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COMPARISON OF VECTOR TIME SERIES AND ANN TECHNIQUES FOR FORECASTING OF WTI OIL PRICE

Abstract: *Forecasting the changes of oil prices is of critical importance for authorities and plays a significant role in the dynamic global economy. This paper employs two prediction tools, including econometric and artificial neural network (ANN) models, for forecasting the price of WTI oil to conduct a comparative study. Forecasts from vector time series (vector autoregressive (VAR) and vector error correction (VEC) models) as econometric models are compared with those from ANN model based. For developing the models, 144 monthly data (2000/1-2011/12) comprising monthly oil price, production, reserves, fright rate, world GDP and inflation is applied. To obtain the best model for forecasting the oil price, various models comprising different combinations of training and testing dataset are tested. For achieving the aim, the most appropriate network structure and model is determined based on prediction accuracy and performance. The performance indexes for evaluating the VAR and ANN models contain of RMSE (Root Mean Square error), MAE (mean absolute error), and coefficient of determination (R^2) criteria, indicate that ANN yields better results.*

Keywords: *Oil price, ANN, VAR, VEC, WTI.*

JEL classification: C01, C13, C45, C53, C58

1. Introduction

Oil price plays an important role in economical and political world systems. The economic importance of crude oil and it's derivatives not only from economical point of view, but also from strategic point of view, playing in the economies of all countries, is important. There is a world acceptance that unexpected large and persistent fluctuations in the real price of oil are detrimental to the welfare of both oil-importing and oil-producing economies (Alquist et al., 2011). The wide variety of products, transportation/storage issues and stringent environmental regulation cause to the world oil market be a capital-intensive environment characterized by complex interactions (Sharma, 1998). From a technical viewpoint, a profound understanding of the interactions between crude oil prices and the main determinants help authorities to make better decisions in the process of policymaking and implementation.

There are many reasons why analysis and forecasting of oil price is important. One of the most important reasons of more accurate forecasts of the oil price is because of its high potential to forecast a wide range of macroeconomic products and improve macroeconomic policy responses (Alquist et al., 2011). Precise forecasting of oil price helps to foresee the circumstances of trends in the future to carry out appropriate exchanges. To formulate the trend of oil price changes, the forecasting model applies the factors influencing the oil prices.

According to the importance of oil price prediction, different methods have been developed, such as artificial neural networks (Raudys, 2005; Yu et al., 2008; Tehrani, Khodayar, 2011; Movagharnejad et al., 2011; Jammazi, Aloui, 2012), hidden Markov model (Silva et al, 2010), and GARCH-type models (Morana, 2001; Kang et al., 2009; Li et al., 2010; Wei et al., 2010; Mohammadi, Su, 2010; Meade, 2010; Zhu, Ling, 2011; He et al., 2011; Hou, Suardi, 2012; Chang, 2012). Generally, the forecasting methods can be classified into three main methods (Abu-Mostafa, Atiya, 1996; Chatfield, 2000):

(a) *Judgmental forecasts* based on subjective judgment, intuition, 'inside' commercial knowledge, and any other relevant information.

(b) *Univariate* methods where forecasts depend only on present and past values of the single series being forecasted, possibly augmented by a function of time such as a linear trend.

(c) *Multivariate methods* where forecasts of a given variable depend, at least partly, on values of one or more additional time series variables, called predictor or explanatory variables.

Each of the aforementioned methods includes a number of approaches to model time series (Tasseven, 2008; Allegret, Sand-Zantman, 2008; Pilinkus, Boguslauskas, 2009; Tasseven, 2009; Ellen, Zwinkels, 2010; Masih et al., 2010; He et al., 2010; Chiu et al., 2010). Vector autoregressive (VAR) and vector error correction

(VEC) models are two of the most common multivariate models for forecasting time series over the recent decades that have demonstrated their potential applications in predicting and forecasting economic, social, engineering, stock, and management problems.

Alquist and Kilian (2010) accomplished a comprehensive evaluation of the forecast accuracy of models based on monthly oil futures prices. Kilian and Murphy (2012) evaluated oil price by using structural VAR models and their results showed that in fact most net oil price increases have contained a large demand component driven by global macroeconomic conditions. Ghaffari & Zare (2009) employed soft computing approaches to forecast the daily variation of the crude oil price of the West Texas Intermediate. Engle and Yoo (1989) demonstrated that the short-term forecasts of the unconstrained VAR models are better than those of the cointegrated VARs.

These models assume that there is a linear relationship between current and past values of two or more explanatory variables and future values of a time series. Therefore, it is not reasonable to assume that model is pre-assumed linear; whereas, the real-world time series are rarely pure linear combinations (Valenzuela et al., 2008). In particular, the political events and many complicated factors contributed to the change of the oil price during the last three decades have made oil prices appear highly nonlinear and even chaotic (Ghaffari, Zare, 2009). For this reason, applying the techniques that can well model the complex behavior of oil price is valuable and useful.

Artificial intelligence (AI) based techniques such as artificial neural networks (ANNs) are efficient in adapting and learning. These methods proved their unique advantages for forecasting in recent times, but they have the negative attribute of the “black box” (Bilgehan, 2011). They also have some shortages for addressing issues of uncertainty and imprecision. On the other hand, it is very difficult to earn a powerful function using traditional mathematical model (Achireko, Ansong, 2000), and these models are principally based on some strong assumptions and prior knowledge of input data statistical distributions.

The main aim of this paper is to compare the capability of VAR and ANN in forecasting oil price changes and predict future oil price. The best-fit model is identified based on the performance criteria including coefficient of determination (R^2), and root mean square error (RMSE), and mean absolute error (MAE).

The rest of the paper is organized as follows: Section 2 describes the oil price modeling by ANN, and VAR models. Section 3 presents VAR and its structure. Section 4 summarizes artificial neural networks. Section 5 analyzes the performance of the models, including comparison of method according to criteria and prediction of oil price changes in twlve month ahead. Finally, the conclusions of the present study are discussed in section 6.

2. Data description and oil price changes

A number of recent studies have conducted a comprehensive analysis on the performance of neural networks in comparison with a variety of statistical techniques for the modeling, forecasting, and classifying problems. In this paper, the prediction of oil price using the backpropagation neural network and VAR models are carried out and the results are compared to obtain the most suitable model. Both techniques employ parameters related to production, reserves, world GDP, world inflation rate, and freight rate as inputs to perform the prediction. Also, the neural network training and testing process and the performance of the network established is discussed in detail.

The data used in this study includes 144 monthly observations of the oil price per barrel against its affecting parameters from 2000 to 2011. Oil price changes during this period are depicted in Fig.4. In order to develop VAR and ANN techniques for prediction of oil price, the available data set, which consists of 144 input vectors and their corresponding output vectors from the historical data of oil price, was separated into training and test sets as depicted in Fig. 1. For achieving the aim, 130 observations (from January 2000 to November 2010) are first applied to establish the primary model and the rest 14 data (from November 2010 to December 2011) are utilized to reflect the efficiency of the constructed models. To construct the models mentioned above, the affecting parameters on oil price are extracted as described in the following part.

Figure 1. Oil price changes (data resource: www.eia.gov)

3. VAR and VEC models

Structural models use the principal concepts of the theory of economic to assign the variables and their effects. VARs as atheoretical econometrics method avoid any apriori endo-exogenous division of variables. The most important limitation of these models, especially for short term forecasting, is the neglectfulness of the need for clearly forecasting the exogenous variables. In the system of a VAR, the current value of each of variables is mathematically expressed as a term that reflects other impacts on the current values plus a weighted average of the lagged values of all the variables. It can be scientifically defined as follows:

$$y_t = B_0 + B_1 y_{t-1} + \ . \ . \ . \ + Bp\ y_{t-p} + u_t \tag{1}$$

where y_t denotes the $m \times 1$ vector of variables and y_{t-i} represent the ith lag of y_t included in the VAR for month t. The uncertainty of error term (u_t) is random vector having a zero mean and is uncorrelated with lagged values of y_t.

The main idea of forecasting with a VAR model contains a two-step process; the first step is to summarize the dynamic correlation patterns among recorded data series and the second step uses this summary to forecast likely future values for each series (Robertson and Tallman, 1998). Structural models for formulating the oil price are recently developed by Kilian (2009), Baumeister and Peersman (2010), and Kilian and Murphy (2010, 2012), among others. The reduced-form representation of the Kilian and Murphy (2010) model corresponds to the four-variable VAR model which has been shown in Baumeister and Kilian (2010) to have superior real-time forecast accuracy compared with the no-change forecast benchmark as well as other forecasting models. It includes World oil production in growth rates, an index of fluctuations in the global real activity constructed by cumulating the growth rate of the nominal shipping rates, the change in crude oil inventories, and the real price of crude oil.

3.1. Granger Causality Tests and Variable Selection

Developing a successful forecasting model needs the selection of the input (explanatory) variables. Granger-causality (G-C) test, a suitable test of the validity of the assumptions, is a robust tool to identify the existence of predictability from one variable to other (Giannone and Reichlin, 2006). The G-C test uses null hypothesis to find the causality between the variables, so that, the lags of a variable do not enter the equations of the other variables when null hypothesis is not rejected, and therefore it is exogenous variable to the model.

Based on the Granger-causality test and recent empirical work, five input parameters for the oil price forecasting were identified: crude oil reserves, oil production, an index of freight rate, world GDP and world inflation. The inclusion of crude oil inventories allows the model to capture forward-looking behavior based on data not observable to the econometrician. It also allows us to exclude data on the oil futures spread (Alquist and Kilian 2010).

The Granger causality tests also indicated that the variables should enter the model at four lags, So 18 parameters, including 4 lags and 1 difference with a constant, are presented in the results.

The data used in this study were derived from several sources from the addresses as presented in Table 1. As shown in Table 1, world Inflation, GDP and oil reserves are annually and other variables are monthly. According to the importance of these variables on the oil price changes, we employed the method of Cubic Spline interpolation to interpolate between known data points due to their stable and smooth characteristics, in order to convert annually data into monthly data.

Table 1. Parameters of used data set

Variable	Type of data	Unit	Symbol	Resource
Oil price(WTI)	Monthly	$/barrel	O	www.eia.gov
Freight Rate	Monthly(2006-2011) Annually(2000-2005)	$/mile	F	wwwhst.com
Oil reserves	Annually	Billion Barrels (bbl)	R	www.indexmundi.com www.eia.gov
World Inflation rate	Annually	Percent (consumer price)	I	www.indexmundi.com
Oil production	Monthly	bbl/day	P	www.eia.gov
World GDP growth	Annually	Percent	Y	www.indexmundi.com

3.2. Tests for stationarity and cointegration

Generating stationary time series, The VAR (p) process is stable, implying that the equation returns to an equilibrium after a shock. The VAR model can be employed when the variables in time series are nonstationary that becomes stationary after their differencing. In order to find trends prior to fitting the VAR, performing a comprehensive analysis on primary (predifferencing) data is useful. In the system of a vector error correction model (VECM), cointegrated non-stationary variables include the cointegration vectors in the VAR with differenced variables. With the 5% Mackinnon critical values, the results of the unit root tests are presented in Table 2. From the table, it can be seen that all the variables are non-stationary and the variables are I (1). As a result, the variables should be differenced once to transfer into stationary. For cointegration amongst the variables, the results of the Johansen tests are presented in Table 3. It can be resulted from Table 3 that there is at most one cointegrating vectors.

Table 2. Result of unit root test

Dickey-Fuller test for unit root				
variable	test Statistic	1% Critical value	5% Critical value	10% Critical value
O	-1.688	-3.495	-2.887	-2.577
D.O	-9.809	-3.496	-2.887	-2.577
P	-0.434	-2.594	-1.95	-1.613
D.P	-21.48	-3.495	-2.887	-2.577
F	0.566	-2.594	-1.95	-1.613
D.F	-18.194	-3.495	-2.887	-2.577
Y	-1.478	-2.594	-1.95	-1.613
D.Y	-15.166	-3.495	-2.887	-2.577
I	-1.001	-2.594	-1.95	-1.613
D.I	-14.316	-3.495	-2.887	-2.577
R	-1.51	-3.495	-2.887	-2.577
D.R	-8.916	-3.496	-2.887	-2.577

Table 3. Tests of cointegration rank

Johansen tests for cointegration					
maximum rank	parms	LL	Eigen value	trace statistic	critical value
0	48	-2633.75	.	119.6788	104.94
1	59	-2604.72	0.33187	**61.6067***	77.74
2	68	-2589.65	0.18887	31.4641	54.64
3	75	-2582.46	0.095	17.0902	34.55
4	80	-2577.84	0.0621	7.8581	18.17
5	83	-2574.57	0.0445	1.3033	3.74
6	84	-2573.91	0.00901		

4. Artificial Neural Network (ANN) Architecture

An artificial neural network simulates the human brain mechanism to implement computing behavior (He, Xu, 2007). ANN has recently shown its great ability in time-series analysis and forecasting (Yao et al., 2000; Zhang and Hu, 1998). ANN technique has some unique futures including (Malinowski, Ziembicki, 2006; Yazdani-Chamzini et al., 2012) (i) parallel processing, (ii) ability to make generalization, (iii) ability to work successfully even when they are party damaged, and (iv) little susceptibility to errors in data sets.

An ANN comprises of three main layers that includes one input layer, one or more hidden layers and one output layer (Boguslauskas, Mileris, 2009; Gradojević et al., 2010; Mileris, Boguslauskas, 2010). In spite the fact that there is no theoretical limit on the number of hidden layers but typically there is just one or two (Sumathi, Paneerselvam, 2009). The network with the aid of changing synaptic weights among several NNs models aims to formulate the relations between output and input layers. In this study, a multi layer feedforward neural network (MLF) model with supervised learning algorithm is employed to forecast the oil price. During the modeling stage, coefficients are adjusted through comparing the model outputs with actual outputs. The process of adjusting the weights is continued until performance measures are satisfied.

Training phase has advantage of being robust and capable of forecasting more precisely although it takes a long time in this type of NNs (Morelli et al., 2004). A typical multi layer feedforward NN structure employed in this study is depicted in Fig. 2.

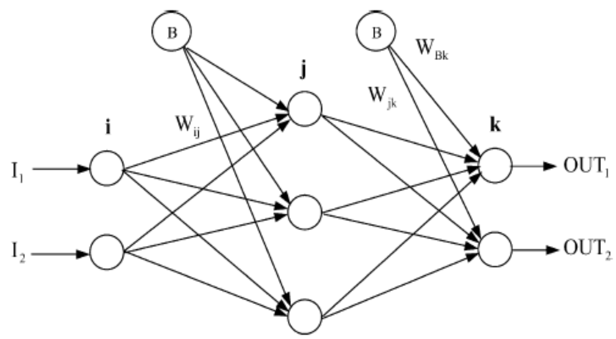

Figure 2. Typical artificial neural network architecture

As seen in Fig. 2; k , j , and i , denote the output layer units, hidden layer, and input layer respectively. W denotes the networks weight and B is networks bias. Out (Output of the neuron) is calculated through Eq. (2):

$$Out_k = f(\sum_{i=1} I_i W_{ik} + W_{Bk}) \tag{2}$$

The transfer function (f) is generally hyperbolic tangent sigmoid (tansig), logarithmic sigmoid (logsig), threshold, linear, and step functions.

5. ANN model

According to the basic concepts of ANNs architecture and applying productive algorithm in MATLAB 7.11 package software for acquiring the most appropriate network architecture; several networks are established in order to evaluate the ANNs efficiency and capability. Before constructing the ANN model, all variables are normalized to the interval of 0 and 1 to provide standardization by using the following equation (Yazdani-Chamzini et al., 2012):

$$X_{norm} = (X - X_{\min}) / (X_{\max} - X_{\min})$$

The best fitted network based on the most proper performance with the test dataset is contained of five inputs, one output, and twenty hidden neurons ($N^{(7\text{-}20\text{-}1)}$). This confirms that simple network structure that has a small number of hidden nodes often works well in out-of-sample forecasting (Areekul et al., 2010; Khashei, Bijari, 2011). This can be due to the over fitting problem in neural network modeling process that allows the established network to fit the training data well, but poor generalization may happen (Yazdani-Chamzini et al., 2012).

6. Evaluating Forecast Accuracy

Forecast Measuring is necessary when deciding on a model specification to generalize the model to unknown outputs. Models performance must be tested by comparing outputs estimated by the each model with real outputs. Standard forecasting models are evaluated to produce low MAE[1], RMSE[2] forecasts or to have high directional accuracy and higher Coefficient of determination (R^2), with little regard to the underlying economic structure. After evaluating the accuracy of forecasts, it is possible to generate more accurate forecasts than others through giving more weight to a forecasting scheme. In this paper, the efficiency of the each model is evaluated by three performance indexes: These measures are calculated by following relations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(A_i - P_i)^2}{N}} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{N}\left|A_i - P_i\right|}{N} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(A_i - P_i)^2}{\sum_{i=1}^{N}(A_i - \bar{A}_i)^2} \tag{5}$$

where P_i is predicted values, A_i is observed values, A_i is the average of observed set, and N is the number of datasets. A value for R^2 close to one shows a good fit of forecasting model and a value close to zero presents a poor fit. MAE would reflect if the results suffer from a bias between the actual and modeled datasets (Khatibi et al., 2011). RMSE is a used measure in order to calculate the differences between the values forecasted via the established model and the values recorded.

A comparative analysis based on the performance of the testing period for the VAR, VEC and ANN models using three performance indexes is accomplished as presented in Table 4. According to the table, for VAR, VEC, and ANN model, the RMSE values are 7.98111, 7.47533, and 7.262278, and the MAE values are 6.142381, 6.123021, and 5.792446; and R^2 values are 0.899, 0.94, and 0.98, respectively.

For all statistical criteria, the ANN model is better than the VEC model, and there are similar conditions to VEC and VAR model, i.e. based on all statistical

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[1] Mean Absolute Error

[2] Root Mean Square Error

criteria, the VEC model is better than the VAR model. This means that ANN outperforms VAR and VEC and presents the best performance, i.e., the lowest RMSE and MAE and highest R^2, for the in sample test periods. The forecasted values of each model are plotted in Fig. 3.

Table 4. Forecasting performance indices of models for gold price

Model	Testing dataset		
	RMSE	MAE	R^2
VAR	7.98111	6.142381	0.899
VEC	7.47533	6.123021	0.94
ANN	7.262278	5.792446	0.98

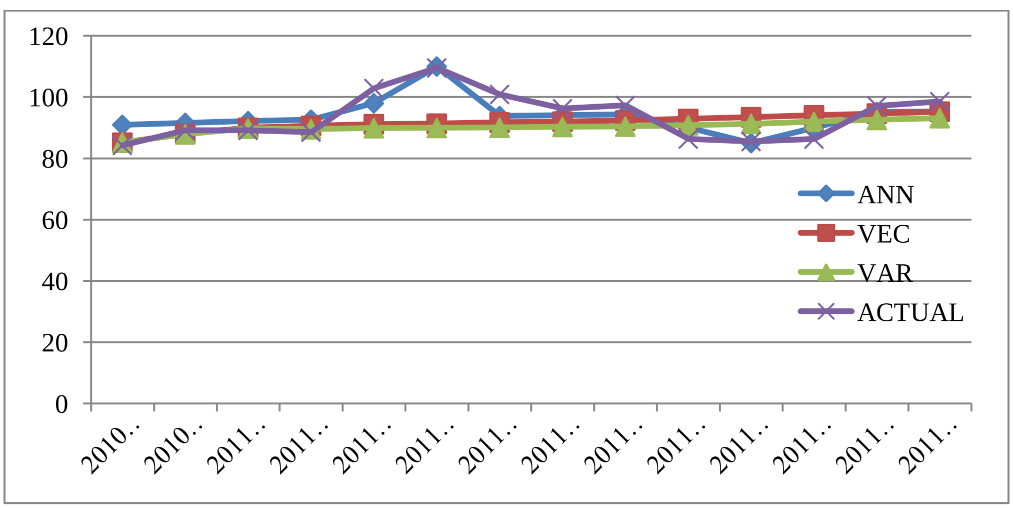

Figure 3. Actual and forecasted values during in sample testing by ANN, VAR and VEC for oil price

The objective of the final part of the paper is to forecast the crude oil price of all 12 month ahead with compared models. Based on comparing used criteria with in-sample data we would give more schemes to ANN forecast because it has lower error and higher accuracy than the others. Table 4 gathers the forecasted values estimated over 12 forecast periods, from 2012m1 to 2012m12 for ANN, VAR and VEC.

According to the results derived from ANN, the oil price of WTI will reach to 129$/b while based on linear methods, potential trend of oil price changes will be low. This is schematically shown in Fig. 4.

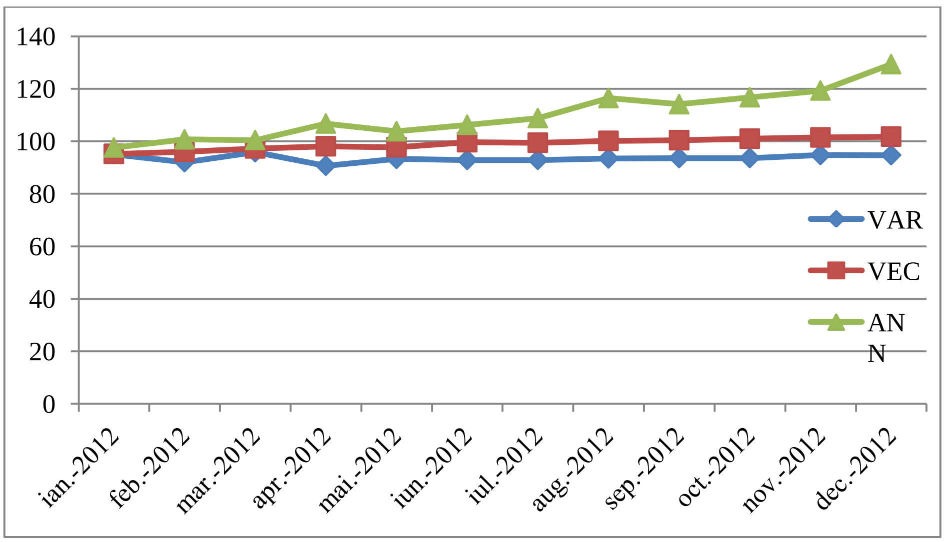

Figure 4. Twelve month ahead forecasted values by ANN, VAR and VEC for oil price

7. Conclusion

The key role of oil as an essential and critical resource in order to develop in economic, culture, and social sectors is well-known. In this study, the performance of VAR, VEC and ANN models in order to forecast the oil price changes basis on three performance evaluation criteria, including MAE, R^2, and RMSE, is investigated. Neural networks, known as powerful techniques in modeling the sophisticated and non-linear patterns involved in data, are selected to model extremely complex functions. Traditional models on the other hand are linear and principally based on some strong assumptions and prior knowledge of input data statistical distributions. The monthly oil price data from 2000/1-2011/12 comprising 144 input vectors and their corresponding output vectors from the historical data of oil price were used to develop various models used in this study. The results show that compared to the VAR and VEC, the ANN can more efficiently model the nonlinear structures involved in oil price, resulting in a more reliable, accurate, and sure model be produced to take into account the temporal information contained in the real world.

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