Sains Malaysiana 51(8)(2022): 2633-2643
http://doi.org/10.17576/jsm-2022-5108-22

Is Facebook PROPHET Superior than Hybrid ARIMA Model to Forecast Crude Oil Price?

(Adakah *PROPHET Facebook* Lebih Hebat daripada Model ARIMA Hibrid untuk Meramalkan Harga Minyak Mentah?)

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Received: 16 August 2021/Accepted: 30 January 2022

ABSTRACT

Oil price forecasting has received a great deal of attention from practitioners and researchers alike, but it remains a difficult topic because of its dependency on a variety of factors, including the economic cycle, international relations, and geopolitics. Forecasting the price of oil is a difficult but gratifying task. Motivated by this issue, we present a robust model for accurate crude oil price forecasting using ARIMA and Prophet models based on machine learning technique to produce a reliable weekly and monthly crude oil price predictions. We apply the Savitzky–Golay smoothing filter to get a better denoising performance for our forecast models. For model evaluation, we apply cross validation with sliding windows on both models and compares the performances using RMSE and MAPE. The results show that the ARIMA-based machine learning approach performs better as compared to the Prophet model for both one-week and one-month forecast ahead intervals.

Keywords: ARIMA; crude oil price; forecasting; Prophet

ABSTRAK

Ramalan harga minyak telah mendapat banyak perhatian daripada pengamal dan penyelidik, tetapi ia kekal sebagai topik yang sukar kerana pergantungannya pada pelbagai faktor, termasuk kitaran ekonomi, hubungan antarabangsa dan geopolitik. Meramalkan harga minyak adalah tugas yang sukar tetapi menggembirakan. Didorong oleh isu ini, kami mempersembahkan model teguh untuk ramalan harga minyak mentah yang tepat menggunakan model ARIMA dan *Prophet* berdasarkan teknik pembelajaran mesin untuk menghasilkan ramalan harga minyak mentah mingguan dan bulanan yang boleh dipercayai. Kami menggunakan penapis pelicinan Savitzky–Golay untuk mendapatkan prestasi nyahbunyi yang lebih baik untuk model ramalan kami. Untuk penilaian model, kami menggunakan pengesahan silang dengan tingkap gelongsor pada kedua-dua model dan membandingkan prestasi menggunakan RMSE dan MAPE. Keputusan menunjukkan bahawa pendekatan pembelajaran mesin berasaskan ARIMA menunjukkan prestasi yang lebih baik berbanding model *Prophet* untuk kedua-dua ramalan satu minggu dan satu bulan ke hadapan.

Kata kunci: ARIMA; harga minyak mentah; ramalan; *Prophet*

INTRODUCTION

Crude oil price forecasting is currently one of the most popular subjects because of its practical uses. However, the prediction of crude oil prices has fundamental challenges. Apart from demand and supply, crude oil prices are heavily impacted by political events, renewable energy production, stock market performance, exchange rates of major oil importers and oil exporters, among others. A sudden change in crude oil price can have huge economic repercussions, with crashes generating reduced economic activity and spikes causing severe inflation (see Adilah et al. 2021; Antoni et al. 2020; Humaida Banu & Yap 2019; Low & Mohd 2019; for examples). The latest Russia-Saudi Arabia oil price war has thrown the oil markets into disarray. Persistent uncertainty in the real economy (due to COVID-19) has impacted crude oil price predictability, which has been exacerbated by large swings in the commodity markets. This may explain why various crude oil price forecasting models have failed to outperform basic time series models, such as the random walk and AR (1) models (Butler et al. 2021). Therefore, having a reliable crude oil price forecasting model is crucial. Based on this premise, this paper offers a new univariate model for crude oil price prediction based on ARIMA and FB-PROPHET that can be implemented in all decomposition conditions. We use machine learning approach with Savitzky–Golay smoothing filter (Sadeghi & Behnia 2018) to get a better denoising performance and improve our forecast estimates. Our findings show that the ARIMA model yields superior results to predict crude oil price in comparison to the FB-PROPHET model.

The 2020 outbreak of the coronavirus has shaken up the energy markets and created widespread upheaval. The energy sector, perhaps more than any other industry, was severely impacted by the pandemic's outbreak. In recent history, the COVID-19 crisis has brought more disturbance than anything else, leaving wounds that will last for years. The demand for oil has plummeted globally following the closure of various national borders and the introduction of travel-related restrictions aimed at stopping the spread of the virus. Further, the need for oil and other forms of energy has been reduced significantly because of social distancing mandates and disrupted shipments. In an unprecedented record of WTI pricing constituting the benchmarking for American crude oil, the price collapsed to minus USD 37.63 per barrel on April 20, 2020. This has never been witnessed in history. This implies that producers pay purchasers to take crude from them due to concerns that storage capacity may be exhausted. As the global lockdown prevented transportation, demand for crude oil plummeted, and producers were forced to rent tankers to store excess oil, causing prices to fall. Although the United States has the biggest number of COVID-19 cases as of May 2021, the virus's impact on the rest of the world cannot be ignored, particularly in mono-economic countries whose economies are solely dependent on the performance of the oil industry.

The crude oil market, the baseline of the petroleum industry, has a far bigger volume of trade than the others. Due to its strong interaction with companies' future strategy, risk management, and household expenses, it has attracted considerable attention in the previous two decades. A large scholarly literature is present on the crude oil market in view of their importance and strong relationship with other commodities, such as gold, stocks, and exchange rates. In the past, huge swings in oil prices have resulted in recessions and even regime collapses which is one of the key dampeners of economic growth after World War II (Hamilton 1983). Over the years leading to fluctuations in the price of oil, some significant events were noted, such as the Iraq War of 2003 to 2011, the Arab Spring that began in the Tunisian protest between 2010 and 2012 (Sheppard et al. 2020), US Shale Oil production boom from 2014 to 2016 and the COVID-19 pandemic till date. Each of the above incidents has had an effect on the oil price in some way, as evidenced by the fluctuation of the oil price in Figure 1.

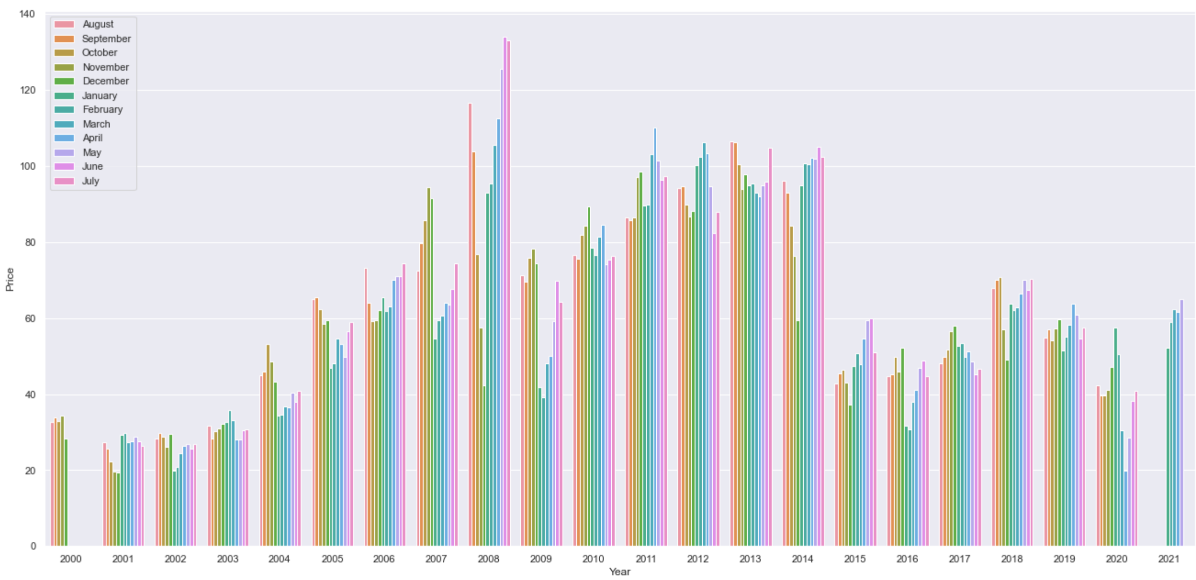

FIGURE 1. Plot of oil prices from 2000-2021

The remainder of this work is structured as follows. Next section gives a brief discussion on past literature. Subsequent section provides detailed explanations of the proposed crude oil price model. The following section illustrates and verifies the suggested models by applying them to crude oil futures prices and measuring their performance using predefined evaluation criteria. Last section summarizes the paper and provides important suggestions for future research.

LITERATURE REVIEW

There is a large body of literature on forecasting oil prices. As historical oil prices are time series, forecasting studies have been carried out mostly with traditional time series regressions. Time series forecasting is a type of forecasting in which historical observations are evaluated to create a model that describes the fundamental link between a series of event outcomes, which is then used to forecast future events. Given the complexity of the crude oil market, numerous modellings of crude oil prices have been exerted over the past, but to date, none of these models have ever succeeded in overcoming the underlying techniques of time-series, such as the Random Walk (RW) and AR (1) models. Machine learning and deep learning are currently being incorporated with conventional time series regression to create better forecast estimates for oil prices.

Crude oil prediction models are generally divided into four major categories: Statistical, structural and/or economic components. Empirical and theoretical observations of oil prices became the foundation of the distinguished methodology of Engle and Granger (1987) which relied on estimations of co-integration. In recent years, several studies have shown that statistical model mixtures work better than basic techniques. Nademi and Nademi (2018) forecast OPEC, WTI, and Brent crude oil prices using a semiparametric Markov switching AR-ARCH model. The empirical results show that the ARIMA and GARCH modelling were outperformed by the model and generated more accurate crude oil pricing forecasts. Moreover, a fusion of the Random Walk (RW) and ARMA models was proposed by Chen et al. (2018) in what is now known as the hybrid grey wave forecasting model. In terms of correct direction forecast, the empirical data shows that the model outperforms multi-step crude oil prices based on the ARMA and RW hybrid model. According to Chai et al. (2018), their unique prediction combination methodology accounts for a variety of changing features, such as regime switching, change points, and high-frequency sequences. Studies such as Ewing and Thompson (2007) and Kaufmann and Ullmann (2009) have also posited that by broadening the spectrum of explicatory variables and enhancing the dynamical integration between these variables, such forecast models of crude oil price will improve. Additionally, studies have shown how observing futuristic behaviours of crude oil prices with speculative emphasis will render better results (Alquist & Kilian 2010; Kaufmann 2011; Kilian & Murphy 2014; Miao et al. 2018; Sornette et al. 2009). In general, economically based predictive models operate better for periods up to 3 months. In contrast, models based on the proliferation of refined pricing of crude oil exhibit better performance for longer intervals of 12 to 24 months (Baumeister & Kilian 2015).

A substantial number of mixed models in neural network literature have been explored in the last few years. Huang and Wang (2018) offer a model that brings together a neural wavelet (NWN) network embedded with a function of random time baseline. This proposed model has been shown by empirical data to generate higher precisions and better accuracy when crude oil variations in price is forecasted. Furthermore, Wang et al. (2020) demonstrates that a heterogeneous combination of multi-granularity technique based on an artificial colony, not only surpasses individual competitive criteria but also uniquely heterogenous and multi-granular approaches in predicting the price of crude oil. Guo (2019) shows several deep learning models performs better than traditional ARIMA models in forecasting WTI crude oil price. Abdollahi and Ebrahimi (2020) employ Adaptive Neuro Fuzzy Inference System (ANFIS), Autoregressive Fractionally Integrated Moving Average (ARFIMA), and Markov-Switching models in a proposed hybrid model. They find that hybrid model with equal weights outperformed the constituent models, as well as hybrid model weighted by the error values. Güleryüz and Özden (2020) compares the accuracy of Long-Short Term Memory (LSTM) and Facebook's Prophet model in crude oil price estimation. The study concludes that the LSTM model has greater accuracy than the Prophet model in predicting oil prices.

While using the proper technique is key, having precise and reliable data is also crucial for getting the best estimate. As a result, recent oil forecasting studies have experimented with a variety of methodologies in order to gather real-time, more accurate, and exact data on oil forecasting. This is demonstrated in a study by Elshendy et al. (2018), who forecasts crude oil prices using various online media sources. Elshendy et al. (2018)

is not the only research that relies on media sources. Bai et al. (2022) used news text into their analysis, as well as Ting and Zhang (2017), who forecasted using the Google index. By using Yahoo Finance to access NYMEX crude oil futures prices, the current study presents a different perspective on real-time data.

A number of previous research in oil price forecasting has addressed the issues of trend, seasonality, holidays, and missing data separately in different studies. Zhou and Dong (2012), for example, consider the seasonality problem while Zhao et al. (2020) and Zhou et al. (2019) considers trend, and Garratt et al. (2019) on missing value. Our study complements these studies by using the FB-PROPHET model, which can simultaneously incorporate trend, seasonality, and outliers under one single technique.

METHOD

ARIMA

The Autoregressive Integrated Moving Average (ARIMA) model is a subset of the ARMA model. The "AR" component of the model denotes the regression of its own lagged values, whereas the "MA" component denotes that the regression error is a linear combination of values that occurred in the past at different times. Each of these characteristics is designed such that the data fits best while being as generic as feasible (Chen 2019). To forecast using the ARIMA model, we must assume that the time series is stationary and that the residuals are uncorrelated and normally distributed. The values for three parameters (*p,d,q*) must be established in order to predict ARIMA time series: *p* – order (number of time lags) of the autoregressive model; *d* – degree of differencing to achieve stationarity; *q* – The moving average (MA) model's order. This is the size of the time series data's "window" function of the moving average model.

In general, ARIMA model is denoted by ARMA (*p*,*q*). The form of the ARMA (p, q) model is,

$$y_t = C + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \epsilon_t + \theta_1 \in_{t-1} + \emptyset_2 \in_{t-2} + \cdots + \theta_q \in_{t-q} \quad (1)$$

where ϵ_t is an uncorrelated innovation process with mean zero and y_t is the actual value and ϵ_t is the random error at time t, $\emptyset_1$ and $\emptyset_2$ are the coefficients, p and q are integers that are typically known as autoregressive and moving average polynomials. For instance, the ARIMA (1,0,1) model can be shown as follows:

$$y_t = \theta_0 + \emptyset_1 y_{t-1} + \varepsilon_t - \theta_1 \varepsilon_{t-1} \quad (2)$$

There are two clear advantages of ARIMA method. Firstly, the relationship between the independent variables and dependent variable is well understood and therefore easily explained based on assumptions from the model. This allows researchers to acquire an in-depth insight not only of the relationship between the current period as a result of previous periods (endogenous variables), but also of any effect outside the series (exogenous variables). Secondly, model selection can be performed automatically for ARIMA models in order to maximize prediction accuracy (Kane et al. 2014). ARIMA models also benefit from the capacity to handle dynamic systems that vary over time by updating the pattern based on recent developments to forecast the future state of a system (Kane et al. 2014).

FB- PROPHET

FB-PROPHET (PROPHET hereafter) model is an open-source tool for strong seasonal time series figures (Taylor & Letham 2017). It was created by the Core Data Science team at Facebook. 'The Prophet model is robust enough to address missing data, shifts in the trend, and outliers' (Rodriguez et al. 2018). The PROPHET employs two models to predict the trend: A saturated growth model and a piece-wise linear model. A model comparable to population growth models is used for growth forecasts in natural ecosystems, when nonlinear growth at a carrying capacity has reached a saturation point. A piece-wise model of constant growth-rate provides an efficient and often beneficial solution for forecasting applications where this saturation point is never reached. The PROPHET's model incorporates Harvey and Peters (1990) decomposition time series with three key components: trend, seasonality and holidays. The equation is given as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t \quad (3)$$

where *y*(*t*): time series of interest; *g*(*t*): linear or logistic growth curve trend; *s*(*t*): periodic seasonal variations with Fourier orders based on dummy variables or annual seasonality; (*t*): analyst's analysis of the impacts of significant irregular holidays or events; *v*) εt : the error term adjusts for any anomalous changes that the model does not account for.

There are two distinct advantages of PROPHET model. First, the model uses a modular regression technique that enables selection and tweaking of parameters for a predicted problem, while performing well with default values. Second, it also includes a forecast tracking and measurement system that allows researchers to adapt and improve predictions through progressive improvements. Basically, PROPHET is an adjustable model which enables to analyze different time series and to give a scalable performance (Taylor & Letham 2018).

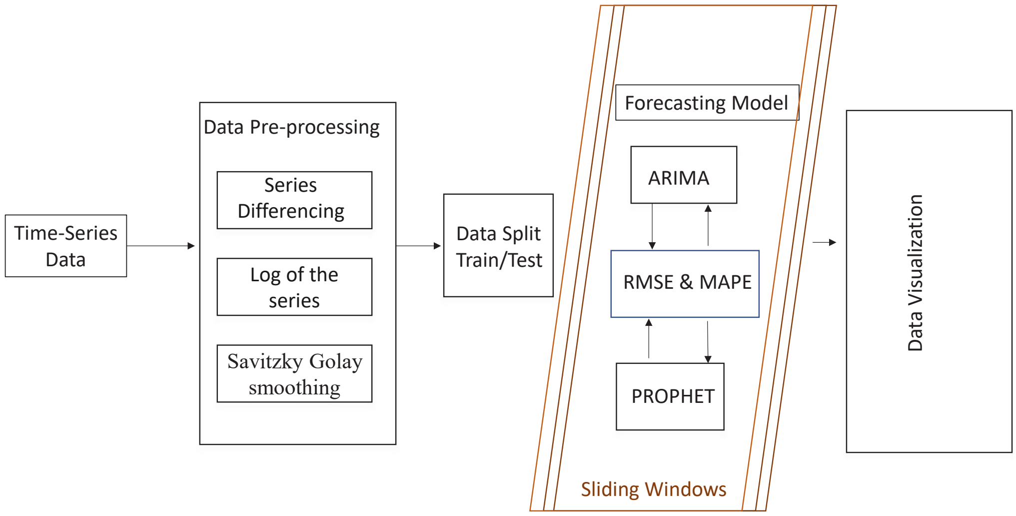

FIGURE 2. Proposed ARIMA- and PROPHET- based Machine Learning Methodology

EXPERIMENTAL DETAILS

DATA DESCRIPTION

To verify the effectiveness of the proposed ARIMA and PROPHET forecasting models, the main crude oil price series, NY Mercantile - NY Mercantile (NYMEX) crude oil futures price is selected as experimental sample. The daily NYMEX crude oil futures price is collected from Yahoo Finance (https://finance.yahoo.com). The sampling period is from August 8, 2000, to May 14, 2021 with a total of 5171 observations.

DATA TRAINING AND TESTING

The literature describes various methods for dividing data into training and testing samples, which can have a significant impact on prediction performance. Many studies have been conducted to examine the performance of a single model in relation to the training dataset to sample size ratio. Wang et al. (2012) tested the model's reliability using different training sets that comprised 60%, 70%, 80%, and 90% of the total data. In addition, Bonaccorso (2018) suggests that increasing the relative ratio to 98 percent may be beneficial. Because oil prices are extremely sensitive to global political, economic, and business cycle factors, organizations like American Energy Information make short-term predictions of oil price (Wang et al. 2018). Short-term forecasting is obviously more practical and valuable to practitioners. Accordingly, this paper sets to forecast crude oil prices for the next 1-week (5 trading days) and 1-month (22 trading days) intervals.

Generally, a complex time-series model may lead to the risk of over-fitting. We reduce this risk by following a machine learning approach in our experiments. First, the data is split into training and testing sets to find the most efficient set of model parameter(s), which has a correct balance between the model generalization capabilities and model complexity. To achieve this, we use the final 2 years of trading data (253 days multiply by 2) for training and the last 5 days (and 22 days) for testing purposes.

DATA PRE-PROCESSING

We use data in first log difference to remove trend and achieve stationarity in the oil price series. In order to reduce the (random) noise, we add a new column in our dataset with smoothed original oil price data using the Savitzky–Golay smoothing filter (Sadeghi & Behnia

2018) to get a better denoising performance. There are two parameters in the Savitzky–Golay filter, the window size parameter which specifies how many data points will be used to fit a polynomial regression function and the degree of the fitted polynomial function. Accordingly, we set 8 as the windows size and 3 for the degree of the polynomial in our Savitzky–Golay implementation.

MODEL SELECTION

The optimum *(p,d,q)* values in our ARIMA is determined by using SARIMAX model from *statsmodels* library in *python* which minimizes the AIC value with seasonality order set to 0. Comparably, we use 'Yearly Seasonality' with changepoint prior scale set to 10 in PROPHET model for best model selection.

EVALUATION CRITERIA

To measure the forecasting performance, two main criteria are used for evaluation of level prediction and directional forecasting, respectively. Firstly, the root mean squared error (RMSE) and the mean absolute percent error (MAPE) are selected to evaluate level prediction accuracy:

I. Root-Mean-Square Error (RMSE): It determines the amount of differences between values predicted by the model and the actual values. In other words, the RMSE shows the standard deviation of differences between forecasted and realized values. RMSE is a criterion for measuring accuracy to compare prediction errors of various models for a particular variable, as it is scale-dependent. The RMSE equation is as follows:

$$RMSE = \left(T^{-1}\sum_{t=1}^{T}\left(Y_{(t)} - Y^{\wedge}{}_{(t)}\right)^2\right)^{1/2} \tag{4}$$

II. Mean Absolute Percentage Error (MAPE): MAPE is applied to measure a model forecasting accuracy. Describing accuracy as a percentage, this method is formulated as shown in the following equation:

$$MAPE = T^{-1}\sum_{t=1}^{T}\left|Y_{(t)} - Y^{\wedge}{}_{(t)}/Y_{(t)}\right| \tag{5}$$

In above formulas, T is the size of sample, $Y_{(t)}$ and $Y^{\wedge}{}_{(t)}$ are the realized and forecasted values at time t, respectively. Overall, when the values of these measures are smaller, the model prediction is more accurate.

RESULTS

TIME SERIES COMPONENT

We decompose the oil price data into its trend, seasonality and residual components by moving average as illustrated in Figure 3. After removing the trend and the seasonality, we can observe that the residuals have stationary features. Besides, since the residual term is stationary after a single decomposition, we may deduce that the ARIMA model's hyperparameter number of nonseasonal differences d is 1.

ARIMA AND PROPHET MODEL SELECTION

The values for three parameters (p,d,q) to predict ARIMA time series selected from SARIMAX procedure is given as (0,1,1) with seasonal parameters set to 0. The nonseasonal differences d is equal to 1 is consistent with the seasonal plot in Figure 2. We also use 'Yearly seasonality' for PROPHET model with changepoint prior scale set to 10.

CROSS VALIDATION

One common approach in employing cross validation is to split the dataset randomly and reserve a list of data points from the available dataset and train the model on the rest of the data. However, with a time-series dataset,

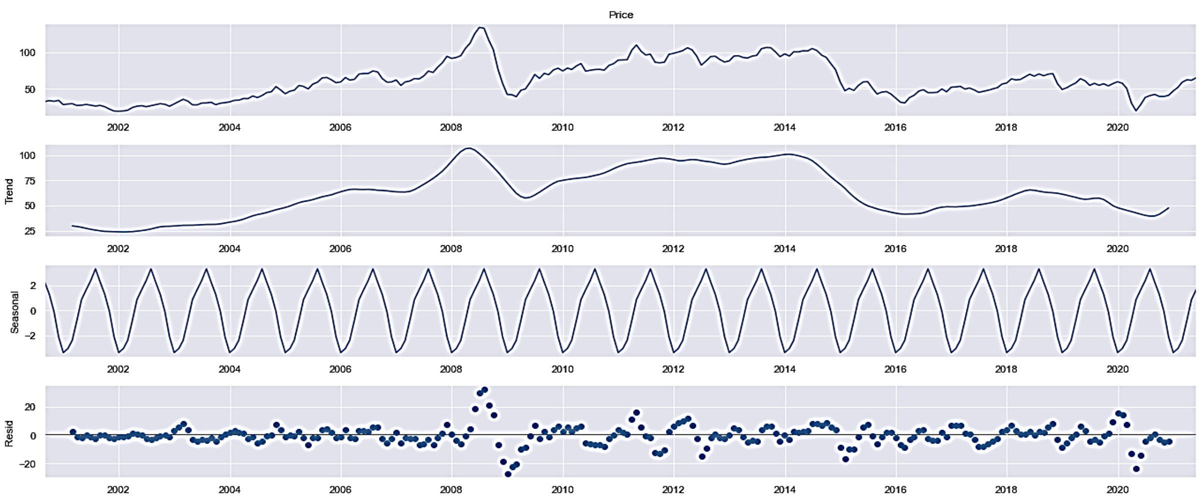

FIGURE 3. Trend, seasonality and residuals decomposition of oil price data

randomly splitting the dataset may not be appropriate since the time section of the data may be scrambled. This is because a time-series dataset is a type of sequential data. Therefore, we propose to use a sliding windows approach in the cross-validation procedure. In our approach, a train dataset which has a minimum number of observations necessary for fitting the model is selected (from 100 sliding windows). Next, we change our train and test datasets with each fold and maintain a fixed size (i.e., the model drops older values from the time series during validation). Finally, the trained models' performance is assessed using the previously specified indicators.; the RMSE and the MAPE.

5-DAY FORECAST

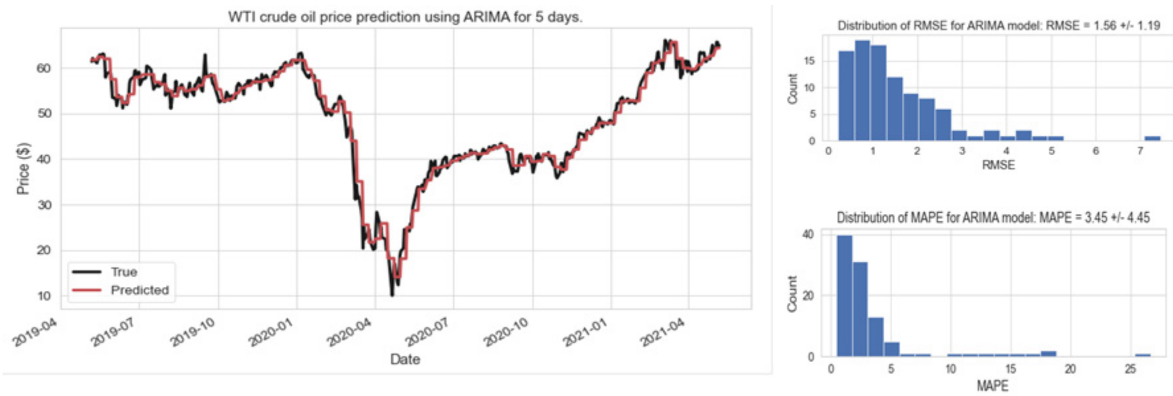

FIGURE 4. Forecast plot using ARIMA for 5 days and the corresponding RMSE and MAPE histogram plots for 100 sliding windows

ARIMA

PROPHET

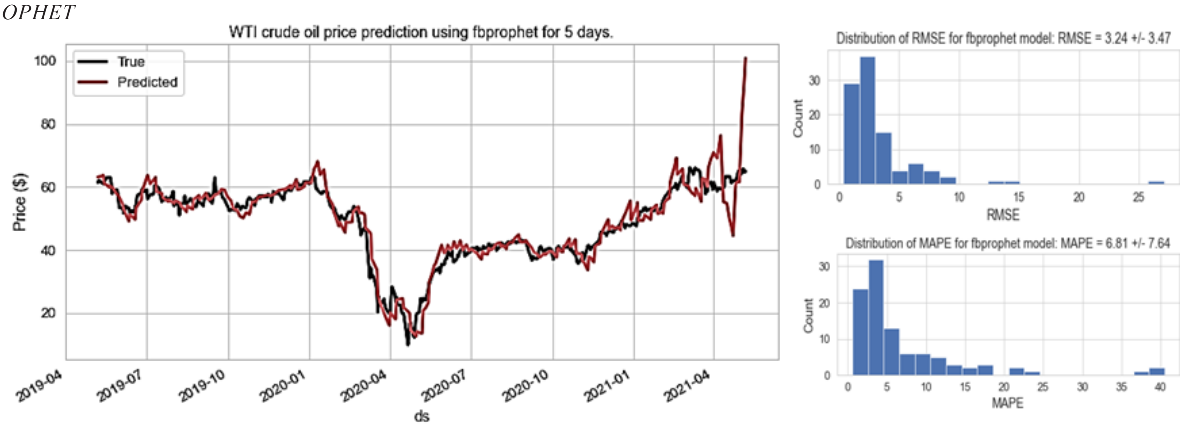

FIGURE 5. Forecast plot using PROPHET for 5 days and the corresponding RMSE and MAPE histogram plots for 100 sliding windows

22-DAY FORECAST

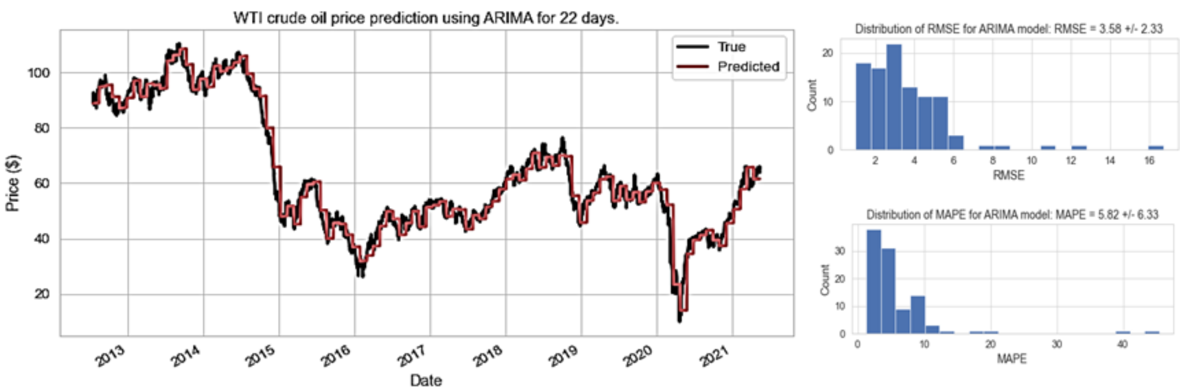

FIGURE 6. Forecast plot using ARIMA for 22 days and the corresponding RMSE and MAPE histogram plots for 100 sliding windows

ARIMA
PROPHET

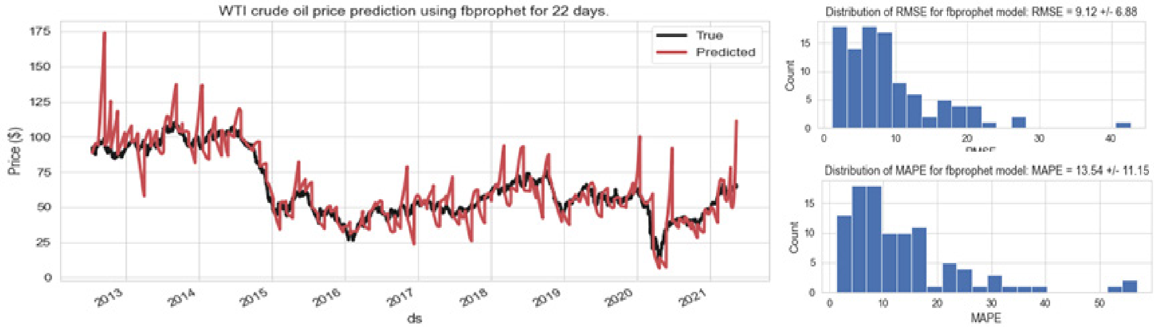

FIGURE 7. Forecast plot using PROPHET for 22 days and the corresponding RMSE and MAPE histogram plots for 100 sliding windows

To find the best accuracy for both models in our experiment, the optimized RMSE and MAPE scores are presented in Figures 4 to 7 for 100 sliding windows. Our ARIMA and PROPHET model are executed on a WINDOWS standard office desktop computer using a NVIDIA 940MX GPU running on an i5 dual-core processor. The tuning and computational effort for ARIMA require approximately 15 minutes. PROPHET, conversely, needs around 50-60 minutes for the entire training and validation process.

Using RMSE and MAPE as measures of forecast accuracy, the ARIMA model generates the best performance as compared to the PROPHET model by having the least error values for one-week (5 days) and one-month (22 days) forecasts intervals. Specifically, the mean RMSE for ARIMA for 5 days and 22 days forecast intervals are 1.56 and 3.58, respectively. In contrast, the mean RMSE and MAPE for PROPHET model are approximately twice that of ARIMA (RMSE=3.24, MAPE=6.81) for the 5-day interval and three times higher than ARIMA (RMSE=9.12, MAPE=13.54) for 22 days forecast interval. To sum up, the mean MAPE score of 3.45% for ARIMA for a 5-day forecast implies that the ARIMA model is about 96.5% accurate in predicting the next observation while the PROPHET model is 3% less accurate with 93.2% accuracy level. The PROPHET model performs even poorer for a 22-day forecast, yielding an approximately 86% accuracy as compared to 94% accuracy level for ARIMA model.

COMPARISON BETWEEN ARIMA AND PROPHET

Side by side comparison between 5-day Forecast and 22-day Forecast

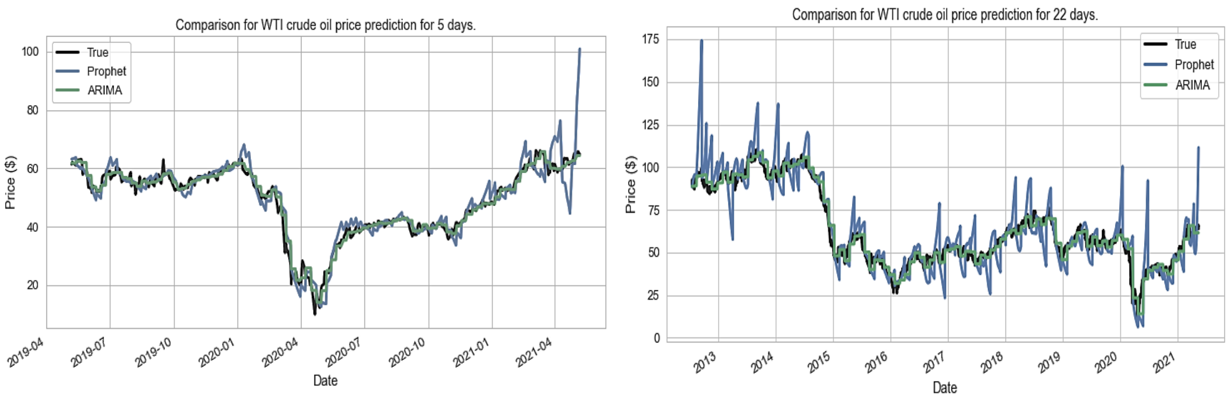

FIGURE 8. Comparison of ARIMA and PROPHET time series plots of actual and forecast values for 5-day and 22-day forecast intervals

Figure 8 illustrates the time series plot of actual and forecast values of crude oil price using ARIMA and PROPHET models for 5-day and 22-day forecast intervals. Consistent with the lower mean of RMSE and MAPE values previously reported in Figures 4 to 7, the forecast time series plot for ARIMA fits better and move in tandem with actual crude oil prices. In contrast, the forecast plot of PROPHET deviates ever so often against the actual crude oil prices, especially for the 22-day forecast interval.

In brief, our results indicate that ARIMA perform significantly better than PROPHET for the forecasting task under consideration. In addition, ARIMA attains the best overall accuracy and requires less time to generate the forecast results. Nevertheless, PROPHET is easy to use but considerably less accurate and requires a longer time to compute in our implementation. Our findings are consistent with Menculini et al. (2021) who document poor PROPHET performances than the ARIMA. Notwithstanding, Menculini et al. (2021) show that their PROPHET takes less time to produce the forecast results when compared to ARIMA, which contradict with ours. This is primarily due to the architecture of our machine learning algorithm. While ARIMA is implemented using Python's low-CPU usage *statsmodels,* PROPHET, on the contrary, requires resource-hungry *pystan* modules. PyStan is a Python interface to Stan, a library for Bayesian inference. Stan® is a cutting-edge platform for statistical modelling and high-performance statistical computation. The module can be downloaded from https://pystan.readthedocs.io/en/latest/.

Conclusion

We develop a machine learning based model for ARIMA and PROPHET to predict crude oil price. Based on estimates of RMSE and MAPE, we conclude that ARIMA model is more superior in forecasting crude oil price for 5-day and 22-day forecast intervals. Our results show that ARIMA forecast accuracy is as high as 97% for 5-day ahead forecast and 94% accurate for a 22-day ahead forecast. In contrast, PROPHET model yields reduced accuracy despite having more tuning parameters built into the system.

Results showed that, while the PROPHET is simple to set up and configure, it falls short of the performance of a well-established time-series forecasting model like ARIMA. Despite our best efforts to improve the accuracy of the PROPHET model, the inclusion of deep learning algorithm and Savitzky–Golay filter do not contribute much to the overall performance of the PROPHET model. Rather, we observe a significant increase in training time and computational resources for PROPHET with respect to ARIMA. Therefore, when needing a swift forecast (albeit less accurate) that can be of the order of one day, one could resort to the standard PROPHET model. Even with its flaws, PROPHET remains favorable because it is open-source and freely distributed software. It is open for collaboration, and anyone can submit pull requests to improve it further. On the contrary, we advocate employing our machine learning-based-ARIMA model, which provides highly accurate forecast results with minimal data pre-processing time. One limitation of our findings is that ARIMA needs model selection and fitting procedures, which may be undesirable to decision-makers who are unfamiliar with statistics.

We also remark that ARIMA—like PROPHET—is univariate. While multivariate forecast models such as Long Short–Term Memory (LSTM) and Convolutional Neural Network (CNN) may offer increased accuracy, it also requires much longer times for the hyperparameter tuning. Likewise, the dynamic effects of COVID-19 on the economy represents a rising challenge for researchers in identifying reliable multivariate datasets when employing such multivariate forecast models, corroborating the earlier stated finding by Butler et al. (2021). Despite the fact that we are using univariate forecasting, we believe that our machine learning-based forecasting models are capable of predicting not only crude oil prices but also commodities that have a high correlation with the oil market, such as gold, silver, and the US dollar (Barunik et al. 2016; Mensi et al. 2021). Our forecast models however may not be suitable to forecast stock markets due to the complexity and speculative-driven nature of these assets. The work done in this paper can be extended in several directions. First, it would be interesting to carry out a similar analysis for forecasting commodities subject to seasonal factors, for example, in forecasting firm level data such as sales volume, and profit volume. In this way, we can benchmark whether PROPHET is better than the ARIMA model. Second, we would like to incorporate our implemented version of PROPHET with the neural-network-based algorithm to estimate crude oil prices. A recent neural network-based PROPHET model may be used in a future model to estimate crude oil prices.

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