data is the weekly West Texas Intermediate oil price and the structure applied consists of a three layer feed-forward network with a hidden layer that has three neurons, a back-propagation network, and learning function of “Levernberg-Marguardt”.

The findings of this study show that by using “UTHEIL”, “MSE”, MAE”, and “RMSE”, ANN renders more accurate and exact forecasts of economic time series than the ARIMA. In view of the above, the “ANN” constitutes one of the foolproof instruments for forecasting economic variables. It is worth mentioning that the applications of neural networks are not constricted to forecasting. They can be applied to other fields such as classification, pattern re-identification, etc.

The fact that neural network models utilized in most of the studies have “Back-propagation Network” as a component must not lead to the illusion that these models are the only ones which can be used for the purpose of forecasting.

Some examples of other models that can affect accurate forecasts include “GRNN”, “ELMAN” which is able to save data for future references, and learn transient patterns. Moreover, there are various learning functions such as Quasi-Newton and Conjugate Gradient methods. “Trainlm” that was used in this study is suitable for small and medium networks, of course, if there is enough memory space, “Trainrp” and/or “Trainscg” are more suitable for large networks.

At the conclusion we suggest that in future studies “Fazzy Logic” and “Genetic Algorithm” and/or a combination of the two with neural network be used and the results obtained from each of them be compared with the ones obtained from the combination.

Appendix

Table1: result obtained from time series data after first differentiation

Null Hypothesis: D(OP) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic based on SIC, MAXLAG=30)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.884	0.000
Test critical values:	1% level	-3.43757	
	5% level	-2.86462	
	10% level	-2.56846	

Table2: result of ARIMA estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob
D(OP(-8))	0.680118	0.159369	4.267565	0
D(OP(-16))	-0.18172	0.068399	-2.6568	0.008
MA(1)	0.114575	0.059115	1.938186	0.0529
MA(8)	-0.51579	0.147894	-3.48757	0.0005
MA(25)	-0.10232	0.047914	-2.13556	0.033
MA(27)	-0.10775	0.046254	-2.32947	0.0201
R-squared	0.092406	Mean dependent var		0.09147
Adjusted R-squared	0.087117	S.D. dependent var		2.317833
S.E. of regression	2.214572	Akaike info criterion		4.434916
Sum squared resid	4207.916	Schwarz criterion		4.467982
Log likelihood	-1909.88	Hannan-Quinn criter.		4.447572
Durbin-Watson stat	1.930143			

Table3: result obtained from Heteroskedasticity Test

Heteroskedasticity Test: Glejser			
F-statistic	0.587768	Prob. F(2,861)	0.5558
Obs*R-squared	1.178024	Prob. Chi-Square(2)	0.5549
Scaled explained SS	1.803269	Prob. Chi-Square(2)	0.4059

Table4: result obtained from Correlation Test

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	2.323351	Prob. F(2,856)	0.0986
Obs*R-squared	2.284544	Prob. Chi-Square(2)	0.3191

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