White Paper

On

Forecasting-based approach: Crude oil prices in Manufacturing

By:

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ABSTRACT

There is a widespread agreement that large and persistent fluctuations in the real price of oil are harmful to the welfare of both oil-importing and oil-producing economies. Reliable oil price forecasts are useful for a variety of applications. India imports its crude oil from Brent crude oil. Many sectors in India are affected by fluctuations in crude oil prices. One such sector is Paint manufacturing sector. It is always crucial to make the right decisions for the forecasts too. As India is a major importer of crude oil, it is important to forecast the oil prices since it affects our economy, manufacturing sector, oil marketing companies, currency exchange rate, stocks, etc. The main focus in this paper is regarding paint manufacturing industry since it is affected the most if crude oil price rises. This second section paper focuses on a forecasting-based approach which helps in decision making in manufacturing sector.

1. INTRODUCTION

Crude oil is a form of basic energy source, chemical material, and strategic resource in socioeconomic development. Crude oil price fluctuations can have a significant impact on a country's economic development, social stability, and even national security. Hence, it is critical to develop scientific methods for accurately forecasting crude oil price movement as much as possible in order to address extreme risks in the crude oil market and find profit-making opportunities.

The manufacturing of paints uses more than 300 raw materials, of which 50% are derivatives derived from crude oil. Since petroleum is a major component of most raw materials, the sector loses from rising crude prices. The sudden spike in oil prices take a toll on company’s operating profit and profit margins.

The crude oil price is primarily determined by supply and demand, but it is also heavily influenced by many irregular past/present/future events such as weather, stock levels, GDP growth, political factors, and so on. These facts result in a highly volatile and non-linear market, and the fundamental mechanism governing the complex dynamic is unknown. Except for the Nasdaq, the oil market is the most volatile and chaotic of all markets. As (Epaminondas et at. [1]) a result of, oil price prediction is an extremely important topic, albeit one that is extremely difficult due to its inherent difficulty and practical applications.

According to the IMF, a 10% increase in oil prices causes a 0.2% decrease in global GDP. As a result, when oil prices reached a record high of $145/bbl in 2008, and then began to fall sharply beginning in 2014, reaching a low of $29/bbl in early 2016, many energy exporting nations such as Russia and Saudi Arabia faced significant revenue shortfalls and economic stress. On the other hand, the availability of cheaper oil has been heralded as a powerful economic stimulus for many net oil importer countries such as China and India, while also keeping inflation in check.

After the Covid lockdowns, the paint sector was already experiencing weak demand; the rise in crude oil prices has been a double whammy. When lockdowns caused the price to fall below zero for the first time in history due to a significant decline in economic activity in 2020 during the pandemic, demand for oil plummeted. Following a solid economic rebound after the lockdowns, oil prices have since increased substantially to almost $100 per barrel. Oil demand rises along with the economy. Concerns over the supply are also being fueled by escalating geopolitical tensions in the Middle East and between Russia and Ukraine. Rising inflation and worries about an economic recovery are being exacerbated by this.

According to (Scheitrum, Carter, & Revoredo-Giha, 2018) WTI and Brent crude oil futures are pricing benchmarks that compete for the top spot as the leading futures market. The price spread between WTI and Brent is also an important benchmark because it influences international oil trade, refiner margins, and the global price of refined products. Furthermore, the shapes of the WTI and Brent futures curves reflect supply and demand fundamentals in the United States versus the global market.

When COVID-19 emerged two years ago, there was a drop-in economic activity and oil demand. Producers were reducing output, but there is only so much one can do without destroying reservoirs or capital. Storage space is also restricted. Furthermore, there was uncertainty about the severity of the economic crisis and how long it would last. These combined factors drove oil prices to levels not seen in decades. There was even a brief period when oil prices fell to minus $40. Oil market jitters are exacerbated by geopolitical tensions between Russia and Ukraine, as well as increased instability in the Middle East.

High oil prices are a challenge for importing countries while working in favour of exporting countries. It truly is a zero-sum game. Profits between oil producing and oil consuming countries shift as prices change. It is very difficult to predict level of prices or even direction of change. Temporary oil price spikes are very likely if the energy transition is not a coordinated effort between demand side changes and supply side adjustments. Forcing supply cuts without adjusting demand will result in structural imbalances that will be difficult to address due to the extremely long investment cycles required to produce oil.

India imports its crude oil from Brent crude oil. Thus, this paper focuses on forecasting the crude oil prices in the paint manufacturing sector and provides a framework for decision making by forecasting the crude oil prices. The second section of the paper focuses on a forecasting-based framework for decision making in manufacturing sector.

2. BACKGROUND WORK

Recently, (Gabralla & Abraham, 2013) emphasized that oil is a significant source of energy, as well as an essential raw material in many manufacturing processes and transportation. Oil prices are subject to high volatility and fluctuations. It is the most active and heavily traded commodity on global markets. Many studies have recently emerged to discuss the problem of predicting oil prices and seeking the best outcomes. Despite these efforts, therewere insufficient studies to serve as a reference covering all aspects of the problem. In thisstudy, a comprehensive survey was used covering previous methods, as well as some resultsand experiments, is presented with a focus on and preservation of the necessary steps when predicting oil prices. It said that for Brent crude oil the following methods were used from last two decades i.e., Fuzzy neural network, which combines RBF neural network, Markov chain based semiparametric model and wavelet analysis.

The growing internet concern (IC) about the crude oil market and related events influences market trading, adding to the oil market's instability. (Wanga, Athanasopoulo, Hyndmanc, & Wang, 2018) propose a modelling framework for analysing the effects of IC on the oil market and predicting crude oil futures price volatility. Using bivariate empirical mode decomposition, this novel approach decomposes the original time series into intrinsic modes at different time scales (BEMD). The relationship between oil price volatility and IC at a single frequency is studied. They also build extreme learning machine (ELM) models with different forecasting schemes using decomposed intrinsic modes as specified characteristics.

(Xie, Yu, Xu, & Wang, 2006) proposed a new support vector machine-based method for forecasting crude oil prices (SVM). Data sampling, sample preprocessing, training and learning, and out-of-sample forecasting are all steps in developing a support vector machine model for time series forecasting. To assess SVM's forecasting ability, they compared its results to those of ARIMA and BPNN. The experiment results show that SVM outperforms the other two methods and is a viable candidate for predicting crude oil prices.

Crude oil price forecasting is a difficult task. (Zhang, Zhang, & Zhang, 2015) proposed a novel hybrid method for forecasting crude oil prices based on the nonlinear and time-varying characteristics of international crude oil prices. First, they decomposed the international crude oil price using the ensemble empirical mode decomposition (EEMD) method into a series of independent intrinsic mode functions (IMFs) and the residual term. The least square support vector machine (LSSVM-PSO) method and the generalised autoregressive conditional heteroskedasticity (GARCH) model are then developed to forecast the nonlinear and time-varying components of crude oil prices, respectively.

And also (Wang.Shouyang, Yu, & Lai, 2004) systematically integrated artificial neural networks (ANN) and rule-based expert systems (RES) with web-based text mining (WTM) techniques, a novel hybrid AI system framework was developed. This approach with conditional judgement and correction is proposed within the hybrid AI system framework to improve prediction performance.

Our Contribution

The research gap is here that most of literature is focused on the forecasting of WTI crude oil prices rather than Brent crude oil prices. Advanced methods were used for forecasting WTI crude oil prices and less of work was done in planning a framework of how this forecasting solution can be applied. India imports most of its oil from Brent so therefore its important to forecast the oil prices since it affects our economy, manufacturing sector, oil marketing companies, currency exchange rate, stocks, etc. The main focus in this paper is regarding paint manufacturing industry since it is affected the most if crude oil price rises. This paper focuses on a forecasting-based approach which helps in decision making in manufacturing sector.

3. NEED FOR THE SOLUTION

There is pressure to stop investing in oil production as we transition, but we must recognize that we also require this supply. So, between now and 2050, we must strike this balance with the energy transition. The **paint manufacturing sector**, which was already suffering from subdued demand as a result of the pandemic, is once again in trouble. Because it is a raw material-intensive industry, crude oil prices have the greatest impact on the decorative paint industry. More than 300 items are required for the production of paint, the majority of which are petroleum-based. Rising crude oil prices raise the cost of manufacturing items such as titanium dioxide, a key ingredient in white paint.

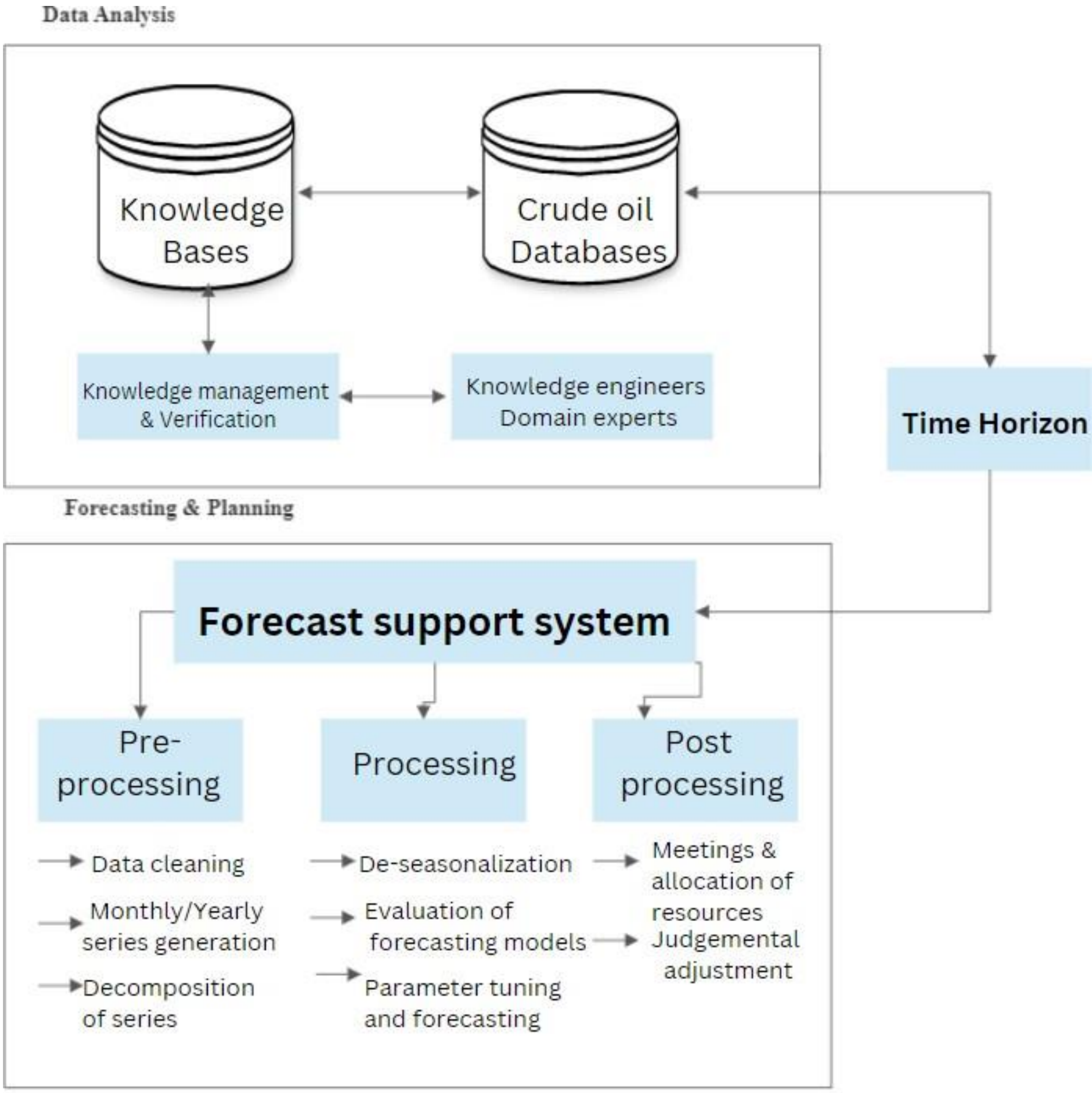
Raw materials account for 55-60% of input costs and have a direct impact on gross margins. Indian paint companies raised their prices several times in recent months, but not enough to offset higher raw material costs. So, there is a need to forecast crude oil prices in order to avoid high input costs and better planning of resources is possible if there is a forecasting-based framework implemented in this sector.

4. METHODOLOGY

Forecasting based approach for decision making: Paint manufacturing sector

Crude oil pricing isn't just important to forecast, it is also important to make decisions based on the forecasts obtained. The following framework can be used for better decision making with forecasts. The below figure represents the forecasting-based approach for decisionmaking. Initially it is important for paint manufacturing industries to analyze the crude oil databases with the knowledge bases. Knowledge bases consists of data inputs from domain expertise in area of crude oil. So, that with the crude oil database will help them to analyze thedata they have currently and with the help of the time-horizon, they can check with theirinventory to make forecasts. The time horizon is to be kept in mind while making forecasts. And then comes the forecasts and planning module. Here, processes start right from pre- processing to post processing. Post processing plays an important role in making important decisions when there is a forecasted hike in crude oil prices.

Figure 1: Forecasting based approach for decision making



4.1 Data Analysis

Data collection is secondary data obtained by the author from the FRED (Federal Reserve Economic Data). Once the data is collected, the next task is to decide the time horizon for forecasting of energy resource. In reference to time horizon, forecasting can be classified in three categories as below:

- **Short-term forecast:** the categorisation of lengths of forecast horizons depends on the application domain. For example, in the energy demand/price prediction, the short-term involves forecasting a few time periods such as minutes, hours, days, weeks, and in between one month to three month ahead (Potocnik et al, 2007).

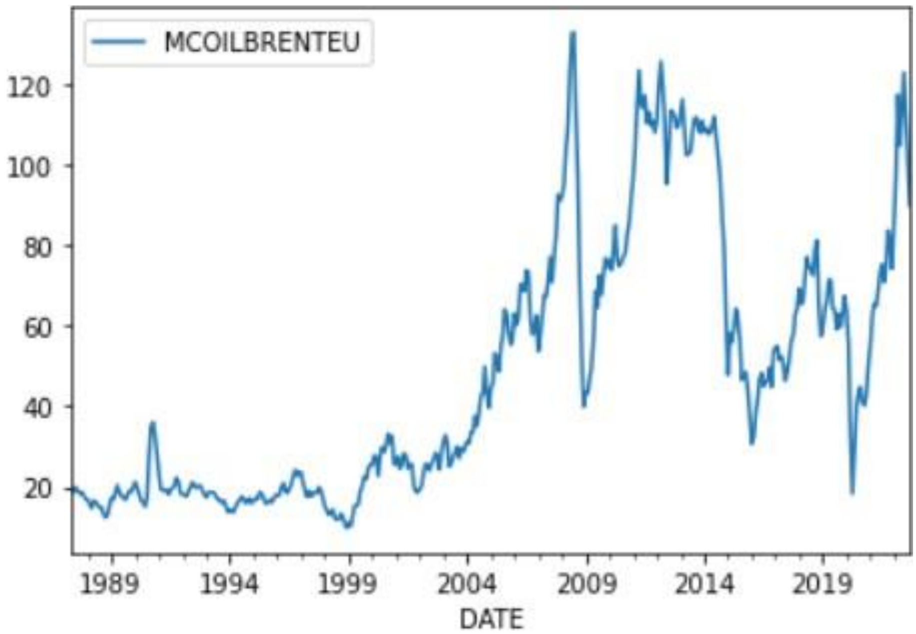
- **Medium term forecast:** the medium-term forecast can be several months (more than three months) to a year in the future (Yoo et al., 2009).
- **Long-term forecast:** it can extend to several years (Sarak and Satman, 2003).

Although three different types of time horizons can be selected, the focus here is on medium-term forecasting. Once the forecast horizon is decided, next comes the selection of the most suitable forecasting technique after validation.

4.1.1 Data Collection and pre-processing

Data has been collected month-wise for Brent crude oil prices from FRED (Federal Reserve Economic Data), for the period from January month of the year 1987 to September month of the year 2022. Time series plot has been given in Figure 2, for assessing the behavior and pattern of this data set.

Figure 2: Monthly Brent crude oil prices



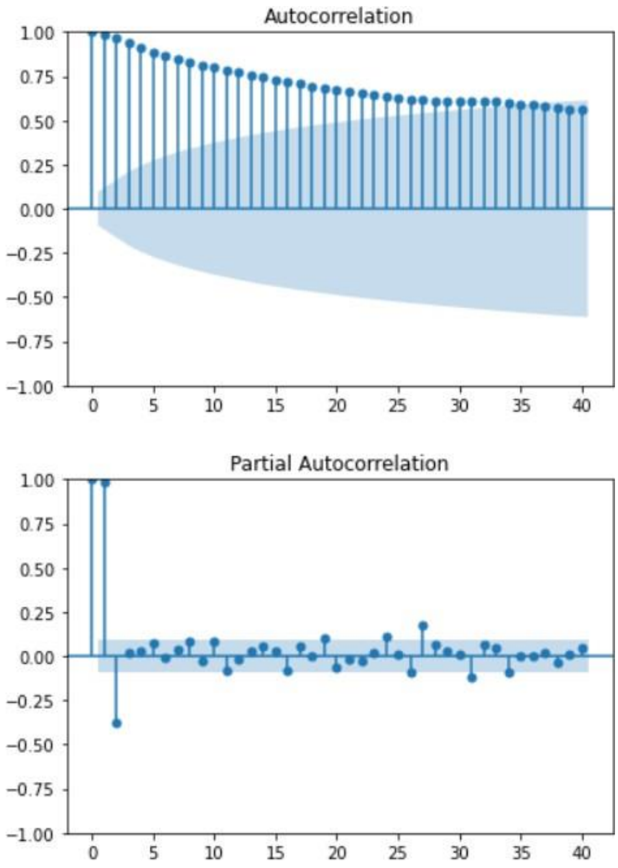
From Figure 2 it can be observed that the dataset is the collection of 426 months Brent crude oil prices. As the collected data set contain 426 observations, in this paper 299 observations are selected as an in-sample period to capture the existing pattern in the series.

- The data of first 299th months is considered as training data for establishing the model.
- The data from 300th month to 426th month is treated as test data for training.

In a forecasting strategy, the anticipating period should be pre-characterized, which necessitates the division of time series into two sections, namely training data and test data. The training set is a collection of data that is used to recognize the relationship between the data. In contrast, a test set is a collection of values used to verify the accuracy of the expected relationship.

Figure 3 depicts an ACF (autocorrelation) plot and PACF (partial) plot. It is utilised to identify relation between lagged values of time series. The ACF has a geometric pattern and PACF has two lag values.

Figure 3: ACF and PACF plots



4.1.2 Time frame

Due to nature of product life cycles and limited availability of data, monthly cycle of natural gas consumption is selected as time horizon for the. In this paper, we have done medium term forecasting for the crude oil prices, on monthly basis for Brent crude oil prices.

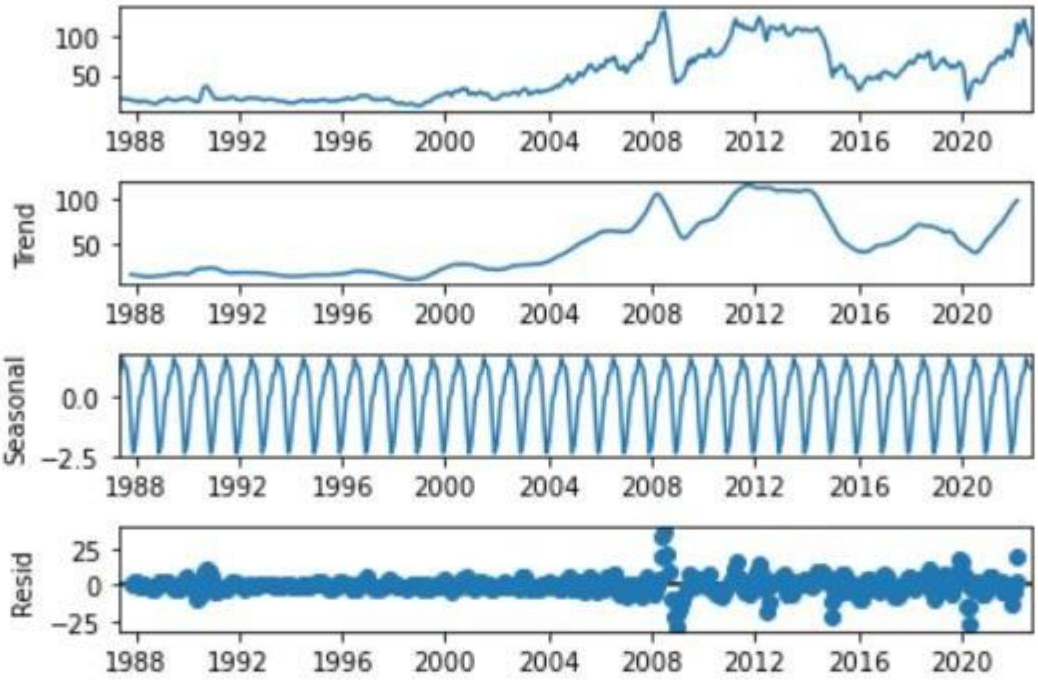
4.2 Forecasting techniques

The forecasting techniques used for the univariate analysis are: Holt's Winter Method, SARIMA (Seasonal Autoregressive integrated moving average), ARCH (Autoregressive Conditional Heteroskedasticity), GARCH (1,1) (Generalized Autoregressive Conditional Heteroskedasticity) and LSTM (Long short term memory).

4.2.1 Selection of forecasting techniques

In Holt's Winter method, we have three parameters i.e., trend component, seasonal component and seasonal periods. Since the seasonal decompose has both seasonal and trend component in Figure 4. We observe that the trend component is additive since the magnitude is not same and seasonal component follows multiplicative pattern since the magnitude is constant.

Figure 4: Seasonal decompose of time series



We go for SARIMA because we observe a seasonal pattern in the seasonal decompose. We choose the seasonal and non-seasonal components of SARIMA by ACF and PACF plots and we verify whether the AR and MA components (both seasonal and non-seasonal) are significant or not.

In ARCH and GARCH (1,1) models we build the models to check whether volatility exists in the data. The ARCH, or Autoregressive Conditional Heteroskedasticity, method models a change in variance in a time series, such as increasing or decreasing volatility. GARCH, or

Generalized Autoregressive Conditional Heteroskedasticity, is an extension of this approach that allows the method to support changes in time dependent volatility, such as increasing and decreasing volatility in the same series.

LSTM is a type of RNN with more memory power that remembers the outputs of each node for a longer period of time in order to efficiently produce the output for the next node. The LSTM model solves the problem of vanishing gradients by introducing a new state known as cell state and incorporating a CEC (Constant Error Carousel) that allows the error to propagate back without vanishing. The optimizer used here is adam optimizer.

These models are selected on basis of the seasonal decomposition and few others are used to check whether volatility exists in the data.

4.2.2 Evaluation of models

The above selected models are evaluated on five evaluation metrics, they are as follows:

a) RMSE (Root mean squared error): The standard deviation of the residuals is defined as the Root Mean Square Error (RMSE) (prediction errors). Residuals are a measure of howfar away data points are from the regression line; RMSE is a measure of how spread out these residuals are. In other words, it indicates how concentrated the data is around the best fit line.
b) MSE (Mean squared error): An estimator's mean squared error measures the average of the squares of the errors, or the average squared difference between the estimated and actual values.
c) MAE (Mean absolute error): The mean absolute error is a measure of the difference in errors between two observations expressing the same phenomenon.
d) MAPE (Mean absolute percentage error): The mean absolute percentage error, also known as the mean absolute percentage deviation, is a measure of a forecasting method's prediction accuracy.
e) AIC (Akaike information criterion): The Akaike information criterion (AIC) is a prediction error estimator that determines the relative quality of statistical models for a given set of data.

Figure 5: Model Evaluation

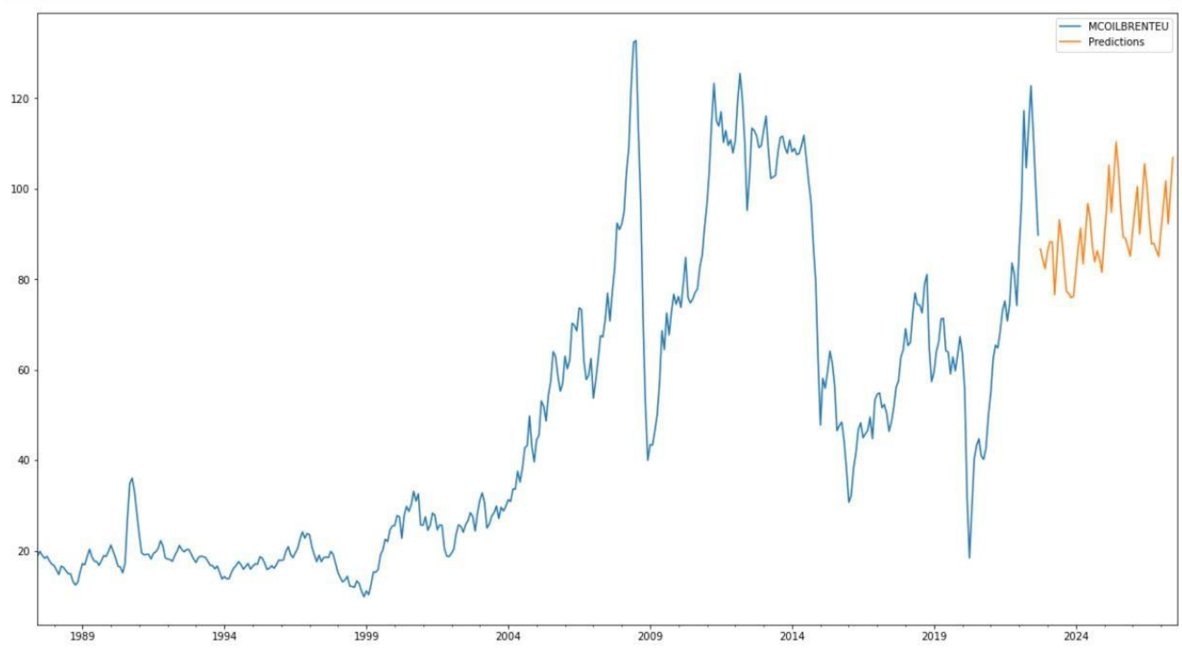
Model	RMSE	MSE	MAE	MAPE	AIC
SARIMA	7.16	51.32	5.48	47.69	2563.187
Holt's winter	675.68	456551.5	555.41	889.8	864.238
LSTM	69	4767.27	67.29	18571.5	-

We observe from the above table that, SARIMA is giving us the best results. The full model is SARIMA (2, 1, 0) (2, 1, 0, 12) since its giving us less values in all the performance metrics we choose it to be the best model as our forecasting solution.

5. PROPOSED SOLUTION

We choose SARIMA (2,1,0) (2,1,0,12) as its giving us the best RMSE. Hence, the forecasting of crude oil prices for medium term forecasting can be forecasted by using SARIMA model. The forecasted value for 36 months can be seen in the figure as follows:

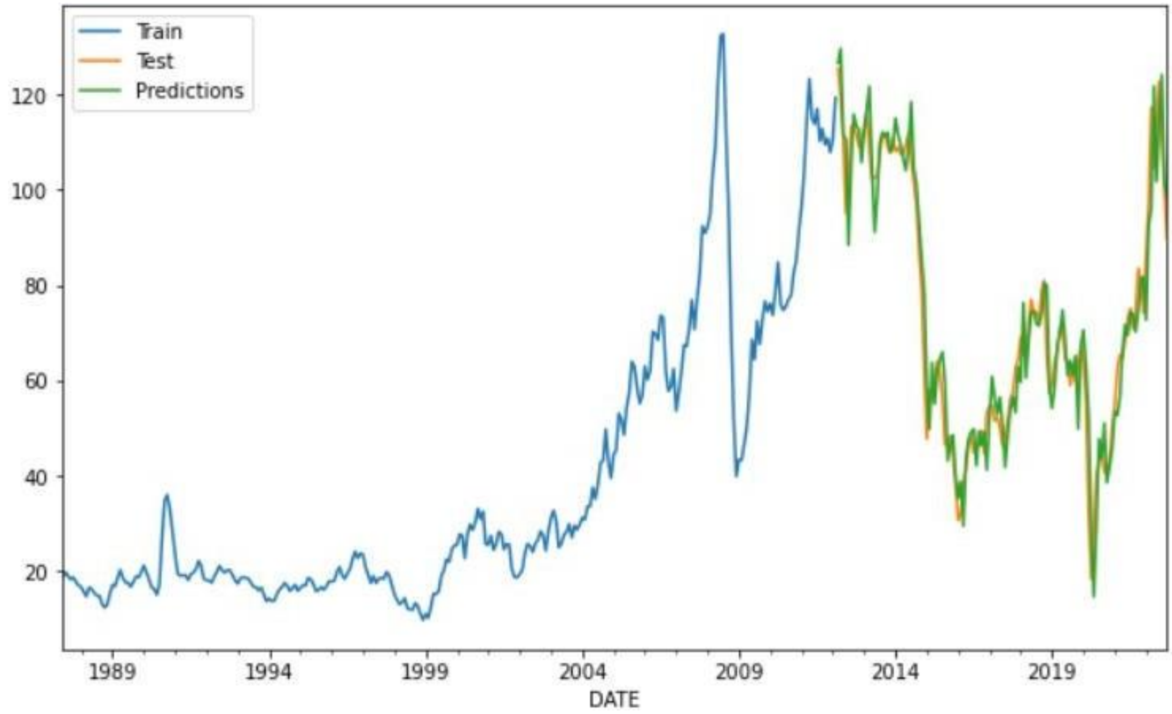
Figure 6: Predictions plot for next 36 months



With the forecasting solution we observe that the crude oil prices are tending to raise further in the upcoming months. Further, in the paint manufacturing industry, it is said that 300 items require crude oil. So, these 300 items can be classified based on the demand for the item in the industry. And based on the demand threshold set they can be categorized as low demand items, medium demand items and high demand items. And if sales is not disclosed, based on the demand of items which fall into high demand category, we forecast the consumption of crude oil based on that and the price they are paying as input costs can be forecasted. This way we are reducing the complexity and forecasting prices based on the consumption of crude oil in the paint manufacturing industry.

The test and predictions values are shown in the below figure.

Figure 7: Train, test and Predictions plot



6. ANALYSIS OF THE SOLUTION

The demand for 300 items in paint manufacturing sector can be classified as:

- Low demand items
- Medium demand items
- High demand items

Thus, these items might be classified based on demand for the particular item in paint manufacturing industry and the crude oil consumption for those items and the price they are spending for high demand items. So, the crude oil consumption and the prices can be forecasted at once and therefore allocation of resources based on that can be done. This is quite a feasible solution. Producers can be cautious at this time to allocate the capital for the raw materials. The forecasting of those high demand items based on the time horizon can be implemented. This can be done by using the forecasting-based framework for decision making.

Cost and benefit analysis

While analyzing a solution it is always important to do a cost and benefit analysis for the proposed solution.

Cost: It is also important to analyze the cost as for paint manufacturing industry there are many input costs with that to implement a data warehouse which consists of historical data of crude oil prices and the knowledge data of consumptions and certain domain expertise people costs the industry.

Particulars	Cost (Per Year in dollars$)
Cloud Storage Solution	1000
On-site Storage Solution	12000
Visualization Software	7000
ETL Software	10000
IT Personnel	228000
Total Expenditure	258000

Figure 8: Cost of Warehouse **Source: Quora**

To build powerful systems for forecasting, there's a cost associated with it per user. It costs somewhere around $5,000 (depending on the system company goes for) and additionally there are charges for IT maintenance, salary for instructors, electricity, etc. Hence the framework where in data warehouse with forecasting system implementation will add a great benefit in analyzing and making right capital investments at a correct time.

Benefit: If the forecasting is done right and poor decision is made it doesn't add any value to the business. Likewise, vice versa is not good too. Thus, if the forecasting with proper decision making is done then the paint industry will save on lot of input costs and their profit margins will further improve.

7. RECOMMENDATIONS

- Crude oil futures contracts are derivative securities that give the buyer the option to purchase a certain number of barrels at a predetermined price months or years in advance. So, by using the forecasted solution and knowledge bases i.e., the sentiment of markets the higher management can decide whether to purchase certain number of barrels when forecasted price is low.
- One simple strategy is to buy current oil contracts, which lock in fuel purchases at today's prices. This is advantageous if you expect prices to rise in the future. Call and put options are other tools to hedge against moving oil prices. This strategy can reduce input costs when prices are high in the upcoming years.
- A call option gives the buyer the right (though not an obligation) to purchase a stock or commodity at a specific price before a specific date. If a paint company buys a call option, this means it is by buying the right to purchase oil in the future at a price that is agreed upon today. Paint manufacturing companies can use call option.
- A collar hedge uses a put option to protect a paint company from a decline in the price of oil if that paint company expects oil prices to increase. In the example above, if fuel prices increase, the paint company would lose $5 per call option contract. A collar hedge protects the airline against this loss. Collar hedge would be a safer option.
- Companies should plan strategies according to the market sentiments and what’s going on around the world and not just stick with the forecasting solution at hand. The capital decisions or investments on the purchase of crude oil should be made very carefully in order to not make losses.

8. CONCLUSION AND FUTURE SCOPE OF WORK

Although the overall solution is encouraging, one of our model's limitations is that it cannot predict price changes caused by factors other than the predictor variables used in the model. In this paper, only univariate analysis was done. War, natural disasters, human expectation, and government intervention are among these factors. When one of these factors is present, the predicted price may differ from the actual price. Given the importance of crude oil prices, managers must predict future oil prices when making operational decisions such as when to purchase material, how much to produce, and which modes of transportation to use. The purpose of this paper is to create a forecasting model for oil prices that will help management reduce operational costs, increase profit, and improve competitive advantage.

The future scope of study can be explored more on neural networks with good hyper parameter tuning. So that the forecasting model solution is completely relied on and accuracy can be improved. Further study can also look at the long-term relationship between the crude oil prices and its petroleum products price such as diesel, gasoline, and natural gas in India. Multivariate time series analyses can be used to predict the relationship between crude oil price and other petroleum products.

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