International Journal of Financial Management (IJFM)
ISSN(P): 2319-491X; ISSN(E): 2319-4928
Vol. 5, Issue 4, Jun – Jul 2016; 23-36
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International Academy of Science, Engineering and Technology
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PREDICT CRUDE OIL PRICES IN THE INTERNATIONAL MARKET

AN ALTERNATIVE FORECASTING TECHNIQUE

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ABSTRACT

The severe clearly unrest in the oil market reflected in the volatility of oil prices, allowed to consider the efficiency of the various forecasting techniques applied. In order to stand on the ability of some models to provide forecasts for decision-makers and to investigate the presence of any sort of seasonality and identify the type of the trend component crude oil prices we used weekly, monthly and annually data collected from the U S Energy Information Administration for the period 1987 to 2015. Appropriate forecasting technique mainly based on a two forms of the "double exponential smoothing" model related to Brown's Linear (i.e., double) Exponential Smoothing and the Holt-Winters Double Exponential Smoothing referred to a more sophisticated version of the first ones is model. After construct short-term forecasts for weekly, monthly and annual data. The “Evaluation statistics” section shows the RMSE and RSS statistics for each of the forecasts. Results have shown the importance of the non-parametric models in providing reasonable forecasts supported by appropriate statistical tests and indicated absence of seasonal effects and also economic cycles of them in terms of their compounds. The slump in the prices will deepen unless the OPEC and non OPEC producers sit together to avoid any further prices collapse.

KEYWORDS: Crude Oil Prices, Forecasting, Double Exponential Smoothing, Brown's And Holt’s Models

INTRODUCTION

Oil is an important source of revenues for oil-exporting countries. Considering that the price of oil is one of the most important economic indicators in the world, its changes is watching of both producers and consumers, in addition to the decision-makers and actors in the financial markets and international. The price volatility disturbed a lot of underdeveloped economies and those mainly dependent on oil export. In this context, and given the importance of this price, seen by many as a measure of the performance of the global economy, the first economists particular importance to the process of predicting future trends across harness a lot of effort to provide appropriate and effective and applicable in different circumstances tools. Because changes in the price of oil can have significant effects on macroeconomic dynamics, it is not surprising that many researchers have applied various econometric techniques that help to model and to forecast changes in the price of oil (Alquist *et al.*, 2013).The great turmoil in oil markets across the world renewal of the importance of these techniques in light of the sensitive changes that have defined time series on the phenomenon studied. Therefore, making reliable forecasts of the price of crude oil become interest for a wide range of applications. For example, policymakers, government and central banks forecasters view the price of oil as one of the key variables in generating economic projections and in assessing macroeconomic risks and policies and to explore alternative hypothetical forecast scenarios.The complexity in prices volatility resorting to the non-free models which requiring stationary or inertness component availability on time series and absence of anomalous values process.Given process complexity of the use of macro regression models caused by the multiplicity of actors variables in the oil market from the economic factors, political and geostrategic. Huntington (1994)indicate the failed of structural models in the prediction of oil prices in the nineties of the last century. In the same way, Artus *et al.* (2010) argue that the experience has shown how much is a complex process to predict the evolution of oil prices. This work focuses on the study of the importance of simple models in providing acceptable predictions can rely on their results in the short and medium term(Artus, Chevalier, Chalmin and D’Autume, 2010).

And that any attempt to model the phenomenon to predict without regard to random blowing out of hand and jumps in the price are not well-defined (mis-specified) productive conciliation weak (poor fitted data) data. So will this work in very sensitive conditions characterized by a period of post-global financial crisis and turmoil in the political world with the spread of proxy wars and conflicts in the Arab and Islamic worlds, and it increased, and spread the risk. At the same time it is assumed that the crude oil price properties in the future will be the same as in the past and the present. A more complex extrapolation scheme that involves a study of the dynamics of changes in characteristics of the crude oil price with due regard for such dynamics within the forecasting interval is less frequently used in forecasting.

Economists and econometricians are pressed to make short- and medium-term predictions on oil prices since they are volatile and depend on various situations. They use a range of forecasting tools and highly complicated mathematical models, which either focus on financials (using spot and future prices), or supply and demand considerations (quantifying variables and testing their explanatory power). The models used most often are regression-based structural models, time-series analysis, Bayesian autoregressive models, and dynamic stochastic general equilibrium graphs. Because economists are still undecided as to which method is most reliable, they use a combination of them all to get the most accurate oil prices answer forecasting. The complexity of the model does not mean superiority over simple wording. Many econometricians have gone to prefer simple to complex models for a number of considerations. Therefore, this article will only deal with exponential smoothing models and will briefly cover more simple models proposed by Holt and Brown. Thus, the article will discourse topics related to the short-term forecasting of crude oil price sequences with slowly changing characteristics on the basis of exponential smoothing models. The "short-term forecasting" should in this case mean forecasting a small number of time intervals ahead instead of forecasting for a period of less than a year as it is usually assumed in economics.

Another important goal is to use both methods for forecasting oil prices, as well as comparing the quality of the forecasts and recommending the method best suited to the actual data. The comparative performance of these models is then considered[1]to show the practical difference, on their forecasting ability, using comparison of the root mean square errors, is conducted on the models’ forecasts for a sample excluded from the modeling process. We examined the difference between the known data and the predicted data using the residual sum of squares (RSS) and the root mean squared error RMSE. This accurate prediction of oil prices is difficult but very important for governments, companies, and investors. The more accurate the forecasts of oil prices, the greater the impact they have on improving the accuracy of

[1]Alternative of Chow tests approach of the error differences between actual price and the price.

forecasts of a wide range of macroeconomic results.

THE OIL PRICE SPECIFICATIONS AND APPROACH OF ABILITY TO FORECAST

Among oil price forecasting literature, there are two main groups of forecasting methods generally used by experts. First ones based on quantitative approach represent numerical and quantitative variables that impact on oil prices and include the econometrics methods and non-standard methods. Among them, econometrics models incorporate three classes of models: time series models, financial models, and structural models. On another side, the main non-standard methods which are recently applied are artificial neural networks and support vector machines. The second group, qualitative methods estimate impact of infrequent events such as wars and natural events on oil prices; these approaches recently gained more reputation among oil price research. However, between various types of qualitative forecasting methods there are small number of them that are applied to forecast oil prices, such as Delphi method, belief networks, fuzzy logic and expert systems, and web text mining method (Bashiri Behmiri and Pires Manso, 2013).

At this point, if a variety of opinion was observed among econometrics researchers on appropriate forecasting models (**Figure1**), especially on finance and oil prices thus to the links of these topics to risk, some ones believe about that functional form play an important role in selecting process of the appropriate technique. For this, the researcher have tendency to prefer using non-linear relationships in those areas, despite the multiplicity of forms in addition to the lack of efficient testing tools orientate preference between certain non-linear forms.Huntington (1994) pointed to the structural models based on supply and demand failed to predict oil prices in the nineties of the last century. He attributed to several reasons including the difficult accuracy to predict the variable (GDP) in particular for developing countries, and also, the weakness to predict the oil offer outside OPEC Organization. In these circumstances, econometricians believed that the use of simple models may have a better performance than other models available in the short term while things may get complicated in the case of most forecasts and the long-term average due to changes that occur at different levels of economic and environmental ones. Therefore, economists and econometricians are pressed to make short- and medium-term predictions on oil prices since they are volatile and depend on various situations. They use a range of models but are still undecided as to which method is most reliable; they use a combination of them all to get the most accurate oil prices answer forecasting. In this context we can find the usage of the time series models which generally include three main categories: naïve models, exponential smoothing models and auto-regressive models such as ARIMA[2] and ARCH[3]/GARCH[4] family models and can be applies to forecasting crude oil prices. We denote that Pindyck (1999)and Sadorsky (2006)have compares different types of forecasting models, including the random walk, historical mean, moving average, exponential smoothing, linear regression model and autoregressive models and argued their adaptation to oil prices modeling. But, the last two decades have notably seen significant developments in exponential smoothing (ES), which has become one of the most noteworthy forecasting strategies. Exponential smoothing was established as a classical method of analysis for forecasting different econometric and financial real-time data prospects (Tavakkoli *et al.*, 2015). The results obtained from data smoothing are operative, simple, accurate and easy to communicate and understand (Broze and Mélard, 1990).

[2] Autoregressive integrated moving average.
[3]Autoregressive conditional heteroskedastisity.
[4]Generalized autoregressive conditional heteroskedastisity.

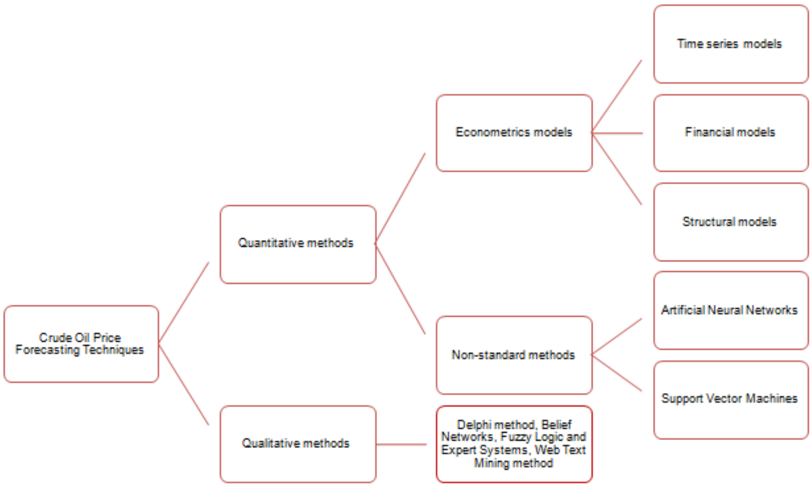

Figure 1: Crude Oil Price Forecasting Classification Techniques

The origin of exponential smoothing forecasting technique was initiated from the operations research activities of the US Navy during the Second World War. Under theses researches in 1944, Robert G. Brown develops a model essentially an exponentially weighted moving average applied to continuous data and in the early 1950s extended the approach to discrete data, developing models that could deal with trends and seasonal patterns below a particular application in forecasting the demand for spare parts in Navy inventory systems, which was so successful in terms of forecast accuracy and data storage savings (Gardner Jr., 1985). The methodology was formalized, generalized and extended in Brown (1963), Brown and Meyer (1961) and D'Esopo (1961). On similar way Charles C. Holt (Holt, 1957) developed a similar method for exponential smoothing of trending time series. His works gained acceptance with Winters (1960), which tested the methods on sales data with such success that they became known as the Holt–Winters forecasting system. Further developments were soon made by fascinated researchers, in view of it being a formulation of 'adaptive forecasting' for the technique (Mills, 2011). The whole area of exponential smoothing developed rapidly during the 1960s, with more consideration to parameter selection, choice of starting values for the recurrence relationships used to compute forecasts, the monitoring of such forecasts, and the adaptive control of the smoothing parameters (Gardner Jr., 1985). Harrison (1967) provided the first synthesis of the exponential smoothing methodology, showing that the various types of exponential smoothing were all particular forms of the Box and Jenkins (1962) polynomial predictor. Recently Holt (2004) give reflection on the genesis of the method. By technical econometrics view, exponential smoothing has proven through the years to be a useful technique in many forecasting situations. It was first suggested by Holt (1957) and generalized Winters (1960). Although ad hoc exponential smoothing (ES) methods which defines an extended class of ES methods and offers a theoretical foundation for analysis have been employed with recent methodological developments and have embedded a collection of ad hoc approaches of these models in a modern dynamic nonlinear model framework (Alquist, Kilian and Vigfusson, 2013).

Finally as Alquist, Kilian and Vigfusson (2013) conclude, although there are a number of works dealing with the problem of predicting the price of oil, it is difficult to reconcile the seemingly conflicting results. Some issues can enumerated, on definition of the oil price variable and its expressed terms (nominal or real), on chosen period for estimation and evaluation, on how the forecast accuracy is evaluated, on whether tests of statistical significance are provided, on conducting analysis in-sample or out-of-sample and whether the methods are parametric or non-parametric.

The limit issue of this work is to try to predict oil prices in the international market relying only on moving averages weighted exponential model.

BUILDING FORECAST METHODOLOGY

In this study, data for weekly, monthly and annually crude oil prices (in US dollar) for the period 1987 May 2015 November, giving about 343 observations is used. The data was gotten from the U S Energy Information Administration (EIA) data survey. In the present work, we focused on an in -sample period, which means that the time series between 1987 M05 and 2015 M11 served to generate the forecasts of models, whereas the time series between 2015 M12 and 2016 M06 served as out -of - sample data against which the accuracies of the forecasts were measured. We will evaluate models' forecast accuracy using the evaluation sample forecast series. Each of the evaluation sample forecast series contains actual data until November 2015, and then forecast data from December 2015 until June 2016. Based on visual assessment of the time series of the spot price of crude oil is plotted (**Figure 2**), we can conclude that there is a systematic component in the form of a linear increasing trend and small random fluctuations.

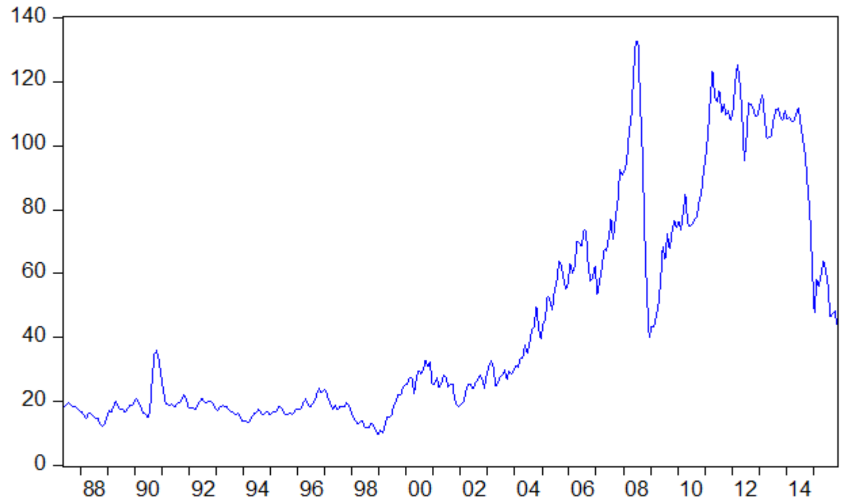

Figure 2: Brent Crude Oil Monthly Price (1987-2015)

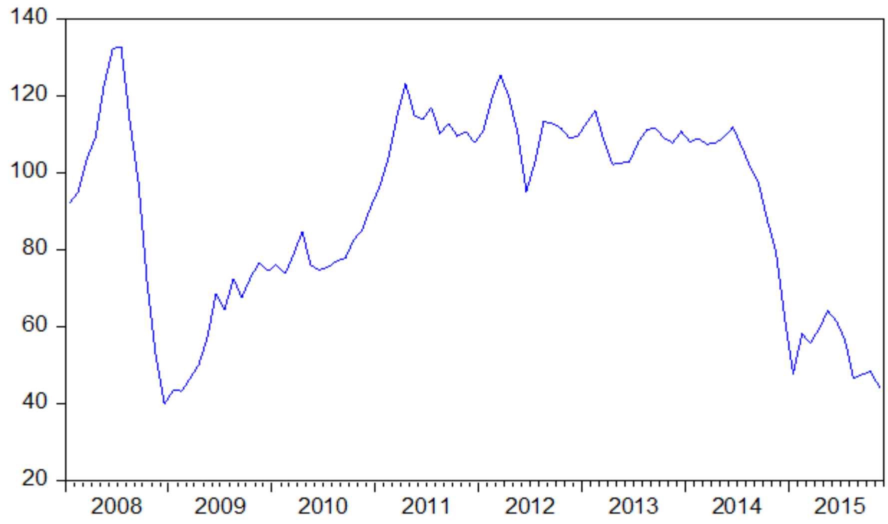

Figure 3: Brent Crude Oil Monthly Price (2008-2015)

Thinking about this case by application of Box-Jenkins method checking be sticky (Hachemane, 2010). The strong volatility chronicled series especiallybetween2008 and 2015(**Figure 3**) have cemented the idea of searching for suitable alternatives methods. Also, this method poses several questions about how the application of severe structural changes in the series characterized by abnormal and may consider it values its problematic when estimating model parameters and let hold a snooze test time series in these circumstances. To apply this technique remains conditional on adding to the above extent linear trend component that did not materialize in time series of variable oil prices. Its appears signs of non-linearity in this component and statistically denied its linear shape by the strong significance of BDS[5] test (Brooks C., 2014)which came for different dimensions and complies with the general understanding in the literature of random time series analysis and not its potential interpretation of non-linear vehicle for the general direction of a series of oil prices weakening results appreciation under this approach.

Table 1: BDS Linearity Test of Oil Prices Series

BDS Test for PB Date: 06/10/16 Time: 19:23 Sample: 1987M05 2016M12 Included Observations: 356					
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**Prob.**	
2	0.187355	0.004091	45.79759	0.0000	
3	0.317485	0.006491	48.91172	0.0000	
4	0.404690	0.007716	52.44811	0.0000	
5	0.461507	0.008028	57.48921	0.0000	
6	0.497278	0.007727	64.35261	0.0000	
Raw epsilon		52.57993			
Pairs within epsilon		82729.00	V-Statistic	0.703185	
Triples within epsilon		21480079	V-Statistic	0.532296	
Dimension	**C(m,n)**	**c(m,n)**	**C(1,n-(m-1))**	**c(1,n-(m-1))**	**c(1,n-(m-1))^k**
2	39614.00	0.679357	40901.00	0.701429	0.492002
3	38331.00	0.661221	40608.00	0.700500	0.343736
4	37125.00	0.644196	40316.00	0.699566	0.239505
5	35975.00	0.627935	40025.00	0.698626	0.166427
6	34871.00	0.612277	39716.00	0.697347	0.114999

Abuse of the forms, the time series can be considered non stationary (as reflected in correlation function) and attempt to build a model based on the first differences for the Brent prices variable and then predict short-period assuming six months and then compare it with the moving averages simple model mentioned above. As expected, this attempt was a disappointing since the model fails tracking the inflexion points and so unable keep up with the decline in prices. In this context, lot of studies show and concur on the weakness of these models in prediction (Bashiri Behmiri and Pires Manso, 2013) due to their linear trait and hence was unable to track non-linear series of Brent prices data, add to the structural change and extreme volatility.

[5] The BDS test (W. A. Brock, W. Dechert and J. Scheinkman) detects nonlinear serial dependence in time series.

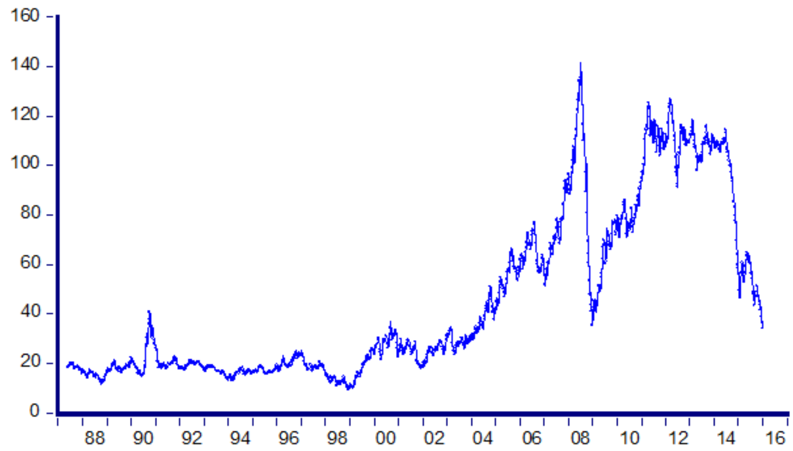

Figure 4: Brent Crude Oil Weekly Price

The **Figure 4** reflect the strength of the volatility of the time series, making them non stationary series and this has consequences on applying random time series analysis technique. It may also springs to mind adopting simple techniques to correct volatility likely moving average for example, or considering volatility as part of outliers and handled in a manner to facilitate the forecasting process and provides acceptable predicted values. In addition, crude oil prices have challenged the forecasting abilities of such models. When, Hendry (2006) proposed the double-differenced forecasting model as alternative, he argue that, when time series are subject to infrequent trend changes, the no-change forecast may be improved upon by extrapolating today's oil price at the most recent growth rate. Going so far, another strategy is to extrapolate from recent trends. Given that oil prices have been persistently trending at times, it is natural to consider a random walk model with local drift designed to capture "short-term fore cast ability".

To avoid all the above we wanted to measure appropriate exponentially weighted moving average models (EWMA) for such forecasting process and investigate the feasibility of the results in the short term (ie, within six months when using monthly data may reach two years in the annual dataset). And, follow events more closely we focused intentionally our prediction using weekly data for easy interactivity with the results and ability to the instantly comparison because of the availability of information. Evoke that these models are characterized amendment feature meaning updating forecasts when any new information from the oil markets was available. The study of this type of time series in terms of their compounds showed the absence of seasonal effects and also economic cycles of them. This result is easy to test the appropriate forecasting technique mainly of Brown's Linear (i.e., double) Exponential and Holt's methods with two parameters. Since both methods are used in the same circumstances. The spotlight of the simplest time-varying trend model which is Brown's linear (i.e., double) exponential smoothing (LES) model, reveal two different smoothed series that are centered at different points in time witch forecasting is based on an extrapolation of a line through the two centers.

SIMPLEST CRUDE OIL PRICE FORECASTING TECHNIQUES

Forecasting methods used in this study were selected based on a detailed graphical analysis of the variable and due to the nature of the identified components, by simplest method allied to the exponential smoothing models. Usually acknowledged, the name 'exponential smoothing' is attributed here to the use of the exponential window function during convolution. It is no longer attributed to Holt, Winters & Brown. The defining equation for simple exponential smoothing is expressed as follows:

$$L_t = \alpha Y_t + (1-\alpha)L_{t-1}$$

Where L_t denotes the singly-smoothed series, Y_t, the past observations and α is the data smoothing factor. Note that the weights assigned to previous observations are in general proportional to the terms of the geometric progression $\{1,(1-\alpha),(1-\alpha)^2,(1-\alpha)^3,...\}$ which is a discrete kind of an exponential function, so this is where the name for this smoothing method originated.

But when there is a trend in the data simple exponential smoothing does not do well[6] which is inconvenient. In such situations, numerous methods were conceived under the "*double exponential smoothing*" or "*second-order exponential smoothing*", which is the recursive application of an exponential filter twice witch introduce a term to take into account of a series exhibiting a trend. This slope component is itself updated via exponential smoothing[7]. Therefore, due to the nature of the data for forecasting the price of oil expressed above, the double exponential smoothing model was used, which generally described by two forms of the smoothing model related to Brown's[8] Linear (i.e., double) Exponential Smoothing and the second, referred to a more sophisticated version of this model, the Holt-Winters[9]Double Exponential Smoothing.

The algebraic form of Brown's Linear (double) Exponential Smoothing model can be expressed in the smoothing equations as the following formula:

$$L_t = \alpha Y_t + (1-\alpha)L_{t-1}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

The interpretation of the trend-smoothing constant γ is analogous to that of the level-smoothing constant α.

Referring to as "Holt-Winters double exponential smoothing", this method divides the time series data into two components: the level, *Lt*, and the trend, *Tt*. These two components can be described by the following formula:

For the Level:

$$L_t = \alpha y_t + (1-\alpha)(L_{t-1} - T_{t-1}) \cdots 0 < \alpha < 1$$

Where, the trend coefficient is also updated by a similar exponential smoothing. To distinguish the trend updating smoothing weight from that for the intercept, γ is used instead.

For the Growth:

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \cdots 0 < \gamma < 1$$

Where L_t Represent the smoothed value for time *t*, and T_t is the best estimate of the trend at time *t.* For parameters α is the data smoothing weight factor, $0 < \alpha < 1$, and γ is the trend smoothing factor, $0 < \gamma < 1$.Hence for a given set parameters, these two components are calculated and L_t is used to obtain the double exponential smoothing of the data at time *t*. Furthermore, the sum of the level and trend components at time *t* can be used as the one-step-ahead ($t + 1$) forecast.

[6] NIST/SEMATECH 'e-Handbook of Statistical Methods', http://www.itl.nist.gov/div898/handbook/, date: April 26, 2016.
[7] "Model: Second-Order Exponential Smoothing". SAP AG. Retrieved April 23, 2016
[8] 'Averaging and Exponential Smoothing Models'.duke.edu. Retrieved April 25, 2016.
[9] KALEKAR, P. S. (2006) Time series Forecasting using Holt-Winters Exponential Smoothing. In *Book Time series Forecasting using Holt-Winters Exponential Smoothing* (ed^eds Editor). City: Kanwal Rekhi School of Information Technology, p.4.

There are actually various well-known forecasting methods that are based only on the analysis of past values of a time laps. The main instrument of these methods is the extrapolation scheme where the sequence properties identified at a certain time lag go beyond its limits. It's evident in this time series, whether monthly, quarterly or yearly they take a similar behavior and do not differ only in terms of volatility intensity. The series also maintains all characteristics and their compounds which allow adopting the appropriate cycle and according to the horizon of forecasting. Despite that Gardner and McKenzie (1985) suggested that the trends should be "damped" to be more conservative for longer forecast horizons[10]. Our work is limited on different forms, including annual to predict the average term by investigate weekly, monthly and annually prices to the short-term forecasting.

Finally, after construct short-term forecasts for several future steps, the "Evaluation statistics" section shows the RMSE and RSS statistics for each of the forecasts, along with the methods. Using residual sum of squares (RSS) to measures the total deviation of the response values from the fit to the response values which is Sum of squared differences between the observed and estimated response[11]. Minimizes values prove that the model has a smaller random error component. Also, Root Mean Squared Error (RMSE) known as the fit standard error or the standard error of the regression. It is an estimate of the standard deviation of the random component in the data. The use of RMSE is very common and it makes an excellent general purpose error metric for numerical predictions. A RSS & RMSE values closer to 0 indicates a fit that is more useful for prediction.

$$RSS = \sum_i (y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_i (y_i - \hat{y}_i)^2}$$

RESULTS FORECASTING

To stand on the importance of Holt's smooth exponential forecasting technique, the weekly prices predictions have been set from the first week of the year 2016 up to the first week of February. This period was selected based on the availability of data to assess the any historical forecasts within the studied sample. Results were as follows:

Table 2: Brent Price and Five (05) Weeks Horizon Forecasting

Weeks	Price	Forecasting from 07 Jan 2016	Forecast Error
31 Dec 2015	36.56	35.20	1.36
07 Jan 2016	34.19	35.74	1.55-
14 Jan 2016	29.10	33.23	4.13-
21 Jan 2016	27.76	32.27	4.51-
28 Jan 2016	31.75	31.31	0.44
04 Feb 2016	32.18	30.35	1.83

Where the RMSE, root mean square error reached 2.54. This test is important while comparing between models, but in this case it is advisable strengthening other tests.

[10] Two smoothing parameters α and γ (with values between 0 and 1), and one damping parameter $0 < \varphi < 1$

[11] quantity minimizes by the least squares estimator.

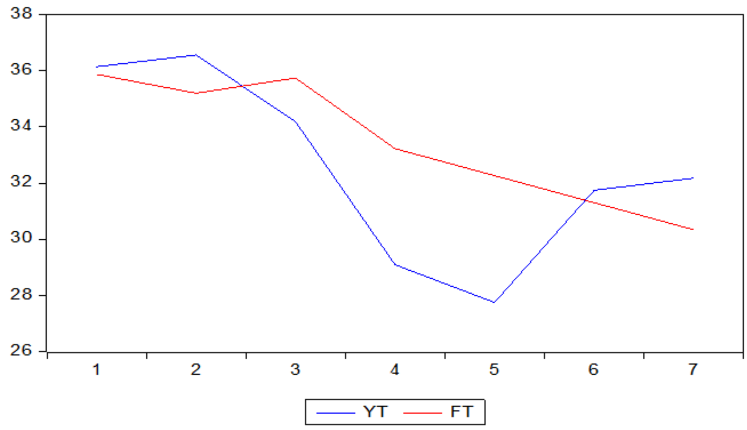

Figure 5: Test the Regressive Prediction Significance

In addition to the previous RMSE test we want to use again the regression technique to determine the importance of prediction. Before this we used the figure above which shows the viewing values and forecasts compatibility curve in terms of the general trend. We support these tests by regression equation where values are represented by dependent variable and predictions as independent variables.

Table 3: Assessing Regressive Forecasting

Dependent Variable: YT **Method: Least Squares** **Date: 04/06/16 Time: 10:30** **Sample: 1 7** **Included observations: 7**				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.293086	17.26175	0.016979	0.9871
FT	0.964348	0.515463	1.870839	0.1203

This estimate underlines the importance of these forecasts from statistical point of view which is compatible with requirements of the test, where we accept the null hypothesis for intercept which is equal to zero, and the slope is equal to one.

We adopt now monthly data to forecast Brent price in international markets. These data showed that the general trend for the price of Brent (according to Holt two smoothing parameters) will continue to decay to levels below thirtieth (30) $. Note if current conditions remained predominant and non-OPEC exporting countries did not contribute to reduce prices. We note also, that Algeria's oil light deserts type and content of sulfur therefore no require additional operations process to preserve environment and rich by gas oil, preferably used in diesel extraction. Also it outclasses by reach four (4$) dollars on price terms the Brent price. The general behavior of this series is no different than the weekly data curve only in terms of volatility; therefore we expect the same behavior of future forecasts. We set the evaluation sample to “2015M12 2016M6”, giving us twelve months of forecasts to evaluate. We choose to evaluate each of the available smoothing methods, and set the training sample for the Least-squares, Mean square error and MSE ranks methods to be “2015M12 2016M6”.

Table 4: Forecasting up to June 2016

Periods	2015.10	2015.11	2015.12	2016.01	2016.02	2016.03	2016.04	2016.05	2016.06
Observed	48.43	44.27	38.01	30.70	32.18	na	na	na	na
Forecast	43.24	47.60	42.70	40.64	38.58	**36.52**	**34.45**	**32.39**	**30.33**

The Holt monthly smoothing results represented in particular to estimate the monthly price at $ 42.70 for December 2015 while $ 44.27 is observed (Actual data) for the same month to reach the value of forecast 30.33 $ in June 2016. These forecasts reflect an expected trend towards continues deterioration of prices for exporters, a conditional scenario of economic survival and political conditions intact and without any agreement between the members of the organization and non-oil producing countries.

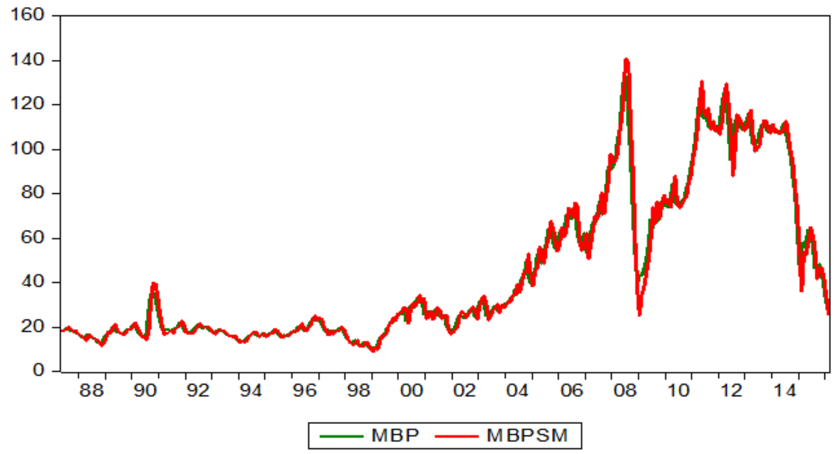

Figure 6: Tracking Performance

As observed on **Figure 5** and **Figure 6**, in magnitude terms the different forecasts adding excess of estimate (overestimation) when the peaks and underestimation (underestimation) on lows which observed in the smooth case, the sensitivity of the forecasting process and how difficult, both in term and the short or medium term. And also, prices decay may be largely due to the improved ability of the United States in unconventional oil production, which is developed by technology that allow an important diminish of costs extraction (Mohaddes and Raissi, 2015)[12]. As well as the ability of US producers in adjusting and control production levels in interaction with price fluctuation, which means its ability to balance between overall demand and aggregate supply and that it might explain continued decline in prices.

Desire to tradeoff between the two approaches, Brown's double exponential smoothing and Holt's smoothing parameters, the forecasting process was conducted within the sample (Ex-ante forecast) and accuracy of model fitting was evaluated by means of two measures: the residual sum of squares (RSS) and the root-mean-square error (RMSE). The fitting errors obtained for both compared models are presented in **Table 5**.

Table 5: Assess the Forecast and Differentiation between the Two Way: Holt with Two Parameters (HW) and Double Exponential Smoothing (DES)

Method	**Period**	**Alpha**	**Beta**	**RSS**	**RMSE**
DES	11-2015	0.77	-	7377	4.63
HW	11-2015	1	0.37	7130	4.56

[12]In "The U.S. Oil Supply Revolution and the Global Economy", p13.

According to these indicators, forecasts are evaluated by standard statistics of forecast accuracy. The common criterion of forecast performance RSS&RMSE showing that Holt's model provides much more accurate forecasts than double exponential smoothing , which should come as no surprise as $\alpha=1$ is greater than 0.77, the value below which (Harrison, 1967) found little difference between the RMSEs of the two approaches.

By against, the prediction failure of the double exponential smoothing may be due to the linear nature of the model, which does not correspond to the behavior of oil prices series and thus adequate with most research and studies above(Mills, 2011).

By reverting to the annual data, the results on applying the two previous approaches have been differentiated and the Holt's forecasts were more optimistic. The superiority of the Holt's method is clearly observed (see **Table 6**) in terms of total of residual sum of squares (RSS) and root-mean-square error (RMSE).

Table 6: Annual Prices Forecasts for Brent Crude 2014-2017

Base Forecast 2013	***2014***	***2015***	***2016***	***2017***	***RSS***	***RMSE***
DES	117.75	103.80	49.57	35.64	7177	15.73
HW	108.98	99.39	52.74	53.16	6242	14.67

Brent crude oil prices are forecast to average \$43/b in 2016 and \$52/b in 2017, respectively. However, the current values of futures and options contracts suggest high uncertainty in the price outlook[13]. Growing global oil supply disruptions, rising oil demand, and falling U.S. crude oil production contributed to the price increase.

CONCLUSIONS

Although registered predict variation, the general trend in prices may continue to decline or be unstable at current low levels production. With circumstances of no arrangement to standing productions level at least close to January 2016 level by the producing countries. The fear now is a continuation of this scenario for the history will repeat itself again and same circumstances beyond the eighties and its accompanying no economic or social policies.

In forecasting the price of crude oil many of the pioneers of econometrics and modeling has gone to prefer simple to complex models for a number of considerations, the most important and cost predictability. We have seen different combination of Exponential Smoothing Model in term of time laps (weekly, monthly and annually) and forecasting horizon. This related to the short-term forecasting of crude oil price sequences with slowly changing characteristics on the basis of exponential smoothing models. The forecasting method which minimize mean squared error have select Holt's method almost optimized better in-sample. The comparative performance of these models is considered to show the practical difference, on their forecasting ability. Where, accurate prediction of oil prices is difficult but very important for governments, companies and investors. The more accurate the forecasts of oil prices, the greater the impact they have on improving the accuracy of forecasts of a wide range of macroeconomic results. The complexity of the model does not mean superiority over simple wording. This suggested some of key questions that arise in forecasting the price of crude oil. What do applied forecasters need to know about the choice of model specifications? How useful are oil futures prices in forecasting the spot price of oil?

[13]In U.S. Energy Information Administration | Short-Term Energy Outlook (Analysis & Projections), June 2016, http://www.eia.gov/forecasts/steo/.

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