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Xin James He
Fairfield University, xhe@fairfield.edu

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Crude Oil Prices Forecasting: Time Series vs. SVR Models

Xin James He, Ph.D.
Department of Information Systems and Operations Management
Dolan School of Business
Fairfield University
xhe@fairfield.edu

ABSTRACT

This research explores the weekly crude oil price data from U.S. Energy Information Administration over the time period 2009 - 2017 to test the forecasting accuracy by comparing time series models such as simple exponential smoothing (SES), moving average (MA), and autoregressive integrated moving average (ARIMA) against machine learning support vector regression (SVR) models. The main purpose of this research is to determine which model provides the best forecasting results for crude oil prices in light of the importance of crude oil price forecasting and its implications to the economy. While SVR is often considered the best forecasting model in the main stream literature, this research investigates its computational insights in terms of parameter selections and overfitting potential, in addition to exploring forecasting accuracy and model comparison. The results of this research can be generalized to forecast other business and economic time series data such as stock market prices, product sales, and government statistics.

KEYWORDS: Oil Prices Forecasting, Time Series, ARIMA, Machine Learning, SVR

INTRODUCTION

Crude oil prices fluctuate significantly. A sudden drop of crude oil prices in the last couple of years has caught many countries and business organizations off-guard scrambling to deal with the resulting economic and financial ramifications. At the same time, consumers around the world seem to enjoy the relatively low gasoline prices that somewhat follow the wild ride of crude oil prices. As a result, crude oil price forecasting has been an interesting and challenging research subject both academically and practically. Academically, this research enhances the knowledge and computational insights on SVR in terms of parameter selections and overfitting potential. Practically, the results of this research can be generalized to forecast other business and economic time series data such as stock market prices, product sales, and government statistics.

This research explores the weekly crude oil price data from U.S. Energy Information Administration over the time period 2009 - 2017 to forecast crude oil prices by comparing time series models against machine learning SVR technique. Xie, Yu, Xu, and Wang (2006) introduced an SVR model to forecast weekly crude oil prices during the period 1970 – 2003, without such computational details as parameter selection and overfitting prevention. Since the majority of research on crude oil prices forecasting in our literature below are either on weekly or monthly data, with few exceptions on daily data (e.g., the deep learning forecasting research by Chen, He, and Tso, 2017), this research is focused on weekly crude oil prices. Forecasting models used in this research include traditional statistical simple moving average (MA) and simple exponential smoothing (SES), more advanced autoregressive integrated moving average (ARIMA), and machine learning support vector regression (SVR) with computational insights to prevent from overfitting for SVR using R. Mean absolute error (MAE), square root of mean squared error (RMSR), and mean absolute percentage error (MAPE) are used to determine which model provides the best forecasting results. To facilitate the analysis and comparison, the entire data is divided into a training set, January 2009 – December 2016, and a testing set, January 2017 - December 2017. There are two reasons that the testing set is only one year, or 1/9 of the entire data set. First, due to wild fluctuation nature of crude oil prices, a relatively short testing set may reflect what is going on currently. Second, since the SVR model, unlike ARIMA or other statistical based forecasting models, cannot fit the testing data set based on parameters estimated from the training data set, which is one of the major drawbacks of most machine learning models such as SVR.

This paper is organized as follows. Section 2 reviews the literature related to crude oil and gasoline prices forecasting methods. Section 3 discusses research methodology in terms of data collections and analytical tools. Section 4 compares various time series models with machine learning SVR. Finally, section 5 offers concluding remarks of this research.

LITERATURE REVIEW

Forecasting models for crude oil prices can be divided into three major categories: traditional time series, more advanced time series ARIMA, and artificial intelligence or machine learning models (Behmiri and Manso, 2013). Traditional time series models such as SES and MA are the most commonly used forecasting methods for time series data, including crude oil prices, U.S. government statistics, and Wall Street stock prices (Huntington, 1994; Abramson and Finizza, 1995). Since regression analysis requires a set of independent variables (Chinn, LeBlanc, and Coibion, 2005; Yang, Han, Cai, and Wang, 2012) and since such explanatory variables relevant to crude oil prices as gross domestic product (GDP) and consumer price index (CPI) are only available on monthly basis, we exclude regression analysis in this research because there are no weekly government statistics. More advanced ARIMA are the most prominent time series methods, in which autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to help select data driven model parameters (Ord, Fildes, and Kourentzes, 2017). When it is done correctly, ARIMA models can provide very accurate forecasting results, especially for short-term time series data (Xiong, Bao, and Zhong, 2013; Cao, Purohit, Bauer, and Faseruk, 2015). MA, SES, and ARIMA models are often used as benchmarks to measure forecasting accuracy on crude oil prices against more complex machine learning models.

Machine learning SVR (Xie et al, 2006), artificial neural network (ANN) (Sehgal and Pandey, 2015), and deep learning (Chen, He, and Tso, 2017) methods have been introduced more recently to forecast crude oil and gasoline prices. Jammazi and Aloui (2012) contend that most machine learning models such as SVR and ANN are facing with model overfitting problems, which may be resolved by "cross-validation" on the test set. Slim (2015) suggests that more research is needed to deal with model overfitting problems with respect to parameter selection. Like regression analysis, we exclude ANN in this research because it lacks a set of explanatory variables such as GDP and CPI for weekly crude oil prices in order to come up with an output variable through a complex function (Haidar, Kulkarni, and Pan, 2008; Shazly and Lou, 2016). SVR is a special case of support vector machines (SVM), where SVM is a type of learning machine technique that implementes the structural risk minimization inductive principle on a limited number of learning patterns (Basak, Pal, and Patranabis, 2007). SVR computes a linear regression function in a high dimensional space where the input data are mapped via a nonlinear function (Vapnik, 1995). However, a major drawback of the SVR analysis is that it is difficult to interpret the process in meaningful statistical or business perspectives due to the fact that it does not have a set estimated parameters as in the case of ARIMA and regression models.

Xie et al (2006) assert that the SVR model outperforms ARIMA based on weekly spot prices of West Texas Intermediate (WTI) crude oil from January 1970 to December 2004. Sehgal and Pandey (2015) concede after reviewing various artificial intelligence methods, including SVR and ANN, that the existing literature is very far from any consensus about a reliable forecasting model regarding crude oil prices. Darbelley and Slama (2000) also raise the doubt whether artificial intelligence models are actually better for short-term forecasting on electricity.

In this research, we compare the forecasting results of MA, SES, ARIMA, and SVR on weekly crude oil prices to determine which model performs the best in terms of MAE, RMSE, and MAPE and to provide computational details for SVR in terms of parameter selection and overfitting prevention.

RESEARCH METHODOLOGY

We collect the weekly spot price time series data ($/barrel) on West Texas Intermediate (WTI) crude oil for the period January 2009 through December 2017. For model development purpose, we focus our attention on the period January 2009 through December 2016 as the training data set, whereas the period January 2017 through December 2017 is considered as testing data set (holdout data) to test the model accuracy and consistency.

Figure 1 illustrates the time series of the entire data set January 2, 2009 through December 29, 2017. It is seen from Figure 1 that crude oil prices fluctuate significantly, from over $110 per barrel in April 2011 to below $30 per barrel in February 2016, with a mean around $75 per barrel. Figure 2 provides the decomposition of this time series, which shows not only a dramatic declining trend over the last three years, but also a seasonal pattern that peaks during the summer months, in addition to the wild nature of the random fluctuations.

Figure 1. Line Plot on Entire Data Set 2009-2017

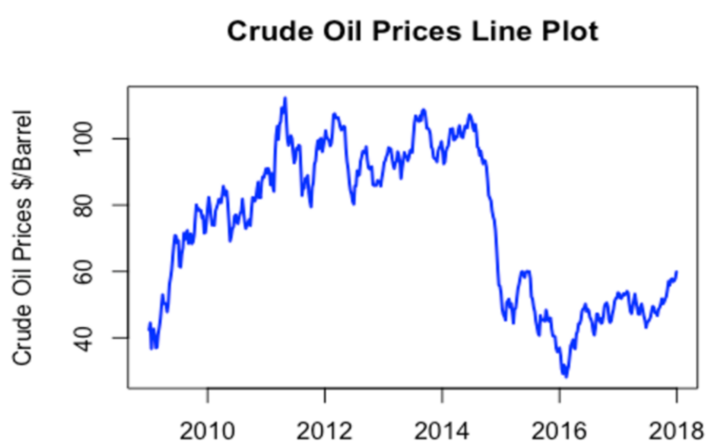
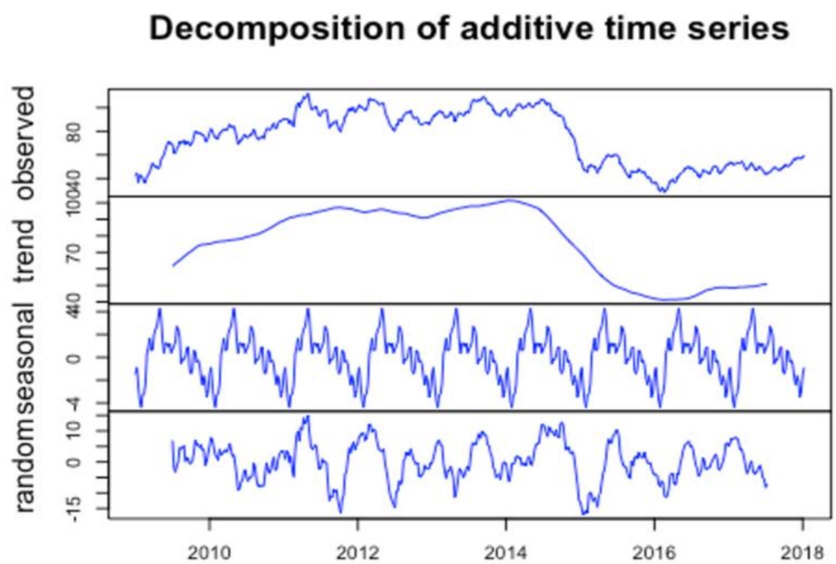


Figure 2. Decomposition on Entire Data Set 2009-2017



TIME SERIES, ARIMA, AND SVR MODELS

We first run each individual forecasting model of the training data set to select the best parameter in each category in terms of MAE, RMSE, and MAPE. We then compare the best models out of each category to determine the overall best model from all categories. Specifically, we select the best model parameters from each of the following three categories: i) moving average MA (n) and simple exponential smoothing SES (α), ii) autoregressive integrated moving average ARIMA (p, d, q), and iii) support vector regression (SVR). Linear Regression (REG) and artificial neural network (ANN) models are not included in this research due to the fact that independent variables such as consumer price index (CPI) and gross domestic product (GDP) are not readily available to match the weekly crude oil prices.

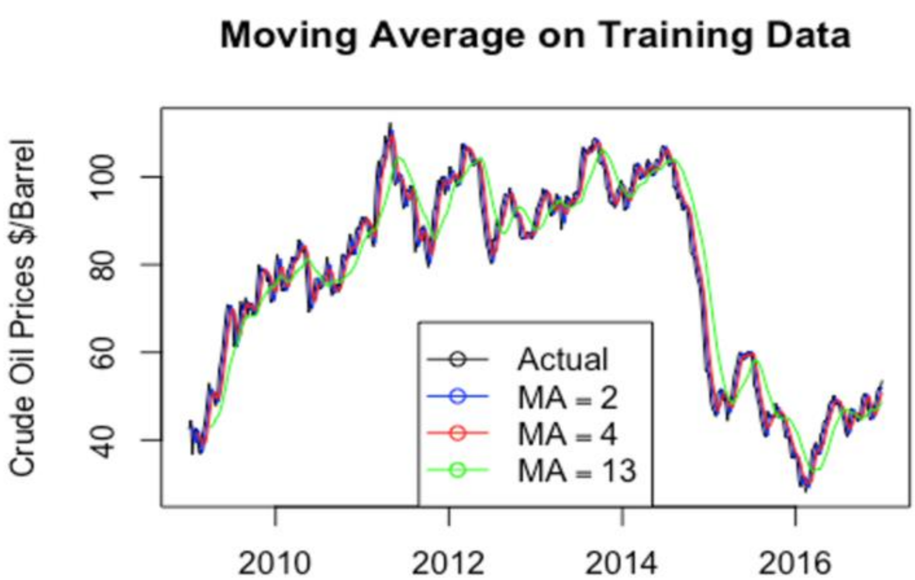
Moving Average Models - Table 1 depicts the forecasting results using moving average for the training data set with n = 2 (bimonthly), 4 (monthly), and 13 (quarterly). The fact that MA(2) shows the smallest forecasting errors is consistent with the theory that the smaller the number of periods (n), the better for the moving average models to forecast a very fluctuating time series. As a result, MA(2) is the best simple moving average model on the training data.

Table 1. Comparison of Moving Average Models 2009 – 2016

Moving Average	**MAE**	**RMSE**	**MAPE**
MA*(2)	2.5107	3.1839	3.1838
MA (4)	3.2988	4.1147	4.7752
MA (13)	5.5514	7.0842	8.1596

Figure 3 shows a graphic comparison among the three simple moving average models, which confirms what is in Table 1 that MA(13) is not appropreate for crude oil price forecasting due to large forcasting errors and MA(2) is the best simple moving average model with all three acuracy measures (MAE, RMSE, and MAPE) being the smallest on the training data set.

Figure 3. Moving Avarage Comparison 2009-2016



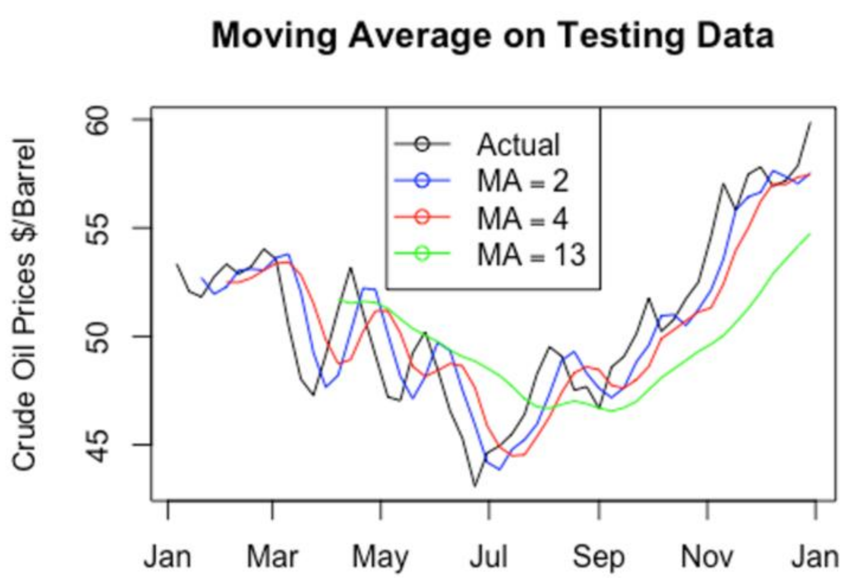
Now we test the moving average model accuracy on the testing data as shown in Table 2. It is seen from Table 2 that MA(2) again outperforms MA(4) and MA(13) to be the best moving average model for the testing data set, which is consistent with what is in Table 1.

Table 2. Comparison of Moving Average Models on Testing Data in 2017

Moving Average	MAE	RMSE	MAPE
MA*(2)	1.4979	3.2162	2.9877
MA (4)	2.5488	3.1283	5.4955
MA (13)	4.7354	6.1971	9.7816

Figure 4 provides a better visualization on moving average model performances regarding the model parameter n. In order words, in case a simple moving average model is used to forecast crude oil prices, an MA(2) is recommended due to its model accuracy for crude oil price forecasting.

Figure 4. Moving Avarage Comparison 2017



Simple Exponential Models - Table 3 presents the forecasting results of the training data set using simple exponential smoothing with α = 0.1, 0.5, and 0.9. The fact that α = 0.9 stands out to be the best SES forecasting model confirms the theory that the larger the α, the smaller for the forecasting error to forecast a very fluctuating time series. In other words, the larger the α, the heavier weight the SES model puts on the difference between the actual and the predicted values of the previous period. Figure 5 illustrates the performance of simple exponential smoothing models using different α on training data.

Table 3. Comparison of Simple Exponential Smoothing 2009–2016

Exponential Smoothing	MAE	RMSE	MAPE
SES (α = 0.1)	5.5551	7.2954	8.3955
SES (α = 0.5)	2.6712	3.3615	3.9140
SES*(α = 0.9)	2.0914	2.6870	3.0616

Figure 5. Exponential Smoothing Comparison 2009-2016

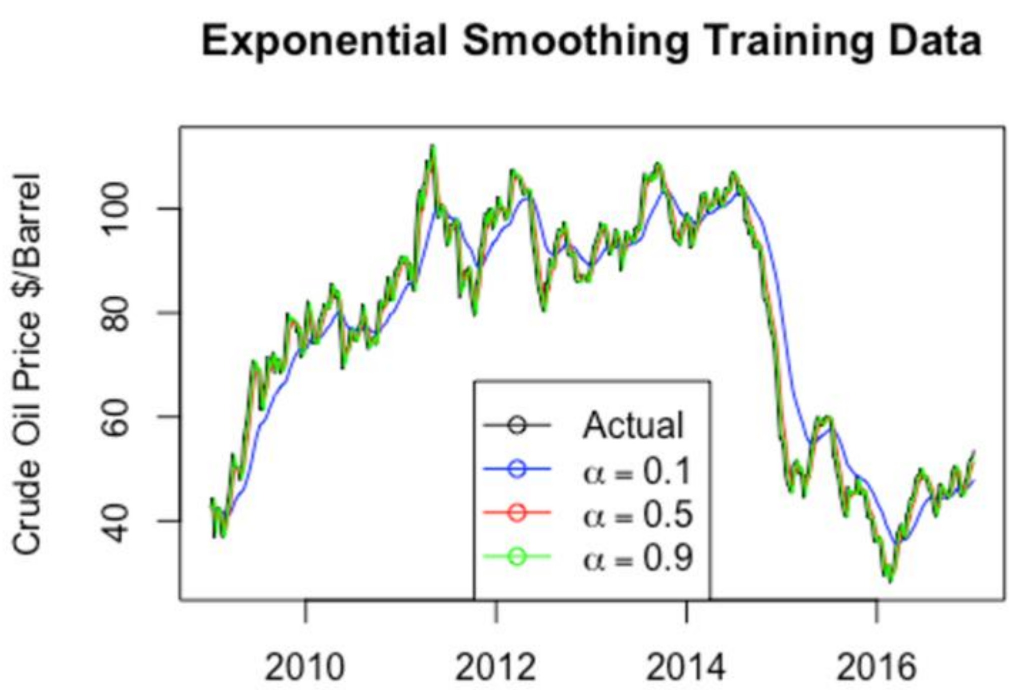
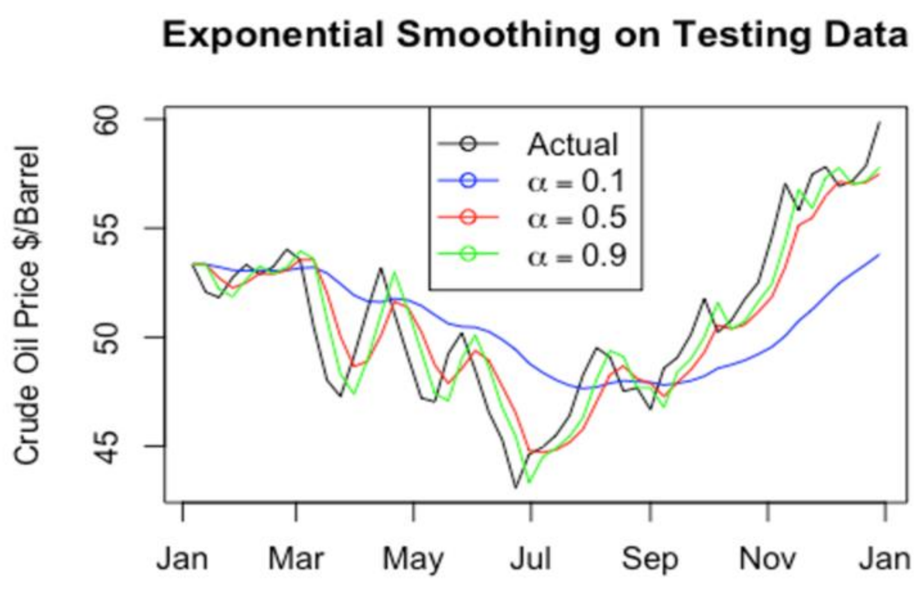


Table 4, along with Figure 6, confirms that simple exponential smoothing models of α = 0.9 performs that best for the testing data set, where α = 0.9 leads to the smallest error measures. In order words, in case a simple exponential smoothing model is used to forecast crude oil prices, an SES (α = 0.9) is recommended due to its model accuracy for crude oil price forecasting.

Table 4: Comparison of Exponential Smoothing on Testing Data in 2017

Exponential Smoothing	**MAE**	**RMSE**	**MAPE**
SES (α = 0.1)	2.8580	3.3338	5.5398
SES (α = 0.5)	1.4492	1.7901	2.8868
SES*(α = 0.9)	1.2700	1.4855	2.5271

Figure 6. Exponential Smoothing Comparison 2017



Autoregressive Integrated Moving Average Model – Since the original time series on crude oil prices in Figure 1 fails to show its stationarity, we tried a first order differencing. Figure 7 suggests that the resulting time series stationary after the first order differencing. After analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) in Figure 8 and comparing several other model structures, we come up with an ARIMA (0, 1, 1) model without a constant term, where the MAE, RMSE, and MPAE are minimized. In addition, Figure 9 shows that the residual of this ARIMA model is approximately normally distributed, indicating a good fitting of the model parameters since the residual time series is randomly distributed without any abnormal patterns. As a result, the ARIMA (0,1,1) on training data produces much smaller forecasting error measures in terms of MAE, RMSE, and MPAE than these of MA(2) and SES (α = 0.9). It is seen from Table 5 that ARIMA (0, 1, 1) model outperforms the MA(2) and SES (α = 0.9) in all three measures with the training data set, with the forecasting model:

$\hat{Y}_t = Y_{t-1} - \theta_1 \epsilon_{t-1}$ where $\theta_1 =$ - 0.2351 and $\epsilon_{t-1} = Y_{t-1} - \hat{Y}_{t-1}$ (1)

Table 5. Comparison of Forecast Models (MA, SES, ARIMA) on 2009-2016

Model	MAE	RMSE	MAPE
MA (2)	2.5107	3.1839	3.1838
SES (α = 0.9)	2.0914	2.6870	3.0616
ARIMA (0, 1, 1)	1.9557	2.5373	2.8591

Figure 7. First Differencing Series Stationary 2009-2016

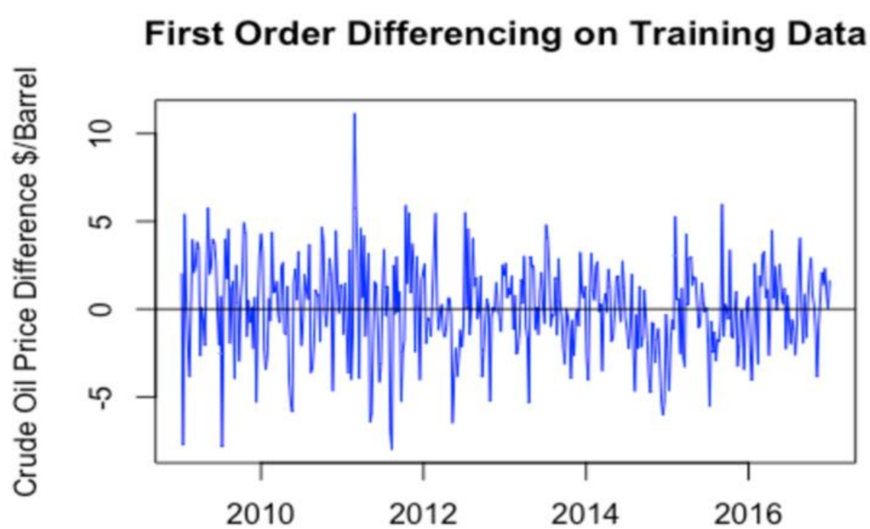


Figure 8. First Differencing ACF and PACF on 2009 – 2016

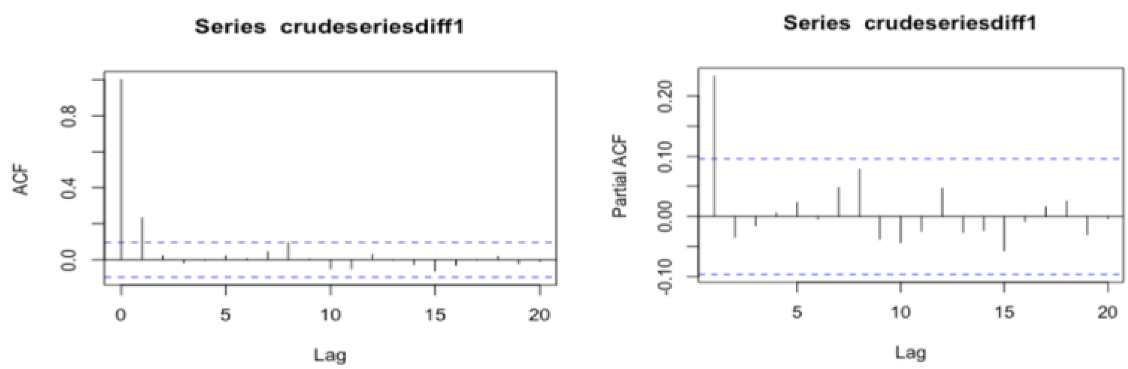


Figure 9. ARIMA (0, 1, 1) Residual Analysis on 2009 – 2016

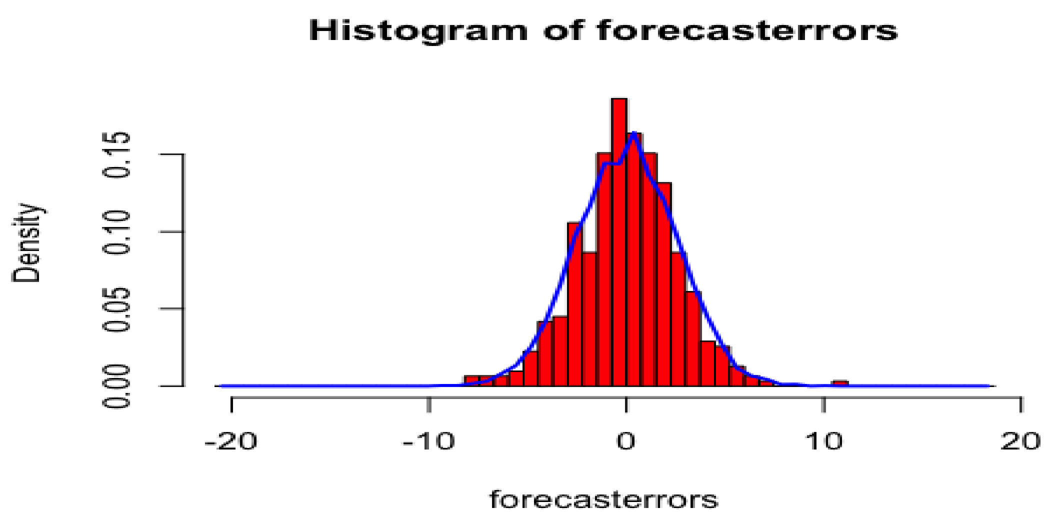
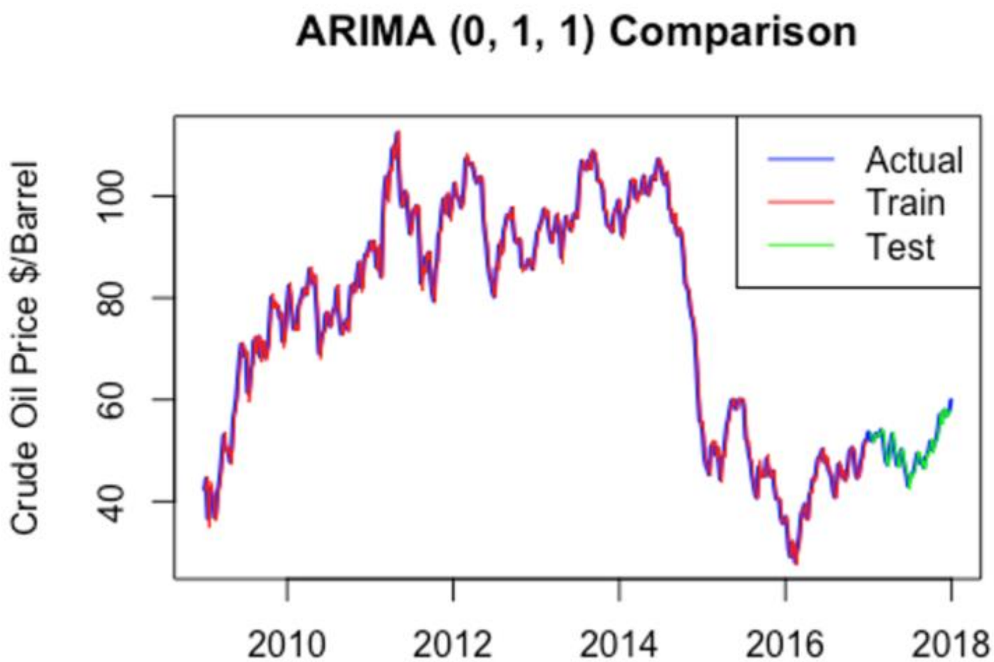


Figure 10 compares the actual crude oil prices against the ARIMA (0, 1, 1) model forecasts on training and testing data sets, both of which are closely following the actual observations.

Figure 10. Actual vs Train & Test on 2009-2017



Support Vector Regression Models – In this research, we use R to train the SVR model with three parameters: cost, gamma, and epsilon. To avoid potential overfitting, we use the default epsilon = 0.1 and unscaled original training data set for the period 2009 through 2016. Having tested numerous combinations of cost and gamma values, we narrow our search range to 2 ~ 6 for the cost and 0.001 ~ 0.01 for gamma. Then we use auto-tune in R package to come up with the optimal combination for cost = 6 and gamma ($\boldsymbol{\gamma}$) =0.01. Figure 11 is an auto-tune heat map produced by R, which indicates that the best performance for the SVR model lies in the upper right corner on the training data set. However, unlike the ARIMA (0, 1, 1) with model parameters as in Eq.(1) and a residual plot as in Figure 9 for model diagnostics, an SVR model does not produce a set of parameters similar to Eq.(1), nor does it have a residual analysis to prevent from model overfitting due to its non-linear nature. Consequently, it cannot be used to forecast for the future.

Figure 11. SVR Auto-Tune Heat Map on Cost and Gamma on Training Data

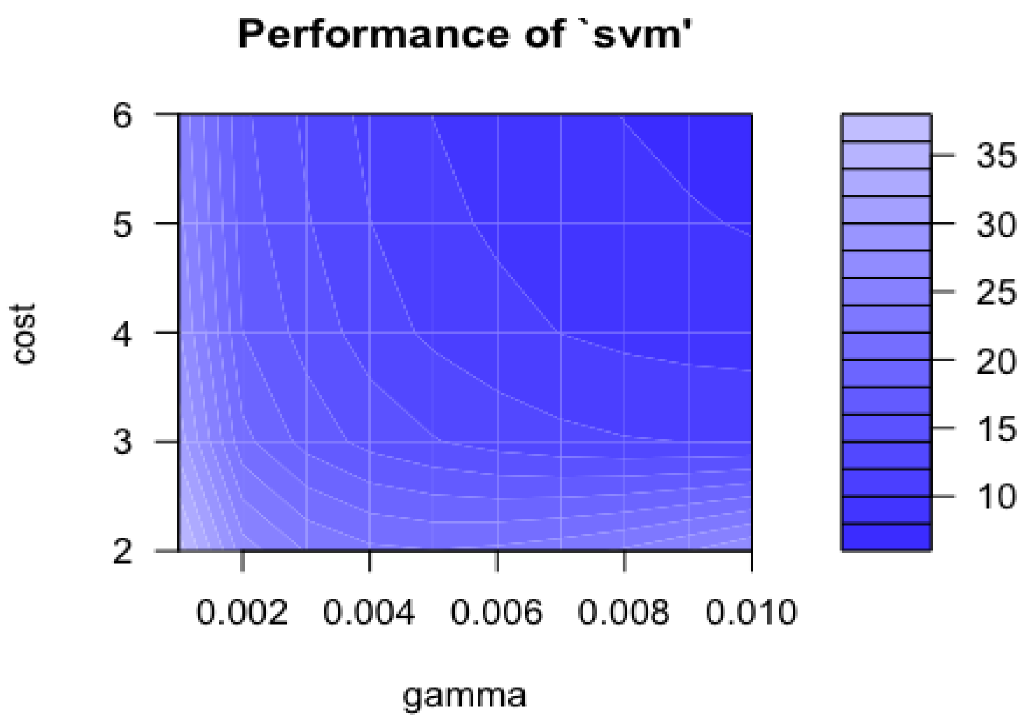


Table 5 compares all four models on weekly crude oil price forecasts on training data set. It is seen from Table 5 that both ARIMA (0, 1, 1) and SVR (c=6, γ=0.01) perform almost the same: the former has a lower RMSE, whereas latter has lower MAE and MAPE. However, both of them outperform MA (2) and SES **(**α = 0.9**)**.

Table 5. Comparison of Forecast Models (MA, SES, ARIMA, SVR) on 2009-2016

Model	**MAE**	**RMSE**	**MAPE**
MA (2)	2.5107	3.1839	3.1838
SES (α = 0.9)	2.0914	2.6870	3.0616
ARIMA (0, 1, 1)	1.9557	2.5373	2.8591
SVR (c=6, γ=0.01)	1.9242	2.6057	2.8533

Figure 12 compares the actual crude oil prices against the SVR (c=6, γ=0.01) model forecasts on training and testing data sets, both of which are closely following the actual observations. While the SVR model in Figure 12 looks similar to the ARIMA model in Figure 10 and by the error measures in Table 5, we reveal useful insights in the next subsection below.

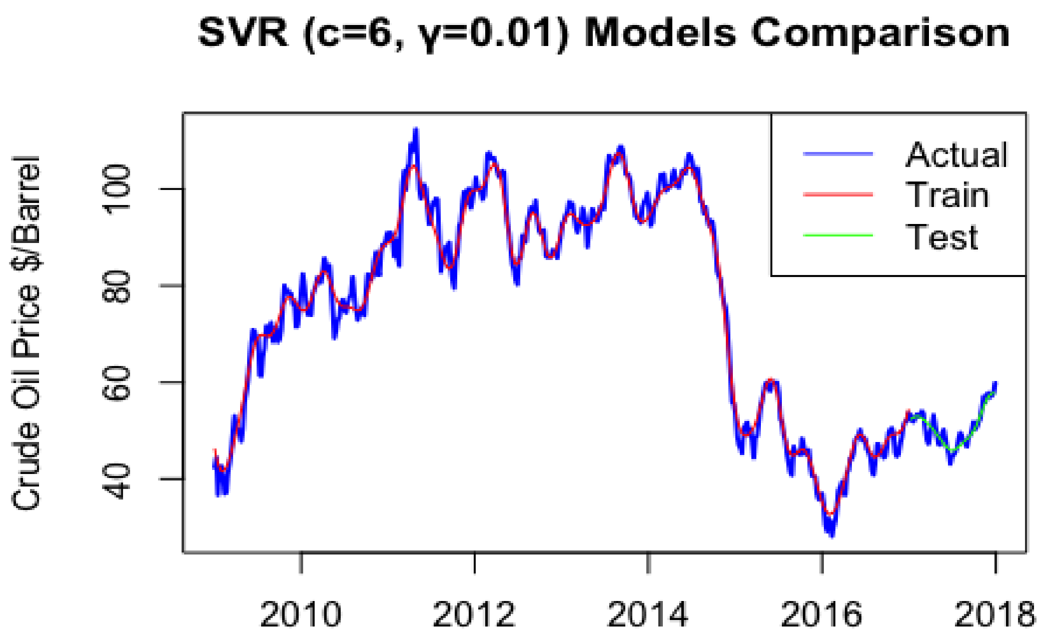


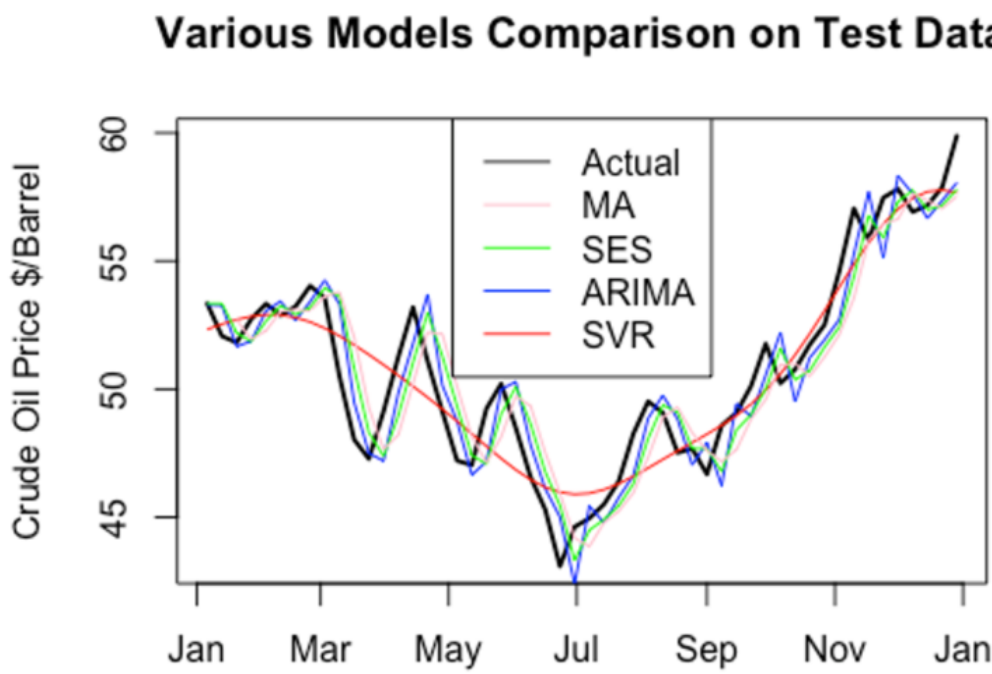
Figure 12. Actual vs Train Data and Testing Data

Forecasting Model Comparison on Test Data – Table 6 summarizes the results of the best forecasting models from each of the four categories on the testing data set of the weekly crude oil prices in 2017. It is seen from Table 6 that as far as the RMSE is concerned, ARIMA (0, 1, 1) outperforms SVR (c=6, γ=0.01), SES (α = 0.9), and MA (2) in descending order. However, SVR (c=6, γ=0.01) has the lowest MAE and MAPE, followed by ARIMA (0,1,1), SES (α = 0.9), and MA (2). Thus, we rank ARIMA (0, 1, 1) and SVR (c=6, γ=0.01) tied for the best model accuracy on weekly crude oil price forecasting, SES (α = 0.9) the second place, and MA (2) the third place.

Table 6. Comparison of Forecast Models (MA, SES, ARIMA, SVR) in 2017

Model*	MAE	RMSE	MAPE
MA (2)	1.4979	3.2162	2.9877
SES (α = 0.9)	1.2700	1.4855	2.5271
ARIMA (0, 1, 1)	1.1433	1.3426	2.2686
SVR (c=6, γ=0.01)	1.1246	1.4885	2.2487

Figure 13. MA, SES, ARIMA, SVR on Test Data in 2017



CONCLUDING REMARKS

In this research, we focus our attention on weekly crude oil price forecasting models to identify the best forecasting model among various forecasting models, including time series and machine learning models. We reveal the following three interesting concluding remarks for practitioners. First, the simple moving average and simple exponential smoothing models such as MA (2) and SES (α = 0.9) can provide reasonably acceptable forecasting accuracy as seen in Tables 5 and 6, with minimum computational complexity, and their model parameters, n=2 for MA and α=0.9 for SES, will remain the same both for the training data and the testing data. Second, the more advanced autoregressive integrated moving average such as ARIMA (0, 1, 1) can offer more accurate forecasting results for most time series data, with reasonable computational complexity, and its model parameter(s) as shown in Eq.(1) can be used to forecast for the future or for the testing data. Third, while it can offer about the same forecasting accuracy as that of the ARIMA (0, 1, 1) model, the machine learning SVR (c=6, γ=0.01) model is not only computationally the most complex among all the forecasting models studied in this research, but also has the potential of model overfitting due to the fact that there are too many parameters to train the model: cost, gamma, and epsilon. In addition, an SVR model cannot be used to test the model accuracy on the testing data the same way as in an ARIMA model since it does not provide a list of model parameters, which also makes the economic or business interpretation very difficult.

Moreover, we provide three computational remarks regarding SVR model optimization for academics. First, the auto-tune heat map produced by R as in Figure 11 is one of the approaches to deal with overfitting problems in search for optimal SVR parameters: cost, gamma, and epsilon, not counting the tradeoff between scaled and unscaled data set. Second, different overfitting prevention approaches may produce different SVR models even with the exact same data set, which makes direct model comparison more difficult. Third, for future research on SVR attention should be focused on overfitting prevention and model optimization.

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