RESEARCH ARTICLE

Forecasting the price of crude oil

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Abstract Crude oil is the mixture of petroleum liquids and gases that is extracted from the ground by oil wells. It is an important source of fuel and is used in the production of several products. Given the important role price of the crude oil plays, it becomes extremely important for managers to predict future oil price while making operational decisions such as: when to purchase material, how much to produce and what modes of transportation to use. The goal of this paper is to develop a forecasting model to predict the oil prices that aid management to reduce operational costs, increase profit and enhance competitive advantage. We first analyze the primary theories related to the forecast of oil price followed by the reviews of two main streams of forecast theory, which are Target Capacity Utilization Rule (TCU) and Exhaustible Resources Theory. We implement a Target Capacity Utilization Rule recursive simulation model and test it on the historical data from 1987 through 2017 to

predict crude oil prices for 1991 through 2017. We tried several variations of the base model and the best method produced MAD, MSE, MAPE and MPE of 12.676, 280.92, 0.2597, 0.028, respectively. We further estimated the forecasts of the oil prices at a monthly level based on our yearly forecast of oil prices from our best method. The calculated MAD, MSE, MAPE and MPE values are 5.66, 82.1163, 0.1246 and 0.038, respectively, which shows our model is promising again at a monthly level.

Keywords Crude oil · Price · Forecasting · Simulation

Introduction

Crude oil is a mixture of hydrocarbons that exist in liquid phase in natural underground reservoirs and remain liquid at atmospheric pressure after passing through surface separating facilities. It is both an important source of fuel and a raw material for many products such as nylon, tires, CD cases and plastic and is present in almost all aspects of our lives and therefore, plays a significant role in how our economy changes. Thus, the changes in crude oil prices are often great indicators as to changes in the overall economy and global markets. However, forecasting the price of oil accurately is difficult across various time periods as there are a multitude of factors that can affect the prices of oil.

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As an example, during the US Recession of 2008, the housing crisis caused the price of crude oil to drop, rendering many forecasting models ineffective in predicting future changes. More recently, the onset of the COVID-19 pandemic in early March 2020 led to a significant decrease in demand for crude oil. When the representatives of OPEC + (the informal alliance of OPEC and non-OPEC countries) met to discuss oil production cuts, Russia, a non-OPEC member of the summit refused the demands to cut production, leading to an oil price war against OPEC countries, and in particular Saudi Arabia, causing the prices of crude oil to plummet dramatically.

These unpredictable actions and events can cause dramatic effects on the prices of crude oil, which in turn can affect the global economy and markets. The ability to forecast these changes in oil prices allows economic participants such as firms to adapt to future market changes and provides decision makers with accurate information with which they can use to select the optimal decision for them. As such, it is vital that we develop a robust model that can forecast the prices of oil and these changes as accurately as possible. To develop a model for forecasting crude oil price, we follow the below five steps in this paper. First, the primary theories related to the forecasting of oil price and its advantages and disadvantages are discussed. Second, the Target Capacity Utilization (TCU) rule is chosen as the framework to forecast the oil price. We present revisions to the application of TCU rule to fit to our experiments. Third, historical data from 1986 through 2017 are used to develop a multiple regression model. Fourth, combined with the multiple regression model, the recursive simulation method is used to generate predicted crude oil prices from 1991 through 2017. And finally, the results are compared to actual values to evaluate the accuracy of the developed forecast models.

Literature review

Many economists realized the necessity to formulate models that could accurately forecast the price of oil, following the oil embargo and the exploitation of the oil prices after the Arab–Israel conflict of 1973. Since then, multiple oil forecasting models have been published. This paper will extensively review one specific model, the Target Capacity Utilization Rule as well as other models. Our paper uses the TCU rule

with regression to forecast the crude oil prices with the data from 1987 to 2017. In addition, we develop several other new forecasting models in this paper.

Target capacity utilization rule

The basic idea of the Target Capacity Utilization (TCU) rule assumes that the Organization of Petroleum Exporting Countries (OPEC) can adjust the oil price according to its capacity utilization rate due to the world's dependency on oil supply from OPEC. When used to forecast oil price, the TCU rule is often combined with recursive simulation, one of the system simulation methods.

Although it makes economic sense, the application of it lacks sound economic theory as a foundation. Many economists can only explain the application of the TCU rule by the “rule of thumb.”

Baumol and Quandt (1964) pointed out that humans rarely behave as economic theories suggest. In contrast, their behaviors are largely influenced by experiences, an idea also noted by Sterman (1987, 1989). It is difficult to model human behavior. Moreover, the distortion, misuse, lagged dissemination, and different interpretation of information also violate the basic assumptions in traditional economic models. Therefore, the behaviors can be predicted if the experiences are understood. If the observed variables can be quantified, the procedure is easy, the cost is affordable, and the result can be replicated, the use of rule of thumb is a feasible way to predict behavior. Unlike an economic model, a rule of thumb is used to determine the function, not a best solution. This function is also called a behavior function under the system simulation method. Additionally, the system simulation method does not have the same assumptions that the economic models include, making more suitable for today's crude oil market (Powell 1990).

Although the behavior function derived from the TCU rule varies from model to model, most models use regression to capture the relationship between the change of oil price and the rate of capacity utilization (Energy Modeling Forum 1992). For instance, in the Oil Market Simulation Model, 1992 (OMS'92 Model) by the department of energy, and the Crude Oil Projection Model by Stanford Research Institute (1991), a general function: $\Delta P/P = \alpha + \beta \cdot (1/(1 - UT))$, where $\Delta P/P$ is the percentage change of price, UT is the capacity utilization rate, and α and β are

regression coefficients, is used to express the relationship. This function is also called the price reaction function.

The main flaw of the TCU rule is the lack of a strict mathematical inference procedure (Refer to Powell (1990), Gately (1983) and Suranovic (1993) for details). Powell (1990) suggests that more explanatory variables be included in the price reaction function to improve the predicting power. He further pointed that the result will vary considerably, if other parameters are used. While in agreement with the composition of the price reaction function, Bacon (1991) states that capacity utilization is not the only factor that concerns OPEC.

Suranovic (1993) examines the result from the system simulation model and from economic models, which use profit maximization as an objective. He found that by using system simulation to set the oil prices, the profit is smaller than that from an economic model. However, the difference is not significant after the profits are discounted. Furthermore, the forecasted prices generated from the economic model are highly variable, not as stable as those from the system simulation model. Thus, using the TCU recursive simulation model to forecast oil price is more appropriate than using an economic model.

Exhaustible resources theory

The Exhaustible Resources Theory plays an important role in the area of natural resources research. According to Houthakker (1983), the idea of exhaustible resources theory was first presented by Javon in 1865. However, the complete theoretical framework had not been developed until the method of calculus of variations was introduced by Hotelling (1931). Following the oil crisis in 1973, Solow used the principles of this related theory into research on oil markets.

The general idea of exhaustible resources theory is that as the stock of resources decrease and user costs, Hotelling Rent,¹ increase, the oil prices will increase.

¹ Hotelling rent, or scarcity rent, is the difference between the marginal cost of producing (extracting) a nonrenewable resource and the market price charged. In a seminal 1931 article in the *Journal of Political Economy*, Hotelling hypothesized that this scarcity rent would increase at the market rate of interest until a point in time when the resource is exhausted. This can be shown to be socially optimal (in the absence of market failures). This theory is known in resource economics as “Hotelling’s Rule.”

However, after the oil price dramatically decreased in 1986, forecast models based on exhaustible resources theory faced serious challenges. Devarajan and Fisher (1981) indicate that when the final production is based on future cost and price, the predicted cost and price should not be used to predict the usage of stock resource.

Powell (1990) also mentioned that exhaustible resources models emphasize the assumption of perfect information, but the uncertain future information does not satisfy this assumption. In addition, a typical exhaustible resources model often focuses on the long-term outcomes and cannot explain short to midterm unrealistic outcomes in the model.

Adelman (1990) states that from an economic point of view, high cost will reduce the investment on the resources or even the abandoning of their use. Moreover, through his knowledge of oil production, he found that as the difficulty of extracting oil increases, it is the increasing marginal cost, not “Hotelling Rent,” which will cause oil price to rise. Most importantly, oil prices rarely follow the predictions of the exhaustible resources model.

Other forecasting models

Alquist et al. (2011) sought a reliable forecasting model for real and nominal oil prices in order to benefit all oil-importing and exporting countries. For nominal prices, they tested a wide range of methods and focused on the ability of monthly and daily oil futures prices to forecast the nominal price. For the real price, they considered alternative methods of forecasting like random walk, AR and ARMA models, and the no-change forecast and tried to prove that vector autoregressive models (VAR) are more accurate than the random-walk forecast and others at short horizons.

The results of the paper exhibit the difficulty to reconcile the different results of the literature. They realized that there are many parameters, such as the definition of the oil price variable, whether one used nominal or real prices, the time periods of evaluation, how the forecast accuracy is evaluated, etc. However, the paper provided strong evidence that the nominal oil price predictability was consistent with economic theory. They also found that over a short horizon, a specifically designed VAR model was more accurate than the no-change forecast.

Alquist et al. (2011) realized that one reason for the importance of oil is its perceived predictive power for US real GDP. They showed that there are only small gains in using the price of oil in forecasting cumulative real GDP growth from VAR models and is useful in finding out whether the price of oil is specified in nominal or in real terms and whether it is treated as exogenous or endogenous. Alquist et al. (2011) also state that linear autoregressive models fail to predict major economic downturns. They claimed that a possible explanation of this forecast failure is that the predictive relationship is nonlinear, so they tested multiple nonlinear joint forecasting models and found that they did not substantially improve forecast accuracy for the real GDP growth. They also found that one should be skeptical of the forecasting success of the nonlinear models during the 2008–2009 financial crisis, as the results suggested that the crisis did not help with the economic decline, which is highly improbable. Lastly, they proved that using structural forecasting models for the real price of oil would provide no insight into what drives the forecast and would not permit the policymaker to explore alternative hypothetical forecasting scenarios, which the VAR models provide.

Other researchers like Kulkarni and Haidar (2009) wanted to find the crude oil spot price in the short-term, three days ahead using the optimal ANN model to reduce the negative impact of the price fluctuations. They used previous research from Moshiri and Foroutan (2005) to rule out the usage of ARMA and GARCH models. Another option they considered was a combination model that includes ANN, ARIMA, and Web mining proposed by Wang et al (2005). They realized that this model would not work because it depended on the knowledge base of human experts, inducing heavy unreliability in the model. Additionally, neither the rules nor the knowledge base were made public. Kulkarni and Haidar (2009) found that applying 3 days simple moving average to the original data, then transforming it into relative change is the best method among the others tested.

Forecasting Brent oil price

Manescu and Van Robays (2014) wanted to forecast the prices of Brent oil rather than the prices of crude oil as they believed that Brent oil pricing is the current benchmark and is monitored more by central banks

than crude prices. Along with that, they wished to find the sensitivity of the forecast accuracies. They did so by assessing the forecasting performance of nine different methods and documented the important time-variation in each performance. Lastly, they proposed the ideal forecast combination for Brent oil pricing, which was a four model combination of the futures, the risk-adjusted futures, a Bayesian VAR model and a DGSE model of the oil market. They also found that none of the individual forecasting methods could consistently predict the Brent oil prices better than the futures or random-walk methods over time or forecast horizons. Using this information, the authors were able to form a forecast combination that is more accurate across horizons and more robust. Their four model combination performed better than the futures, the random walk, and the other individual models up to 11 quarters ahead and would produce a forecast whose performance was remarkably robust over time.

Beckers and Beidas-Strom (2015) decided in their paper to forecast the nominal price of oil rather than the real price due to the direct interest to the IMF forecasts. Forecasters have since used futures to predict the price of oil, but with the recent VAR models, practitioners have alternate methods for forecasting in short to medium terms. As a result, their paper wanted to find the ideal VAR model for the purpose of oil prediction. The results they obtained showed that in the short-term (1–12 months), the VAR models performed far better than the futures and random-walk models, but in the medium term (12–24 months), the futures model outperformed all the other models. During the short term, the futures model performed far worse than all other models because its high bias led to severe underprediction of its forecast. Over the full sample, the VAR models suffered from instability of small alterations to the specifications, subsamples, and lag lengths. The performance of the various models was dependent on the time period. The random walk worked better at stable prices, while the VAR performed better after the stock market collapse of 2008. Because of all these differences, Becker and Beidas-Strom (2015) concluded that forecasting the prices over a long sample is very difficult to do.

Recent research

More recently, Dritsaki (2018) found that a certain configuration of a hybrid ARIMA-GARCH model was the most suitable for forecasting the returns of oil prices over a short term. He had decided on a hybrid model as he had noticed that the models individually could not handle the nonlinearity and volatility of the data. Since the ARIMA model was a robust linear model and the nonlinear GARCH model was powerful at handling volatility and risk return of oil price, he found that combining them created an accurate short-term oil price forecasting model.

Funk (2018) tested many forecasting models and combinations of models to determine what combination of individual models is beneficial for the forecasting performance. He used the no-change benchmark (denoted RW in his paper), AR and ARMA models (AR and ARMA), the Futures model (Futures), forecasts based on crude oil inventories (Inventories OECD), a VAR model of the global oil market (VAR CLI), and a non-oil industrial raw materials real-time forecast (CRB Index), and watched price movements with oil sensitive stocks (Oil Stock). In all, he found that individually, the Futures model had the most gains in lowering the MSPE ratio and was substantially better than the no-change benchmark. However, he found that a combination consisting of four models, Futures, Inventories OECD, VAR CLI, and CRB Index showed lower MSPE ratios than the best individual models and therefore concluded that the combination would be the most reliable in forecasting crude oil prices.

An et al. (2019) used a machine learning approach to predict oil price. Their results stated that the price of oil was most affected by the US Federal Reserve rates and the US dollar index, and that factors such as instability in the Middle East had little to no effect on the prices of oil through their machine learning-based model. Al-Fattah (2019) used a hybrid approach of artificial intelligence with a genetic algorithm (GA), artificial neural network (ANN), and a datamining time series (DMTS) to construct a GANNATS model to forecast the prices of West Texas Intermediate crude oil. He found that his model closely matched the historical data of WTI futures price volatility and demonstrated capability in predicting the direction of crude oil price movements.

The examination of TCU rule

Published by Stanford University in 1992, International Oil Supplies and Demand—Energy Modeling Forum (1992) researched eleven popular oil price forecast models. Among these, nine use the TUC rule combined with the recursive simulation method to forecast oil price. It is clear that the TCU rule has become the standard in forecasting oil price.

The economic meaning of TCU rule

The concept of the TCU rule came from Forchheimer's dominant-firm model in oligopoly theory.

In this model, OPEC is the core firm and plays the role of price leader. Other non-OPEC entities are small players and they compete with each other. They cannot decide the market price by themselves and hence, follow the price set by the core firm. After their supply is subtracted from total demand, the residual demand can be estimated. The core firm will then use the residual demand to set the market price based on maximizing profit.

This static model does not match the response of the dynamic market place (Carlton and Perloff 1990 and Scherer and Ross 1990). In reality, the market condition varies every minute. It is difficult for OPEC to estimate its revenue and cost at earlier stages. Instead of setting a price that will maximize their profit at earlier stages, setting an acceptable price dynamically is a better way to represent OPEC's behavior, Tussing and Harris (1992). As the change in price will alter current and future world demand and non-OPEC's supply, the TCU rule should be used with a recursive simulation model to forecast the oil price.

Application of the TCU rule

The world demand for crude oil depends heavily on OPEC which has a cost advantage in oil production, and thus OPEC has the ability to control the world's oil price Adelman (1990, 1993). Based on this phenomenon, the idea behind the TCU rule is as follows. If world demand for crude oil increases, forcing OPEC's capacity to approach its limit, OPEC will have a stronger influence over the oil price and thus will raise it. In contrast, if the world demand decreases, the price will drop. In other words, OPEC's capacity utilization rate can be viewed as an indicator

of the change in world oil price. This idea can be converted to the equation:

$$\Delta P/P = \alpha + \beta(1/(1-UT)) \quad (1)$$

where $\Delta P/P$ is the percentage change of price, UT is the capacity utilization rate, and α and β are regression coefficients. This equation is the so-called price reaction function. The capacity utilization rate (UT) can be computed by dividing demand on OPEC's production by OPEC's capacity.

And the demand on OPEC's production (D^{OPEC}) can be computed by subtracting non-OPEC's supply ($S^{\text{non-OPEC}}$) from world demand (D^{world}), as shown through those two equations;

$$D^{\text{OPEC}} = D^{\text{world}} - S^{\text{non-OPEC}} \quad (2)$$

and

$$UT = D^{\text{OPEC}}/\text{Capacity} \quad (3)$$

Figure 1 illustrates the process of forecasting oil price using the TCU recursive simulation model.

In general, the price in the previous period is set as the initial price (PR). For world demand and non-OPEC's supply, there are different ways to compute these in different models. After world demand and non-OPEC's supply are known, the OPEC's capacity utilization rate, the percentage change of price and, thus, the current oil price (PS) can be calculated. If PS is not equal to PR, then PR will be set to PS and the whole process is repeated until PS is equal to PR. This PS is the final prediction of current oil price.

The examination of the price reaction function

The price reaction function implies that when the capacity utilization rate approaches one, the oil price will approach infinity. This phenomenon does not coincide with reality. During the simulation, if the price is so low that the demand on OPEC's production is over the capacity, the oil price will start to decrease. This is another unreasonable phenomenon. In addition to the unreasonable outcomes, there are some disadvantages of using capacity utilization rate. First, the estimate of capacity is not so easy because it involves the various issues of technology, geology, market price, and cost. Moreover, the exact volume of capacity is confidential and hence general researchers

cannot gather this information easily. And usually, the producers adjust its capacity according to market demand and supply. However, in the TCU recursive simulation model, the capacity is viewed as a parameter, which does not relate to market demand and supply.

The revision of price reaction function

Because of all the reasons mentioned before, some revisions of the price reaction function will be made. As shown in Eq. 3, the capacity utilization rate can be computed by dividing demand on OPEC's production by capacity. Moreover, OPEC will adjust its capacity according to previous and current market demand. Thus, the demand on OPEC's production in the current and previous periods must play an important role in the determination of oil price. Replacing capacity utilization rate by demand on OPEC's production has some advantages; Compared to the estimate of capacity, the estimate of demand on OPEC's production is relatively simple. As shown in Eq. 2, the demand on OPEC's production can be computed by subtracting non-OPEC production from world demand. Also using demand on OPEC's production in the price reaction function can solve the problem of viewing capacity as a parameter. To replace the capacity utilization rate, the original price reaction function will be revised into the following equation.

$$\Delta P/P_{t-1} = \alpha + \beta_1 (D_{t-1}^{\text{OPEC}}) + \beta_2 (D_t^{\text{OPEC}}) \quad (4)$$

where D_{t-1}^{OPEC} is last period's demand on OPEC's production, D_t^{OPEC} is current period's demand on OPEC's production, and α , β_1 , and β_2 are regression coefficients. Using historical data² from year 1987 to 2017, the regression coefficients can be calculated. The regression results are shown in Table 1.

As one can see in Table 1, the explanatory power of predictors is only 5.65%.

Hence, more revisions need be made. In Eq. 4, $\Delta P/P_{t-1}$ can be decomposed into $(P_t - P_{t-1})/P_{t-1}$. If P_{t-1} is moved from the left side of the equation to the right side, viewing P_{t-1} as another predictor variable, the new equation can be re-written as

² The average F.O.B. cost of crude oil from all OPEC countries is used as the crude oil price. All prices have been adjusted to US dollars.

Fig. 1 Flowchart of TCU recursive simulation model

Table 1 Summary of regression result—Eq. 4 (1987–2017)

Predictor	Coefficients
Intercept	0.017801673
Demand OPEC (t)	5.3124E–05
Demand OPEC ($t - 1$)	– 5.2402E–05
R-squared	0.056480549

Table 2 Summary of regression result—Eq. 5 (1987–2017)

Predictor	Coefficients
Intercept	– 22.00949477
Demand OPEC (t)	0.002908871
Demand OPEC ($t - 1$)	– 0.001796465
Price ($t - 1$)	0.763724436
R-squared	0.817352292

$$P_t = \alpha + \beta_1(P_{t-1}) + \beta_2(D_{t-1}^{\text{OPEC}}) + \beta_3(D_t^{\text{OPEC}}). \quad (5)$$

The regression result is summarized in Table 2. As one can see, the explanatory power dramatically increased from 5.65 to 81.74%. This may be caused by some unusual observations.

After historical data have been reviewed, three unusual observations were found. In 1990, there was a spike in the price of crude oil due to the uncertainty associated with Iraq's invasion of Kuwait and the resulting Gulf War. Recession in 2008, and again recession at a smaller scale in 2015 contributed to uncertainty in crude oil prices.

The increase or decrease of crude oil price in these years is caused by many factors other than price, demand, and supply. Because these factors are not included in Eq. 5 as explanatory variables, the data in these years should be excluded. The regression result excluding data in 1990, 2008, and 2015 is shown as follows: As you can see in Table 3, the explanatory power increased from 81.74 to 90.19%. This result is quite acceptable. Therefore, Eq. 5 will be used as the new price reaction function. This equation, combined with coefficients in Table 3, will then be used in our crude oil price forecast model.

The crude oil price forecast model

In the previous section, the TCU rule has been examined and revisions of the price reaction function have been made. To forecast the crude oil price, two more equations are required. One is to calculate the world demand, and the other is to calculate the non-OPEC's supply.

World demand function

Equation 5 was obtained through a process of trial and error. In this process, all possible predictor variables and their transformation forms³ were first put together. Then, all possible combinations of these variables were used in multiple regression analysis and their explanatory powers were recorded. Finally, the combination with the highest explanatory power was selected. The process may not be mathematically justified. The composition of Eq. 5 may lack appropriate explanation and support from economic theory. However, as mentioned earlier, the purpose of the TCU recursive simulation model is to predict human behavior. Therefore, as long as the behavior pattern can be captured and the observed variables can be quantified, this process can be regarded as a method to predict oil price.

To obtain the world demand function, the same process is used. Using historical data from years 1987 through 2017, excluding unusual observations,⁴ the regression result is summarized in Table 4, and the world demand function can be written as

$$D_t^{\text{world}} = \alpha + \beta_1(P_t) + \beta_2(1/P_t) + \beta_3 \ln(D_{t-1}^{\text{world}}) \quad (6)$$

where P_t is current oil price, D_t^{world} is current world demand, and D_{t-1}^{world} is world demand in previous period.

³ When there is a nonlinear relationship between dependent and independent variables, the transformation of independent variable can be employed so that the resulting relationship with the dependent variable is linear. Four of the most common transformations used to generate new independent variables are the reciprocal, the log, the square root and the square.

⁴ As mentioned earlier, the increase or decrease of crude oil price in years 1990, 2008, and 2015 is caused by factors that are not used as predictor variables in the multiple regression model. Therefore, these unusual observations should be excluded from the multiple regression analysis.

Table 3 Summary of regression result—Eq. 5 (excluding unusual observations) Years: 1990, 2008, 2015

Predictor	Coefficients
Intercept	− 21.6609319
Demand OPEC (t)	0.003532678
Demand OPEC ($t - 1$)	− 0.002558957
Price ($t - 1$)	0.853754153
R-squared	0.901956471

Table 4 Summary of regression result—Eq. 6 (1987–2017)

Predictor	Coefficients
Intercept	− 657,562.0139
Price (t)	− 1.657597015
Ln demand ($t - 1$)	65,358.55041
$1/P(t)$	− 13,351.50338
R-squared	0.975315889

As one can see in Table 4, the explanatory power is 97.35%. The result is thus acceptable. Thus, Eq. 6 will be used as world demand function in the forecast model.

Non-OPEC's supply function

To obtain non-OPEC's supply function, the same process and data set is used. The summary of regression result is presented in Table 5, and non-OPEC's supply function can be written as

$$S_t^{\text{non-OPEC}} = \alpha + \beta_1(P_t) + \beta_2(S_{t-1}^{\text{non-OPEC}}) \quad (7)$$

where $S_t^{\text{non-OPEC}}$ is current non-OPEC's supply and $S_{t-1}^{\text{non-OPEC}}$ is the supply in the last period.

The predictor variables explained most the variation of dependent variable, non-OPEC's supply. Thus, there should be no hesitation to use Eq. 7 as the non-OPEC's supply function in the forecast model.

Basic assumptions

Before the forecast process starts, some basic assumptions need to be reviewed. Firstly, the crude oil price is

Table 5 Summary of regression result—Eq. 7 (1987–2017)

Predictor	Coefficients
Intercept	70.66790116
Non-OPEC production ($t - 1$)	0.99793886
Price (t)	5.51108737
R-squared	0.950371597

heavily influenced by OPEC. According to Forchheimer's dominant-firm model, because of OPEC's production advantage, OPEC has the power to decide the crude oil price; non-OPEC can only follow the price set by OPEC. Secondly, the indicators of crude oil price should be considered.

OPEC should play the role of price leader. As discussed in previous sections, current demand on OPEC's production, last period's demand on OPEC's production, and last period's crude oil price should be the only indicators of crude oil price. Also, markets can respond fully and immediately. Because the forecast model is a dynamic system simulation model, it must be assumed that once a price is given, the market demand and supply can be determined immediately. Before the market achieves equilibrium, excess demand caused by price that is too low or excess supply caused by price that is too high will keep supplier and consumer adjusting their production and consumption behaviors until the market achieves equilibrium.

Forecasting annual crude oil price

In this section, Eqs. 5, 6, and 7 are used in the forecast model to predict crude oil price. We illustrate the model in Fig. 2. We experimented with four different methods (**Method 1, Method 2, Method 3 and a Combination Method**). The flowchart below demonstrates our methodology of using the coefficients and equations to calculate the forecasted price for the next year. However, the equations and steps to derive the forecasted value are the same for all methods.

An example to forecast crude oil price in year 2017 in Microsoft Excel is presented following the discussion of the flowchart in Fig. 2.

In all tables where forecasts were presented using the above methods (Method 1, Method 2, Method 3

and a Combination Method), the notation “DNE” refers to “Does not Exist.”

As the forecast is reported only from 1991 to 2017 in our analysis, we report forecasts from 1986 to 1990 as DNE.

The following is an example of using Microsoft Excel to forecast the crude oil price in 2017 with the coefficients from Method 1. All calculations for forecast are the same with every method, and it is simply that the process of deriving the coefficients of the equation is different for each method and will lead to different coefficients:

- Step 1 Enter the predictor variables of the previous period. Since we are forecasting the price of crude oil for 2017, the previous period would be 2016. As a result, the predictor values would be the price (43.1451923959272), world demand (80,841.606), the Non-OPEC Production (45,226.765), and demand OPEC (35,614.841).
- Step 2 Set the initial price PR to the actual price of the previous period, in this case 2016. As a result, PR = 43.1451923959272.
- Step 3 Using Eq. 6, calculate the World Demand of crude oil using the actual world demand of the previous 2016 period. As a result, the forecasted World Demand of 2017 should be $80,624.77925 = -657,562.013925192 + (-1.65759701517087 * 43.1451923959272) + (65,358.5504135525 * \ln(80,841.606) + (-13,351.5033831124 * 1/43.1451923959272))$.
- Step 4 Using Eq. 7, calculate the non-OPEC's supply using non-OPEC's supply from the previous 2016 period. As a result, the forecasted non-OPEC's supply of 2017 should be $45,441.99115 = 70.66790116 + (0.99793886 * 45,226.77) + (5.51108737 * 43.1451923959272)$.
- Step 5 Using the results from Steps 3 and 4 as well as Eq. 2, calculate the demand of OPEC production. As a result, the demand for OPEC production in 2017 should be $35,182.79 = 80,624.77925 - 45,441.99115$.

Step 6 Using the demand for OPEC production from Step 5, the demand for OPEC production from the previous period, PR, and Eq. 5, we can calculate the PS, or the current crude oil price. As a result, PS should be $48.32707271 = -21.6609319036754 + (0.00353267816445286 * 35,182.79) + (-0.0025589570889436 * 35,614.841) + (0.853754152644323 * 43.1451923959272)$.

Step 7 As we can see, PR = 43.1451923959272 and PS = 48.32707271. Since PR does not equal PS, PR will be set to PS, so PR = 48.32707271, and the steps will be run through repeatedly until PR = PS. In the end, with the coefficients from Method 1, the final PS of 2017 is 76.1074395660732. So, the forecasted crude oil price of 2017 is 76.1074395660732.

Method 1

We ran a regression on all the data from 1987 to 2017 in order to come up with the coefficients for each of these equations. As a result, the coefficients that are in the tables are the only set of coefficients used for the forecasting.

$$\Delta P/P_{t-1} = \alpha + \beta_1 (D_{t-1}^{\text{OPEC}}) + \beta_2 (D_t^{\text{OPEC}}) \quad (4)$$

See Table 1.

$$P_t = \alpha + \beta_1 (P_{t-1}) + \beta_2 (D_{t-1}^{\text{OPEC}}) + \beta_3 (D_t^{\text{OPEC}}). \quad (5)$$

See Tables 2 and 3.

$$D_t^{\text{world}} = \alpha + \beta_1 (P_t) + \beta_2 (1/P_t) + \beta_3 \ln(D_{t-1}^{\text{world}}) \quad (6)$$

See Table 4.

$$S_t^{\text{non-OPEC}} = \alpha + \beta_1 (P_t) + \beta_2 (S_{t-1}^{\text{non-OPEC}}) \quad (7)$$

See Table 5.

The forecasted values obtained using **Method 1** are given in the below table. As stated earlier, DNE refers to “Does not Exist.”

Fig. 2 Flowchart of annual crude oil price forecast model

Year	Actual	World demand	Non-OPEC production	Demand OPEC	Forecasted price
1986	15.03	56,325.61	38,453.61	17,872	DNE
1987	19.17	56,650.07	38,640.75	18,009.32	DNE
1988	15.98	58,696.86	38,652.86	20,044	DNE
1989	19.64	59,801.83	38,023.25	21,778.59	DNE
1990	24.47	60,496.75	37,563.68	22,933.07	DNE
1991	21.50	60,127.63	37,255.58	22,872.05	25.34403
1992	20.56	60,100.2	35,897.92	24,202.28	23.49511
1993	18.45	60,172.95	35,210.09	24,962.86	34.72071
1994	17.19	61,173.47	35,783.9	25,389.57	40.22087
1995	18.44	62,433.68	36,376.1	26,057.58	44.98176
1996	22.11	63,818.23	37,228.31	26,589.92	51.01424
1997	20.61	65,805.95	37,856.04	27,949.92	55.51825
1998	14.45	67,031.77	37,985.36	29,046.41	64.28711
1999	19.26	65,967.39	38,064.91	27,902.49	70.48958
2000	30.30	68,526.65	38,820.06	29,706.59	63.97958
2001	25.95	68,131.91	39,296.32	28,835.6	73.32451
2002	26.11	67,290.17	40,112.02	27,178.15	68.49023
2003	31.12	69,460.24	40,788.42	28,671.83	59.08099
2004	41.44	72,595.18	41,323.25	31,271.93	66.11404
2005	56.49	73,869.21	41,096.58	32,772.63	76.30616
2006	66.02	73,621.39	41,138.02	32,483.37	82.25424
2007	72.32	73,330.83	41,094.98	32,235.84	81.14913
2008	99.57	74,301.01	40,578.15	33,722.85	80.37065
2009	61.65	73,120.57	41,053.98	32,066.59	86.75108
2010	79.40	74,887.25	41,839.47	33,047.78	79.8512
2011	94.88	74,908.39	41,779.05	33,129.34	81.26497
2012	94.11	76,367.46	42,023.42	34,344.04	81.68731
2013	97.91	76,448.82	43,154.69	33,294.13	84.62633
2014	93.26	78,361.77	45,021.37	33,340.39	78.20684
2015	48.69	80,755.05	46,186.55	34,568.5	72.12382
2016	43.15	80,841.61	45,226.77	35,614.84	70.24915
2017	50.88			35,467.53	76.10744

Method 2

We ran a regression on all the data from 1986 to 1990 to get the coefficients for Eqs. 5, 6, and 7 mentioned in

the example forecast with Method 1 for 1991. From there, we incremented the year by one and added the previous year's data to the data that was used in the regression. For example, the coefficients for 1992

were from a regression of the data from 1986, 1987, 1988, 1989, 1990, and 1991. The coefficients for 2017 were from a regression of the data from 1986 to 2016. When forecasting the price of crude oil for a certain year with Method 2, the coefficients used were the coefficients that were associated with the previous

year. For example, forecasting the price of crude oil for year 1992 will use the coefficients for 1991.

$$P_t = \alpha + \beta_1(P_{t-1}) + \beta_2(D_{t-1}^{\text{OPEC}}) + \beta_3(D_t^{\text{OPEC}}). \quad (5)$$

Year	Intercept	Demand OPEC (t)	Demand OPEC ($t - 1$)	Price ($t - 1$)	R-squared
1991	5.198102	– 0.00098	0.002069	– 0.35896	1
1992	6.677646	– 0.00107	0.002066	– 0.339	0.991835
1993	14.40669	– 0.00107	0.001382	– 0.03405	0.493459
1994	17.40085	– 0.0009	0.0008	0.235676	0.284812
1995	17.30478	– 0.0009	0.00081	0.225707	0.290868
1996	15.23411	– 0.00089	0.000987	0.137695	0.246331
1997	13.78803	– 0.00072	0.000859	0.159763	0.266174
1998	18.96838	– 0.00121	0.001094	0.196801	0.153403
1999	18.80984	– 0.00114	0.001008	0.215022	0.153484
2000	10.84204	0.001014	– 0.00067	– 0.00674	0.118157
2001	6.458585	0.000427	– 8.3E–05	0.256301	0.210529
2002	6.250947	– 1.9E–05	0.000349	0.307606	0.278247
2003	0.90667	0.000658	– 0.00024	0.46844	0.362239
2004	– 7.8645	0.001817	– 0.00128	0.727879	0.587846
2005	– 14.3536	0.001984	– 0.00149	1.097245	0.780625
2006	– 14.4942	0.001873	– 0.00141	1.151682	0.884085
2007	– 14.7638	0.001959	– 0.00145	1.099958	0.925201
2008	– 14.7638	0.001959	– 0.00145	1.099958	0.925201
2009	– 24.9569	0.003311	– 0.00201	0.637088	0.825986
2010	– 29.6232	0.004208	– 0.00279	0.702558	0.834277
2011	16.00549	0.001968	0.001964	0.133701	0.854656
2012	– 30.4922	0.004448	– 0.00308	0.792459	0.88501
2013	– 29.6161	0.004114	– 0.00281	0.830278	0.900323
2014	– 29.8075	0.004099	– 0.00278	0.823033	0.912469
2015	– 29.8075	0.004099	– 0.00278	0.823033	0.912469
2016	– 20.7537	0.003546	– 0.00262	0.859233	0.901773

$$D_t^{\text{world}} = \alpha + \beta_1(P_t) + \beta_2(1/P_t) + \beta_3 \ln(D_{t-1}^{\text{world}}) \quad (6)$$

Year	Intercept	Price (t)	Ln demand ($t - 1$)	$1/P(t)$	R-squared
1991	– 590,794	958.6609	55,440.24	438,617.3	0.914016
1992	– 570,686	1019.849	53,408.99	456,913.5	0.917362
1993	– 529,888	1068.156	49,587.72	459,771	0.913784
1994	– 550,451	1094.031	51,330.45	477,943.4	0.928264
1995	– 613,039	996.1872	57,308.24	457,147.6	0.916873
1996	– 685,904	1091.293	63,642.25	486,003.6	0.914104
1997	– 766,919	1016.363	71,238.52	467,800.1	0.929635
1998	– 637,854	150.3882	62,820.44	89,563.87	0.939271
1999	– 582,852	517.1611	56,537.73	222,145	0.934024
2000	– 590,117	706.3997	56,569.36	284,178.2	0.951216
2001	– 571,105	722.1395	54,754.36	296,557	0.956574
2002	– 554,407	728.4099	53,183.34	305,333.1	0.955725
2003	– 554,251	747.9182	53,101.28	312,347.3	0.962784
2004	– 567,345	418.9849	55,511.97	178,630	0.965195
2005	– 584,512	114.9131	58,289.29	36,462.21	0.954165
2006	– 592,837	24.78802	59,431.34	– 11,064.3	0.953217
2007	– 598,510	– 2.91539	60,068.63	– 26,510.3	0.956858
2008	– 595,893	3.776775	59,798.13	– 22,004.6	0.961927
2009	– 586,095	4.658961	58,894.43	– 19,031.6	0.961946
2010	– 583,607	11.34089	58,644.43	– 16,427	0.964079
2011	– 583,949	6.675203	58,702.08	– 20,300.5	0.966742
2012	55,983.49	21.19092	5002.125	35,527.19	0.96904
2013	– 582,975	11.1244	58,590.24	– 17,008.3	0.971515
2014	– 588,110	16.86857	59,015.24	– 10,626.8	0.972326
2015	– 641,470	1.905646	63,896.4	– 14,044.8	0.969978
2016	– 651,193	– 0.28337	64,779.66	– 13,553.1	0.972959

$$S_t^{\text{non-OPEC}} = \alpha + \beta_1(P_t) + \beta_2(S_{t-1}^{\text{non-OPEC}}) \quad (7)$$

Year	Intercept	Non-OPEC production ($t - 1$)	Price (t)	R-squared
1991	10,030.07	0.774753	– 81.8824	0.816474
1992	– 23,743.3	1.612909	– 1.65425	0.844339
1993	– 9220.11	1.257628	– 48.9493	0.901768
1994	2401.882	0.977552	– 96.5621	0.840716
1995	5527.834	0.898684	– 101.697	0.813502
1996	7745.215	0.810134	– 40.8787	0.726127
1997	7659.028	0.808499	– 29.8292	0.696327
1998	7586.125	0.815514	– 38.8999	0.709374
1999	7210.478	0.826384	– 39.4444	0.718787
2000	5209.664	0.844991	30.12606	0.713394
2001	3988.66	0.873058	40.02221	0.751543
2002	1995.388	0.921447	50.72065	0.793232
2003	1430.173	0.933924	55.81661	0.844306
2004	1768.546	0.931979	42.84179	0.87895
2005	714.371	0.979264	8.783592	0.881328
2006	201.2863	0.996499	2.521949	0.895189
2007	– 137.934	1.00737	– 0.66393	0.905012
2008	– 1286.83	1.041661	– 6.89937	0.908175
2009	– 1414.98	1.04461	– 5.81319	0.912077
2010	– 1092.66	1.034037	– 2.35854	0.915165
2011	– 1164.04	1.036402	– 3.08264	0.922112
2012	– 1100.49	1.034318	– 2.46776	0.928433
2013	– 823.294	1.024907	0.601758	0.930688
2014	– 2624.28	1.072095	0.779161	0.932088
2015	– 4217.77	1.115893	– 1.82093	0.946349
2016	318.654	0.991142	5.889455	0.943537

The forecasted values obtained using **Method 2** are given in the below table. As stated earlier, **DNE** refers to “Does not Exist.”

Year	Actual	World demand	Non-OPEC production	Demand OPEC	Forecasted price
1986	15.03	56,325.61	38,453.61	17,872	DNE
1987	19.17	56,650.07	38,640.75	18,009.32	DNE
1988	15.98	58,696.86	38,652.86	20,044	DNE
1989	19.64	59,801.83	38,023.25	21,778.59	DNE
1990	24.47	60,496.75	37,563.68	22,933.07	DNE
1991	21.50	60,127.63	37,255.58	22,872.05	DNE
1992	20.56	60,100.2	35,897.92	24,202.28	21.94895
1993	18.45	60,172.95	35,210.09	24,962.86	21.54681
1994	17.19	61,173.47	35,783.9	25,389.57	20.28092

continued

Year	Actual	World demand	Non-OPEC production	Demand OPEC	Forecasted price
1995	18.44	62,433.68	36,376.1	26,057.58	19.03475
1996	22.11	63,818.23	37,228.31	26,589.92	18.89789
1997	20.61	65,805.95	37,856.04	27,949.92	19.88638
1998	14.45	67,031.77	37,985.36	29,046.41	19.6061
1999	19.26	65,967.39	38,064.91	27,902.49	17.73101
2000	30.30	68,526.65	38,820.06	29,706.59	18.97899
2001	25.95	68,131.91	39,296.32	28,835.6	20.67131
2002	26.11	67,290.17	40,112.02	27,178.15	21.76323
2003	31.12	69,460.24	40,788.42	28,671.83	21.98432
2004	41.44	72,595.18	41,323.25	31,271.93	22.87479
2005	56.49	73,869.21	41,096.58	32,772.63	Did not Converge
2006	66.02	73,621.39	41,138.02	32,483.37	Did not Converge
2007	72.32	73,330.83	41,094.98	32,235.84	Did not Converge
2008	99.57	74,301.01	40,578.15	33,722.85	Did not Converge
2009	61.65	73,120.57	41,053.98	32,066.59	Did not Converge
2010	79.40	74,887.25	41,839.47	33,047.78	46.80165
2011	94.88	74,908.39	41,779.05	33,129.34	55.37141
2012	94.11	76,367.46	42,023.42	34,344.04	171.5954
2013	97.91	76,448.82	43,154.69	33,294.13	1704.521
2014	93.26	78,361.77	45,021.37	33,340.39	73.22561
2015	48.69	80,755.05	46,186.55	34,568.5	42.64115
2016	43.15	80,841.61	45,226.77	35,614.84	56.01625
2017	50.88			35,467.53	73.90768

Method 3

We ran a regression on all the data from 1986 to 1990 to get the coefficients for Eqs. 5, 6, and 7 mentioned in the example forecast with Method 1 for 1991. From there, we incremented the year by one and ran a regression of the previous 5 years' data in order to get the coefficients for Eqs. 5, 6, and 7. For example, the coefficients for 1992 were from a regression of the data from 1987, 1988, 1989, 1990, and 1991. The coefficients for 2017 were from a regression of the

data from 2012 to 2016. When forecasting the price of crude oil for a certain year with Method 3, the coefficients used are the coefficients that were associated with the previous year. For example, forecasting the price of crude oil for year 1992 would use the coefficients for 1991.

$$P_t = \alpha + \beta_1(P_{t-1}) + \beta_2(D_{t-1}^{\text{OPEC}}) + \beta_3(D_t^{\text{OPEC}}). \quad (5)$$

Year	Intercept	Demand OPEC (t)	Demand OPEC ($t - 1$)	Price ($t - 1$)	R-squared
1991	5.198102	– 0.00098	0.002069	– 0.35896	1
1992	6.677646	– 0.00107	0.002066	– 0.339	0.991835
1993	14.40669	– 0.00107	0.001382	– 0.03405	0.493459
1994	17.40085	– 0.0009	0.0008	0.235676	0.284812
1995	17.30478	– 0.0009	0.00081	0.225707	0.290868
1996	15.23411	– 0.00089	0.000987	0.137695	0.246331
1997	13.78803	– 0.00072	0.000859	0.159763	0.266174
1998	18.96838	– 0.00121	0.001094	0.196801	0.153403
1999	18.80984	– 0.00114	0.001008	0.215022	0.153484
2000	10.84204	0.001014	– 0.00067	– 0.00674	0.118157
2001	6.458585	0.000427	– 8.3E–05	0.256301	0.210529
2002	6.250947	– 1.9E–05	0.000349	0.307606	0.278247
2003	0.90667	0.000658	– 0.00024	0.46844	0.362239
2004	– 3.73584	0.003224	– 0.00254	0.488824	0.871768
2005	58.81733	0.001254	– 0.00463	2.418189	0.938083
2006	– 87.531	0.003058	0.000419	0.720866	0.997704
2007	– 87.9475	0.002327	0.001291	0.651156	0.998461
2008	– 87.9475	0.002327	0.001291	0.651156	0.998461
2009	– 48.9632	– 0.00748	0.011858	– 0.4684	0.829242
2010	– 755.646	0.019426	0.005797	0.044272	0.308865
2011	– 710.137	0.025221	– 0.00156	0.196666	0.791732
2012	– 2282.41	0.023753	0.053359	– 2.18053	0.999798
2013	– 1022.47	0.017133	0.018577	– 0.91076	0.903998
2014	– 124.216	0.000723	0.005362	0.164194	0.838836
2015	– 124.216	0.000723	0.005362	0.164194	0.838836
2016	477.2234	– 0.00932	– 0.00378	0.617744	0.958748

$$D_t^{\text{world}} = \alpha + \beta_1(P_t) + \beta_2(1/P_t) + \beta_3 \ln(D_{t-1}^{\text{world}}) \quad (6)$$

Year	Intercept	Price (t)	Ln demand ($t - 1$)	$1/P(t)$	R-squared
1991	– 590,794	958.6609	55,440.24	438,617.3	0.914016
1992	– 570,686	1019.849	53,408.99	456,913.5	0.917362
1993	– 529,888	1068.156	49,587.72	459,771	0.913784
1994	– 550,451	1094.031	51,330.45	477,943.4	0.928264
1995	– 613,039	996.1872	57,308.24	457,147.6	0.916873
1996	– 685,904	1091.293	63,642.25	486,003.6	0.914104
1997	– 766,919	1016.363	71,238.52	467,800.1	0.929635
1998	– 637,854	150.3882	62,820.44	89,563.87	0.939271
1999	– 582,852	517.1611	56,537.73	222,145	0.934024
2000	– 590,117	706.3997	56,569.36	284,178.2	0.951216

continued

Year	Intercept	Price (t)	Ln demand ($t - 1$)	$1/P(t)$	R-squared
2001	– 571,105	722.1395	54,754.36	296,557	0.956574
2002	– 554,407	728.4099	53,183.34	305,333.1	0.955725
2003	– 554,251	747.9182	53,101.28	312,347.3	0.962784
2004	– 336,199	– 316.037	39,221.21	– 636,798	0.983969
2005	– 486,766	– 368.84	53,027.92	– 682,033	0.992917
2006	– 165,073	– 233.236	23,466.51	– 593,208	0.999916
2007	117,991.3	– 188.907	– 1969.9	– 646,010	0.999809
2008	– 82,217.7	25.66934	13,682.36	55,799.48	0.713039
2009	344,405.5	63.41434	– 24,917.8	270,532.4	0.877985
2010	4,061,974	430.4331	– 362,668	3,220,356	0.9996
2011	– 45,647.1	– 130.855	12,848.69	– 1,075,619	0.704993
2012	– 372,629	– 333.613	44,943.68	– 2,328,615	0.823996
2013	– 829,343	– 657.706	90,057.81	– 4,135,712	0.882695
2014	– 919,007	– 1751.24	114,807.2	– 1.2E + 07	0.920274
2015	– 1,067,208	– 854.916	112,726.7	– 3,931,119	0.968909
2016	– 767,692	– 453.863	80,856.82	– 1,969,092	0.982085

$$S_t^{\text{non-OPEC}} = \alpha + \beta_1(P_t) + \beta_2(S_{t-1}^{\text{non-OPEC}}) \quad (7)$$

Year	Intercept	Non-OPEC production ($t - 1$)	Price (t)	R-squared
1991	10,030.07	0.774753	– 81.8824	0.816474
1992	– 23,743.3	1.612909	– 1.65425	0.844339
1993	– 9220.11	1.257628	– 48.9493	0.901768
1994	2401.882	0.977552	– 96.5621	0.840716
1995	5527.834	0.898684	– 101.697	0.813502
1996	7745.215	0.810134	– 40.8787	0.726127
1997	7659.028	0.808499	– 29.8292	0.696327
1998	7586.125	0.815514	– 38.8999	0.709374
1999	7210.478	0.826384	– 39.4444	0.718787
2000	5209.664	0.844991	30.12606	0.713394
2001	3988.66	0.873058	40.02221	0.751543
2002	1995.388	0.921447	50.72065	0.793232
2003	1430.173	0.933924	55.81661	0.844306
2004	1731.066	0.976354	– 4.75576	0.983
2005	– 15,402.8	1.450602	– 60.6428	0.989761
2006	9540.945	0.789723	– 14.7269	0.875059
2007	23,993.95	0.425805	– 5.93882	0.461446
2008	42,433.49	– 0.01383	– 12.1964	0.898117
2009	39,604.67	0.056022	– 12.8044	0.851664
2010	19,887.09	0.546172	– 14.9758	0.183346
2011	– 4457.03	1.159738	– 24.3561	0.489499

Year	Intercept	Non-OPEC production ($t - 1$)	Price (t)	R-squared
2012	– 18,723.9	1.535193	– 36.9795	0.768861
2013	1562.389	0.974418	0.156847	0.626734
2014	– 35,175.8	1.989812	– 60.6386	0.896525
2015	– 64,124.5	2.367465	75.9743	0.981528
2016	– 12,577.5	1.238784	37.76309	0.711579

The forecasted values obtained using **Method 3** are given in the below table.

Year	Actual	World demand	Non-OPEC production	Demand OPEC	Forecasted price
1986	15.03	56,325.61	38,453.61	17,872	DNE
1987	19.17	56,650.07	38,640.75	18,009.32	DNE
1988	15.98	58,696.86	38,652.86	20,044	DNE
1989	19.64	59,801.83	38,023.25	21,778.59	DNE
1990	24.47	60,496.75	37,563.68	22,933.07	DNE
1991	21.50	60,127.63	37,255.58	22,872.05	DNE
1992	20.56	60,100.2	35,897.92	24,202.28	21.94895
1993	18.45	60,172.95	35,210.09	24,962.86	21.54681
1994	17.19	61,173.47	35,783.9	25,389.57	20.28092
1995	18.44	62,433.68	36,376.1	26,057.58	19.03475
1996	22.11	63,818.23	37,228.31	26,589.92	18.89789
1997	20.61	65,805.95	37,856.04	27,949.92	19.88638

Year	Actual	World demand	Non-OPEC production	Demand OPEC	Forecasted price
1998	14.45	67,031.77	37,985.36	29,046.41	19.6061
1999	19.26	65,967.39	38,064.91	27,902.49	17.73101
2000	30.30	68,526.65	38,820.06	29,706.59	18.97899
2001	25.95	68,131.91	39,296.32	28,835.6	20.67131
2002	26.11	67,290.17	40,112.02	27,178.15	21.76323
2003	31.12	69,460.24	40,788.42	28,671.83	21.98432
2004	41.44	72,595.18	41,323.25	31,271.93	22.87479
2005	56.49	73,869.21	41,096.58	32,772.63	42.51041
2006	66.02	73,621.39	41,138.02	32,483.37	Did not converge
2007	72.32	73,330.83	41,094.98	32,235.84	77.71237
2008	99.57	74,301.01	40,578.15	33,722.85	79.20913
2009	61.65	73,120.57	41,053.98	32,066.59	96.94699
2010	79.40	74,887.25	41,839.47	33,047.78	59.91716
2011	94.88	74,908.39	41,779.05	33,129.34	Did not converge
2012	94.11	76,367.46	42,023.42	34,344.04	Did not converge
2013	97.91	76,448.82	43,154.69	33,294.13	Did not converge
2014	93.26	78,361.77	45,021.37	33,340.39	Did not converge
2015	48.69	80,755.05	46,186.55	34,568.5	93.39229
2016	43.15	80,841.61	45,226.77	35,614.84	98.73517
2017	50.88			35,467.53	Did not converge

The forecast error metrics for each of the three methods is as below:

	MAD	MSE	MAPE	MPE
Method 1	23.45651	727.6283	0.838836	− 0.78215
Method 2	83.82119	96,984.95	1.025901	− 0.36583
Method 3	28.91879	1909.927	0.485201	0.214237

MAD (Mean Absolute Deviation) is the average of absolute forecast errors (The differences between actual and forecast values); MSE (Mean Squared Error) is the average of squared forecast errors; MAPE (Mean Absolute Percentage Error) is the average of absolute forecast errors divided by actual values; MPE (Mean Percentage Error) is the average of forecast errors divided by actual values.

As we felt, we could improve the results further, we decided to use a method that combines the above three models.

Combination model

Our Combination Model combines both Methods 1 and 3 because they had significantly lower errors than Method 2. We first calculated the forecasted values for the years 1991 through 2017 using both Methods 1 and 3. After obtaining the values of the forecasted crude oil prices, we compared them with the prices of the previous period. For example, we would compare the forecasted price of 1991 for Methods 1 and 3 with the actual price from 1990, and take the forecasted value that was closer to the actual price of the previous period. If a Method did not produce a forecast for the period in question, we would use the other method. Based on that comparison, the forecasted value of the period in question would be either Method 1 or 3, depending on whichever Method produced a closer forecast to the previous period. Using this methodology, we obtained the below table of forecasted values:

The forecasted values obtained are given in the below table.

Year	Actual	Forecast price (Method 1)	Forecast price (Method 3)	Forecast price (combination)	Method
1986	15.03	DNE	DNE	DNE	DNE
1987	19.17	DNE	DNE	DNE	DNE
1988	15.98	DNE	DNE	DNE	DNE
1989	19.64	DNE	DNE	DNE	DNE
1990	24.47	DNE	DNE	DNE	DNE
1991	21.50	25.34403	DNE	25.34403	1
1992	20.56	23.49511	21.94895	21.94895	3
1993	18.45	34.72071	21.54681	21.54681	3
1994	17.19	40.22087	20.28092	20.28092	3
1995	18.44	44.98176	19.03475	19.03475	3
1996	22.11	51.01424	18.89789	18.89789	3
1997	20.61	55.51825	19.88638	19.88638	3
1998	14.45	64.28711	19.6061	19.6061	3
1999	19.26	70.48958	17.73101	17.73101	3
2000	30.30	63.97958	18.97899	18.97899	3
2001	25.95	73.32451	20.67131	20.67131	3
2002	26.11	68.49023	21.76323	21.76323	3
2003	31.12	59.08099	21.98432	21.98432	3
2004	41.44	66.11404	22.87479	22.87479	3
2005	56.49	76.30616	42.51041	42.51041	3

Year	Actual	Forecast price (Method 1)	Forecast price (Method 3)	Forecast price (combination)	Method
2006	66.02	82.25424	Did not Converge	82.25424	1
2007	72.32	81.14913	77.71237	77.71237	3
2008	99.57	80.37065	79.20913	79.20913	3
2009	61.65	86.75108	96.94699	96.94699	3
2010	79.40	79.8512	59.91716	59.91716	3
2011	94.88	81.26497	Did not Converge	81.26497	1
2012	94.11	81.68731	Did not Converge	81.68731	1
2013	97.91	84.62633	Did not Converge	84.62633	1
2014	93.26	78.20684	Did not Converge	78.20684	1
2015	48.69	72.12382	93.39229	93.39229	3
2016	43.15	70.24915	98.73517	70.24915	1
2017	50.88	76.10744	Did not Converge	76.10744	1

The forecast error metrics for the Combination Method are as below:

	MAD	MSE	MAPE	MPE
Combination method	12.67652	280.9213	0.259782	− 0.02787

The errors for this Combination Method are significantly lower than any of the other three methods, and this method was chosen for prediction of our forecasted values.

Forecasting monthly crude oil prices

The monthly crude oil price has a high co-relation to the annual crude oil price, and hence forecasting the monthly crude oil price is performed using a simple

regression utilizing the annual crude oil price. The equation can be summarized as below:

$$P^{\text{month}} = \alpha + \beta(P^{\text{annual}}) \quad (8)$$

where P^{month} is the monthly crude oil price and P^{annual} is the annual crude oil price.

In order to predict monthly crude oil price, the annual crude oil price must be known as the monthly crude oil price is dependent on the annual crude oil price. But, as we do not know the actual annual crude oil price until the year is over, we use the forecasted annual crude oil price. Since, in the previous section, the method of deriving the forecasted annual crude oil price was introduced, the forecasted annual crude oil price can be used as the annual crude oil price in Eq. 8. The table below lists the coefficients for each month of the year along with their corresponding R-square values based on a simple regression of the monthly data values from 1987 to 2017.

Month	Intercept	X-Variable	R Square
January	1.798174388	1.01516493	0.955660642
February	3.11239183	0.982188395	0.956459646
March	3.617377098	0.934706194	0.975288062
April	3.762271009	0.904444111	0.973271328
May	3.112401377	0.910227427	0.965484705
June	4.161813726	0.879087694	0.947909655
July	4.202809267	0.870103136	0.966824892
August	1.464031469	0.933482055	0.979218601
September	− 0.290228973	0.975941258	0.980763525
October	− 1.622652992	1.020355323	0.94178581
November	1.112219771	0.983138895	0.875008791
December	4.393831192	0.932305451	0.790770935

Applying the coefficients from the table above to Eq. 8 to forecast the monthly crude oil prices, we achieved the following table of monthly forecasted prices:

Year	Forecasted monthly price											
	January	February	March	April	May	June	July	August	Sept	October	November	December
1992	22.67199	23.30815	22.8368	22.35945	21.82849	22.23761	22.09387	20.65829	19.77707	19.35789	21.32752	23.56389
1993	20.52955	21.2353	20.86416	20.45068	19.90752	20.38235	20.25757	18.68823	17.71741	17.20449	19.25267	21.59632
1994	19.24941	19.99675	19.68549	19.31016	18.75971	19.27381	19.16036	17.5111	16.48673	15.91781	18.01291	20.42067
1995	20.51585	21.22204	20.85155	20.43847	19.89523	20.37049	20.24583	18.67563	17.70424	17.19072	19.2394	21.58374
1996	24.24653	24.83154	24.28655	23.76226	23.24027	23.60109	23.44341	22.10613	21.29077	20.94048	22.85238	25.00992
1997	22.72066	23.35524	22.88162	22.40281	21.87214	22.27976	22.13558	20.70304	19.82386	19.40681	21.37465	23.60859
1998	16.46523	17.303	17.12197	16.82964	16.26332	16.86283	16.77402	14.95094	13.81012	13.11939	15.31656	17.86374
1999	21.35142	22.03047	21.6209	21.18291	20.64443	21.09406	20.962	19.44397	18.50752	18.03057	20.04861	22.35111
2000	32.55825	32.87326	31.9395	31.16744	30.69281	30.79867	30.56743	29.74907	29.28134	29.29469	30.90189	32.64322
2001	28.13743	28.59605	27.86907	27.22879	26.72898	26.97044	26.77833	25.68396	25.03134	24.85128	26.62054	28.58324
2002	28.30859	28.76164	28.02666	27.38128	26.88243	27.11865	26.92502	25.84135	25.19588	25.0233	26.78629	28.74042
2003	33.39059	33.67857	32.70588	31.90901	31.43912	31.51944	31.28084	30.51444	30.08153	30.13129	31.70797	33.40762
2004	43.86849	43.8161	42.35334	41.24411	40.83392	40.59284	40.2615	40.14926	40.15459	40.66277	41.85532	43.0303
2005	59.14651	58.59783	56.42046	54.8558	54.53264	53.82292	53.35636	54.19796	54.84229	56.01889	56.65135	57.0613
2006	68.81824	67.95538	65.32565	63.47267	63.20461	62.19821	61.64606	63.09148	64.14033	65.74008	66.01796	65.94361
2007	75.21102	74.1405	71.21175	69.16821	68.93656	67.73407	67.12534	68.96988	70.28611	72.16554	72.20906	71.81459
2008	102.8798	100.9105	96.68762	93.81927	93.74526	91.69403	90.84042	94.41239	96.88586	99.97582	99.00499	97.22503
2009	64.38589	63.66702	61.24459	59.52375	59.23043	58.36	57.84707	59.01578	59.87924	61.28507	61.72545	61.87304
2010	82.39728	81.09332	77.82846	75.57069	75.37999	73.95706	73.28472	75.57792	77.19471	79.38855	79.16862	78.4143
2011	98.11195	96.29752	92.29763	89.57141	89.47023	87.56526	86.75384	90.02814	92.3022	95.18356	94.38752	92.84631
2012	97.33675	95.5475	91.58387	88.88075	88.77516	86.89397	86.08942	89.31532	91.55695	94.40439	93.63678	92.13438
2013	101.1886	99.27421	95.13042	92.31249	92.22884	90.22949	89.39085	92.85723	95.25996	98.27593	97.3671	95.67183
2014	96.47012	94.70902	90.78593	88.10865	87.99812	86.14351	85.34663	88.51842	90.72381	93.53334	92.79749	91.33849
2015	51.22555	50.93417	49.12729	47.79876	47.43047	46.96372	46.56727	46.91435	47.22738	48.05743	48.98028	49.78686
2016	45.59766	45.4891	43.94546	42.78469	42.38434	42.09022	41.74358	41.73929	41.81694	42.40077	43.52994	44.61833
2017	53.45333	53.08959	51.17851	49.78356	49.42797	48.89288	48.47671	48.96288	49.36909	50.29661	51.13778	51.83281

The above monthly forecasts are then compared with the actual data on monthly crude oil prices (from Federal Reserve Economic data), and the forecast error metrics calculated are as below:

Error table: monthly crude oil price

	MAD	MSE	MAPE	MPE
1992–2017	5.658286	82.1163	0.124643	– 0.03888

Evaluation of the Forecast Model—Annual Price

To evaluate the forecast models, the actual crude oil prices from year 1991 to 2017 are compared with the forecasted price obtained from the models. We tested several forecasting methods and the best method was a combination model. As seen in the earlier section, the MAD is 12.68, meaning that on average, the forecast price is 12.68 cents above or below the actual price. The MAPE is 25.97%, meaning that on an average, the difference between actual and forecast price is about 25.97% of actual price. Finally, the MPE is – 2.78% which shows that a small percentage of over forecast resulted with the combination model. Overall, the results are promising and it shows the strength of our forecasting models in predicting the price of crude oil.

Following this, we estimated the forecasts of the oil prices at a monthly level and calculated the forecast error metrics. The MAD, MAPE and MPE values are 5.66, 12.46% and 3.89%, respectively, which shows our model is promising again at a monthly level.

Comparison of our methods to Box–Jenkins (ARIMA) models

We implemented ARIMA models through MINITAB 19 software. The plot of the data of the oil prices from 1986 to 2017 showed an increasing trend. This was further confirmed through the observation that the first several autocorrelations are persistently large and trailed off to zero rather slowly. We differenced the data to eliminate the trend and create a stationary series. A plot of the differenced data appeared to vary about a fixed level.

The sample autocorrelations and the sample partial autocorrelations for the differenced data are then plotted. Comparing the autocorrelations with their error limits, the only significant autocorrelation was at lag 1. Similarly, only the lag 2 partial autocorrelation was significant. The autocorrelations appear to cut off after lag 1, indicating MA (1) behavior. At the same time, the partial autocorrelations appear to cut off after lag 2, indicating AR (2) behavior. Neither pattern appears to die out in a declining manner at low lags. So, we decided to fit both ARIMA (2, 1, 0) and ARIMA (0, 1, 1) models to our data.

We compared the ARIMA models with the Combination Method discussed earlier in our paper. The forecast error metrics for the Combination Method are as below and are based on the best of the Method 1 and Method 3 presented in the paper (please refer to earlier discussion on this in the paper).

	MAD	MSE	MAPE	MPE
Combination Method	12.67652	280.9213	0.259782	– 0.02787

Note that, our Method 1 methodology involves running a regression on all the data from 1987 to 2017 to obtain the coefficients used for forecasting the price of oil for each of the year's from 1987 to 2017.

Our Method 3 methodology involves running a regression of past 5 years' of data to obtain the coefficients used for forecasting the price of oil for the next year. For example, the coefficients for 1992 were from a regression of the data from 1987 to 1991. The coefficients for 2017 were from a regression of the data from 2012 to 2016. When forecasting the price of crude oil for a certain year with Method 3, the coefficients used are the coefficients that were associated with the previous year. For example, forecasting the price of crude oil for year 1992 would use the coefficients for 1991.

We cannot apply Method 1 type static data analysis for ARIMA models and thus use only the type of data analysis used in Method 3 for the forecast of oil prices from the ARIMA (2, 1, 0) and ARIMA (0, 1, 1) models.

To be clear, we use the past five years' of data to forecast the price of oil for the next time period.

We present below the results for the ARIMA (2, 1, 0) and ARIMA (0, 1, 1) models. For example, the forecast of oil price for 1992 is based on the data from 1987 to 1991. The forecast of oil price for 2017 is based on the data from 2012 to 2016, etc.

We next present the results from the ARIMA (2, 1, 0) and ARIMA (0, 1, 1) models in the below tables.

ARIMA(2, 1, 0) Forecast Results with five past five periods of data for next period forecast

Year	Time	Actual	Forecasts
1986	1	15.03	–
1987	2	19.17	–
1988	3	15.98	–
1989	4	19.64	–
1990	5	24.47	–
1991	6	21.50	16.9584
1992	7	20.56	15.9197
1993	8	18.45	23.7565
1994	9	17.19	19.7446
1995	10	18.44	15.0828
1996	11	22.11	20.9461
1997	12	20.61	25.6314
1998	13	14.45	16.714
1999	14	19.26	14.8582
2000	15	30.30	23.4524
2001	16	25.95	26.024
2002	17	26.11	14.029
2003	18	31.12	30.234
2004	19	41.44	22.8305
2005	20	56.49	56.7333
2006	21	66.02	72.7245
2007	22	72.32	65.4209
2008	23	99.57	72.7825
2009	24	61.65	105.872
2010	25	79.40	97.6857
2011	26	94.88	96.4187
2012	27	94.11	58.5503
2013	28	97.91	78.9061
2014	29	93.26	101.481
2015	30	48.69	97.0379
2016	31	43.15	– 14
2017	32	50.88	86.321

ARIMA(0, 1, 1) Forecast results with five past five periods of data for next period forecast

Year	Time	Actual	Forecasts
1986	1	15.03	–
1987	2	19.17	–
1988	3	15.98	–
1989	4	19.64	–
1990	5	24.47	–
1991	6	21.50	23.0434
1992	7	20.56	21.0656
1993	8	18.45	20.8095
1994	9	17.19	20.4972
1995	10	18.44	17.3419
1996	11	22.11	19.2997
1997	12	20.61	24.1962
1998	13	14.45	20.6595
1999	14	19.26	11.5126
2000	15	30.30	18.4863
2001	16	25.95	34.5257
2002	17	26.11	24.3153
2003	18	31.12	26.1288
2004	19	41.44	28.5115
2005	20	56.49	47.2823
2006	21	66.02	64.0383
2007	22	72.32	68.4805
2008	23	99.57	76.7584
2009	24	61.65	118.45
2010	25	79.40	73.4083
2011	26	94.88	74.0308
2012	27	94.11	85.7632
2013	28	97.91	88.5758
2014	29	93.26	102.578
2015	30	48.69	94.0001
2016	31	43.15	19.3672
2017	32	50.88	44.9767

The forecast error metrics for each of the two methods are as below:

	MAD	MSE	MAPE	MPE
ARIMA (2,1,0)	14.08033	456.8168	0.296836	0.02373
ARIMA (0, 1, 1)	10.84226	287.6069	0.238679	– 0.00596

Comparing the above solutions to our Combination Method below, we infer that our Combination Method performs better than ARIMA (2, 1, 0) across all metrics, and is better than ARIMA (0, 1, 1) on the MSE metric. ARIMA (0, 1, 1) performs slightly better than our Combination Method on the MAD, MAPE and MPE metrics.

	MAD	MSE	MAPE	MPE
Combination Method	12.67652	280.9213	0.259782	– 0.02787

Note that, we also estimated the forecasts of the oil prices at a monthly level based on our annual forecasts of oil prices from our Combination Method and the calculated forecast error metrics are as follows (also presented earlier in the paper).

Error table: monthly crude oil price				
	MAD	MSE	MAPE	MPE
1992–2017	5.658286	82.1163	0.124643	– 0.03888

These numbers are even more promising and hence show the viability of our approach compared to traditional methodology such as the ARIMA models.

Conclusions

Although the overall results of our forecast models are promising, one of the limitations of our model is that it cannot predict the price changes caused by factors other than predictor variables that are used in the model. These factors include war, natural disaster,

human expectation, and government interference. When one of these factors exists, the forecasted price may deviate from the actual price.

The purpose of the forecast model is to predict OPEC's behavior of setting oil price.

Behaviors may change from time to time. Therefore, the regression equation should be updated frequently to maintain the model's accuracy.

In summary, our forecast model is a good predictor of oil price. The data required are readily available, the number of variables is small, the forecast process is easy to follow, and the cost is very low; even individuals can afford it. Moreover, our model forecasts both annual and monthly oil price. Managers can use annual forecast price to develop long-term operation plans and monthly price to make short-term operation decisions. We hope that this model will help companies and management to lower costs, increase profit and gain advantage over their competitors.

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