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Analyzing the robustness of ARIMA and neural networks as a predictive model of crude oil prices

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Abstract. *The paper is focusing in analyzing the robustness of the Auto Regressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) as a predictive model in forecasting the crude oil price. The paper has identified stochastic trend in the daily time series data starting from (03.01.2011 to 11.10.2019). The time considered in the study is subject to high volatility, which makes this paper unique from the current stock of knowledge. During this time frame it has been identified that there is no structural break. The empirical analysis furnishes that the ARIMA is the best suited model. The decision criterion for the selection of the best suited model depends on ME, RMSE, MAE and MASE. From the results of the criterion it has found that both the models are providing almost closed results but again ARIMA is the best suited model for the current data set.*

Keywords: ARIMA, ANNs, Crude-Oil.

JEL Classification: G1, G17, G170.

Introduction

World economies in general and developing economies in particular largely depend on crude oil. The overall structure or sectors of the economies depends on one of the crucial commodity i.e. crude oil. The volatility, spillover, conitegration, forecasting are the buzzword now a days (Gulzar et al., 2019). The increase in $ per barrel crude is meant a lot for the developing economies. Developing economies in particular, because of high potential to expand and high growth, where their import bills are largely driven on crude, any increase in the prices, directly affects the sectors, trade deficit, rupee depreciation, output and inflation. The increase in crude oil prices accentuates the cost push inflation and after a lag converges into general inflation called as imported inflation (Prakash and Sharma, 2016). Crude price sensitivity with various sectors or industries has been done that analysed the impact of changes in crude on the performance of various sectors (Sarwar et al., 2017). Narayan and Sharma (2011). Several studies have been done on the spillover effect of crude prices on various countries stock market like Asian, European and developed countries (Irshad et al., 2014; Maclaury, 1978; Sarwar et al., 2018). These studies are imperative for the portfolio managers by investing in negative correlated asset class to provide the complete hedge against financial and economic turmoil. These studies reflect the fascination of portfolio manager towards the crude oil as base commodity. Thus, economists and policy makers are largely interested in predictive modelling of base commodity i.e. crude oil prices. Investors who invest in commodities market are interested to forecast the future trend and simultaneously predict the futuristic movement of other asset class to earn abnormal returns from their investments and hedge their current portfolio. The studies also provide their insight to the policy makers for the future plan of action regarding the importing strategies. This motivates the author to make a predictive model of crude oil prices. Several studies already been done on the prediction of crude oil prices but this study considers the period of high volatility. Thus, to the best of my knowledge because of the coverage of the study makes the study unique from the current stock of knowledge.

Several studies are based stock prices predictive modelling, based on ARIMA, GARCH & ANNs. After studying the current stock of knowledge based on the predictive modelling of crude oil prices, mostly the authors applied ARIMA, GARCH and ANNs (Jaya Selvi et al., 2018; Hale, 2018; Ahmed and Shabri, 2014; Mo and Tao, 2016, etc.) This further motivates the author to take a further analysis of predictive modelling on crude prices with a unique data set and very few studies are focusing on the robustness of the available model. Papers that applied ARIMA and Neural Networks for predicting the crude prices had varied consensus in the results. This motivates author to further analyse the crude oil prices with more than decadal data. ARIMA is to be considered as one of the robust method to predict the future realizable value of time series. But again the model is having a constraint that the future values depend on its past/ lagged realized values. This is limiting the theory of dynamic model that considers exogenous factors apart of lagged values. Since, ARIMA Modeling is based on assumption of future depends on its past performance, which limits its scope static rather dynamic. Again the paper has applied machine learning i.e. Artificial Neural Networks (ANNs) that is again limited to the inputs based on its past values. Despite of the limitation, these models are considered by analysts to understand a broad outline/behavior of the time series in future. The robustness of the model has been derived from the results of ME, RMSE, MAE and MASE.

The study would be relevant for investors, portfolio managers and policy makers to consider the future trends of the crude and understand the best suited model for the given time series and evolve or formulate their respective strategy accordingly.

Literature review

Several studies has been done on forecasting model to predict the crude prices, as discussed very large studies have been done on spillover or co integration of crude prices on various stock markets. The literature review considers the review of the papers done on predictive modeling and forecasting techniques. The section also captures the few studies done on spillover.

Selvi J., Shree R.K. and Krishnan J. (2018), study based on crude oil forecasting the paper is an attempt in predicting the crude oil prices through ARIMA models. The study considered yearly data from 1946 to 2016. The study predicts the crude prices from 2017 to 2021. The study leaves a scope for further study to analyze daily price data. Another study done by Hale (2018), *Predicting Oil Prices*, the paper considered daily WTI oil price data from January 1986 to November 2017. The study applied both ARIMA and Neural Networks for predicting the oil prices. Mixed results had come out, where the ARIMA builds a simple lagging version of the input data and the neural network sees either over fitting of the training set or under fitting of both the training and test sets. The results are in consensus of our study that to make analyse the most dynamic model. This study could include more inputs that effect demand and supply of crude oil. In the same league one study done by, Ahmed and Shabri (2014), in his study considers the ARIMA, GARCH & SVM technique in predicting crude oil prices. The results show the Support Vector Machine is the most robust among the three methods. The conclusion is based on RMSE & MAE. Mo Z. and Tao H. (2016), the study considered *ARIMA and RBF neural network*, the study finally analysed that both the models are equally robust in predicting the crude oil prices. Zhao and Wang (2013), in his study the author applied auto regressive model to predict the crude prices. The data considered in the study from 1970 to 2006. Further the study has used SAS and the results are based on the MAPE i.e. 4.059%. Further the study analyzed that the model is showing robust results in short term. Kulkarni and Haidar (2009), The author forecasted the crude oil prices using *ANN*. Moshiri and Foroutan (2005), also examined the chaos and nonlinearity in crude oil futures prices by the application of ARIMA, GARCH and ANN. The author applied neural networks on the West Texas Intermediate (WTI) Crude data. The author as usual considered two basic parameters to judge the performance of the model i.e. RMSE & MAE. The Author applied two models i.e. ARIMA and GARCH had shown RMSE i.e. 0.9856 and 1.0134 respectively.

Studies have done on exclusive usage of ANN, Adly et al. (2014), Zhang (2014). Refenes et al. (1994), Castillo and Melin (1995), Giles et al. (1995), Donaldson and Kamstra (1996), Kamstra and Boyd (1995) and Sharma et al. (2003), these studies demonstrated that the ANN is the most superior techniques.

The studies on crude oil prices and its spillover on emerging, Asian and developed countries are Studies conducted on the spillover effect of oil prices on stock markets , out of which few studies are showing negative relations , Maclaury (1978), Melick et al. (1997), Basher et al. (2016), Ederington et al. (2010), Filis et al. (2011), Arouri et al. (2012), Awartani et al. (2013), Narayan et al. (2014), Du and He (2015), Khalfaoui et al. (2015), Ghosh et al. (2016), Sarwar et al. (2018) and few studies are showing positive relation, Narayan et al. (2010), Zhu et al. (2014), Degiannakis et al. (2014), Silvapulle et al. (2017), whereas some studies have shown mixed results, Apergis et al. (2009), Miller and Ratti (2009), Reboredo et al. (2014), Hatemi et al. (2017).

Research methodology

Objective of the study

To analyze the robustness of ARIMA and Neural Networks as a predictive model of crude oil prices.

Data

The study considers the West Texas Intermediate (WTI) Crude oil price data from 03.01.2011 to 11.10.2019. The rationale of taking up WTI, to have a consensus with previous study done (Ahmed and Shabri, 2014; Hale, 2018, etc.). The data compiled from World Bank. The software used for predictive analysis is R studio.

Rationale of the study

Many studies had already done in the past to analyse the best predictive model of Crude oil prices at different data point. Mostly done on yearly or monthly prediction, only few researches to the best of my knowledge conducted on daily spot prices. The rationale of the paper that gives uniqueness from the current stock of knowledge, that motivates the author for further study that none of the paper considered this time period. The uniqueness of this period is that from 2011 to 2013 the crude oil prices became at its peak i.e. more than 100$ per barrel and around 90$ per barrel then it came down steadily. This volatile time frame has been considered for study to make the consensus from the results of the previous studies.

Methods and models

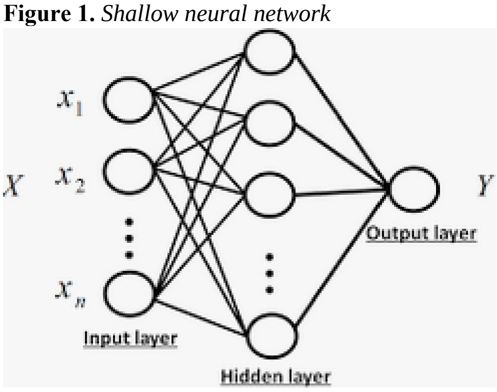
ARIMA: An autoregressive integrated moving average (ARIMA) model has been used widely to forecast the future realized values, this model is an extension of autoregressive moving average (ARMA) model in time series analysis. ARIMA models are used in a time series that are not stationary. It has been denoted as p, d and q, where p is autoregressive model, d is integrated and q is moving average model. The non-stationary time series has to be converted into stationary by going first order or second order or next level of differencing, till the series comes to be stationary. AR and MA as a constituents of ARIMA, AR i.e. Auto regressive reflects that the future values depends on its past values, having lead and lagged structure pattern, where the MA i.e. Moving average reflects regression error is a linear combination linear combination of error terms whose values occurred contemporaneously and at various times in the past. ARIMA models can be estimated following the Box- Jenkins approach. The ARIMA Model for crude oil price returns could be formulated as:

$$C(R)_t = a_0 + a_1 Ret_{t-1} + a_2 Ret_{t-2} + \cdots a_n E_{t-n} + a_{n+1} E_{t-2} \ldots \ldots a_{n+1+m} E_{t-n+1+m} + \mathcal{E}t \quad (1)$$

Where, $C(R)_t$ is Crude Oil Return, Ret_{t-1} is lagged return and E_{t-n} is the lagged error.

Artificial Neural Network: Artificial Neural Network has been used by the analyst to predict wide range of time series data. The paper applied shallow neural network with one hidden layer. The input that has considered in the model i.e. lagged values of the crude oil price returns.

Figure 1. *Shallow neural network*



Source: Course era.

Empirical results

Analysis of the results of descriptive statistics

The descriptive statistics of WTI crude oil prices from 3 Jan 2011 to 11 Oct 2019 is given in Table 1. The daily price data having number of realizations i.e. 2282. The lowest price of crude to be incurred during the time period is 26.21 $ per barrel whereas the highest is 113.93. Over the time, the average price is realized as 71.67$. The variance and standard deviation is 530 and 23 respectively. It shows the skewedness in the data i.e. 0.117. Where the peakedness is -1.491, it reflects the data departs from its normality. This inference further cross validated from box plot and Jarque Berra Test. Although in auto regression functions, normality is not the desired assumption.

Table 1. *Descriptive statistics of WTI crude oil prices*

Crude Price	
nobs	2282.00
Minimum	26.21
Maximum	113.93
1. Quartile	50.79
3. Quartile	94.87
Mean	71.67
Median	65.86

Sum	163560.86
SE Mean	0.48
LCL Mean	70.73
UCL Mean	72.62
Variance	530.06
Stdev	23.02
Skewness	0.12
Kurtosis	-1.49

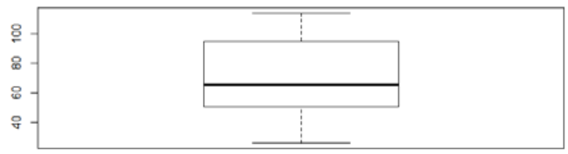
Source: Authors own work.

Analysis of the Results of Normality

The above descriptive statistics could be further strengthen by the results of normality. The crude method to check the normality in the data set, Jarque Berra Test has been applied. Although in time series normality is not important, rather stationary is the crucial aspect.

For normality check, null hypothesis is data is normal and alternate is data is not normal; less than 0.05 Null Hypothesis rejected. Thus, series is not normal. For the time series data normality is not having a great relevance, especially in stochastic trend rather stationarity having great importance for running regression. Further the analysis furnishes the results of stationarity.

Chart 1. *Box plot*



Source: Authors own work.

Table 2. *Result of normality*

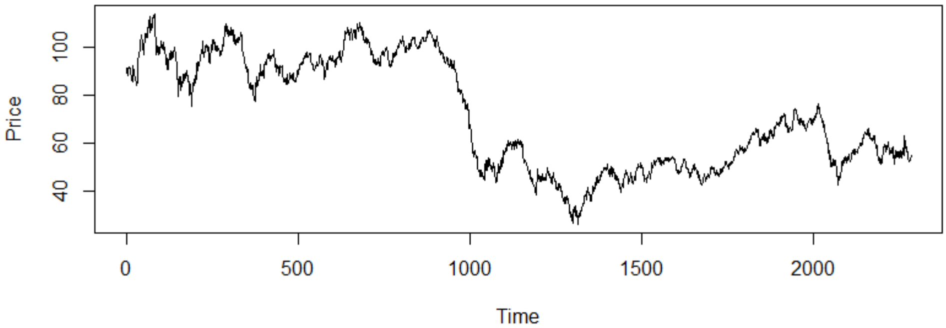
Result of Jarque Bera Test
data: Spot Prices
X-squared = 54.018, df = 2, p-value = 1.862e-12

Source: Authors own work.

Analysis of the plot

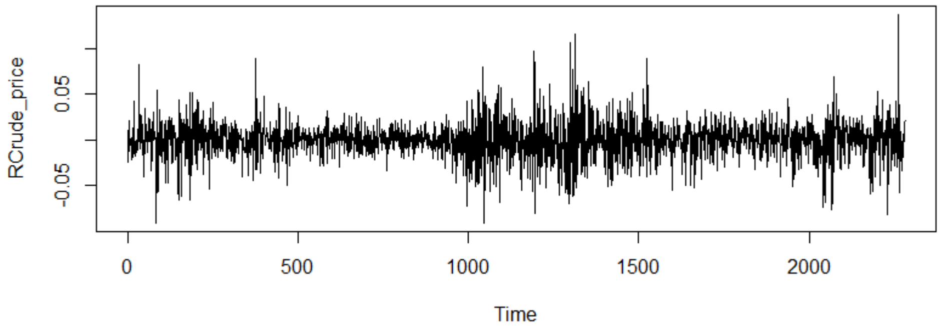
The Plot of the crude price data shows the prima facie visual effect of trend exists in the data set. Chart shows that it is a stochastic trend rather than deterministic trend. To further validate the presence of stochastic trend in crude oil price time series, Auto Correlation Function (ACF) and Partial Auto Correlation Function have (PACF) have to be applied. From the results of ACF & PACF, analyst can infer that the current price depends on previous price; this lead and lagged structure between the prices have been validated by the correlation function. The ACF & PACF should be applied on returns of crude price data. The results of ACF & PACF of returns of WTI Crude price are as followed:

Chart 2. *Plot crude spot price*



Source: Authors own work.

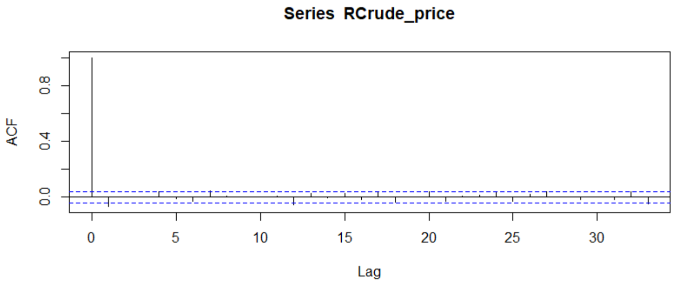
Chart 3. *Plot crude spot price returns*



Source: Authors own work.

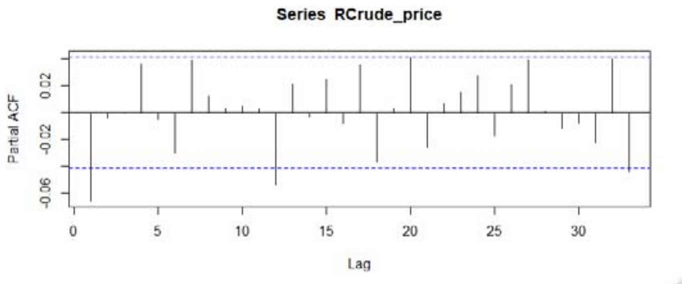
Analysis of the Results of PACF and ACF: Chart 4 presents the result of Autocorrelation Function (ACF) which is a correlation between variables but with its own lag. There exist various lags and autocorrelation in X-axis and Y-axis respectively. ACF helps to determine the suitable lag for moving average through error term. As per Chart 3, there is correlation in error term in lag 1, lag 12, lag 18 and lag 32 because the ACF of these lags are either higher than upper bound or lower than lower bound. It gives base for forecasting the series associated with error term. Similarly, Chart 5 presents the result of Partial Autocorrelation Function (PACF). PACF is correlation between observations X_t and its lag after removing the linear relationship of all observations that fall between X_t and its lag. PACF helps to determine the suitable lag for autoregressive in Autoregressive Integrated Moving Average (ARIMA). The various lags and partial autocorrelation functions are presented by X –axis and Y-axis respectively. The PACF are significant in lag 1, lag 12 and lag 32 as their spikes are either higher than upper bound or lower than lower bound in these lags. It can be said that ACF and PACF gives ARIMA order for predicting a series. ACF is denoted by "q" and PACF is denoted by "p" in ARIMA model but the best order is tested with the help of auto.arima command in R Studio.

Chart 4. Plot of ACF



Source: Authors own work.

Chart 5. Plot of PACF



Source: Authors own work.

Analysis of the results of stationarity

As discussed earlier before forecasting of time series data, it is crucial to determine the data should be stationary otherwise the results of regressions are spurious and not appropriate for further forecasting. The results is shown in Table 3, the results of Dickey Fuller and Phillips Perron of unit root test are in consensus, both tests are showing the p value less than 0.05, the null hypothesis is rejected that data is not stationary and alternate is selected that infers the data is stationary thus integrated at I(0).

Table 3. *Result of stationarity*

Results of Augmented Dickey-Fuller Test
data: RCrude_price
Dickey-Fuller = -12.756, Lag order = 13, p-value =0.01
alternative hypothesis: stationary
Result of Phillips-Perron Unit Root Test
data: RCrude_price
Dickey-Fuller Z(alpha) = -2464.3, Truncation lag parameter = 8, p-value = 0.01
alternative hypothesis: stationary

Source: Authors own work.

Analysis of the results of structural break point

Further for preparing the robust predictive model, the structural break in time series should be required to identify otherwise the results of the forecasting model becomes spurious. Thus to make model effective the structural break has to identified. The results of the test shows that there is no structural change as the P value is greater than 0.791, thus null hypothesis still intact and the series shows no structural break points.

Table 4. *Result of structural break point*

supF test
data: model_rspotprices
sup.F = 1.9867, p-value = 0.791

Source: Authors own work.

Comparison as a predictive model in ARIMA & ANNs

The comparison in between ARIMA and ANNs reflects that both are showing approximately same results with same level errors. Despite of same level of error in predicting the crude oil prices, ARIMA is a robust model than ANNs. The conclusion has inferred from the results of RMSE, MAE and MASE. The outputs of the summary of the predicting model are given hereunder:

Table 5. *Results of ARIMA model*

Predictive Model	*RMSE*	*MAE*	*MASE*
ARIMA	0.02070857	0.01480789	0.6825379
ANNs	0.02075406	0.0148408	0.6840548

Source: Authors own work.

Conclusion

The study considers the crude oil as a vital commodity for a developing economy in particular. Thus, the study focuses on the prediction of crude oil prices by identifying the best way to predict future by considering its own lagged values. The study identified that the crude data more than decadal i.e. from 2011. The stochastic trend has been identified by the plot of the price data and its returns. It has been identified that the data is not normal but stationary. This further provides a way to apply the ARIMA Model. With the results of PACF and ACF it has validated that the future values depends on the lagged values and error term.

It has also been identified that the data used in study has no structural break. The results of the study are in consensus of the research done previously (Mo and Tao, 2016; Hale, 2018, etc.), but not in the consensus of (Ahmed and Shabri, 2014; Moshiri and Foroutan, 2005 etc.). It has found that the two models are approximately giving the same results but with some minor differences the ARIMA model is found more close model then ANNs. Lest all of the two model is restricted with its exogenous variables or inputs, this makes the model static. If it includes variables like gold prices, Fed interest rate, demand and supply side factors, makes model more dynamic and robust (Hale, 2018). This leaves enough scope for further intense study.

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