APPLICATION OF GEOMETRIC BROWNIAN MOTION MODEL FOR SIMULATING CRUDE OIL FUTURES IN THE INDIAN CONTEXT

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ABSTRACT

The derivatives market is a human-made system that changes with time. Therefore, researchers may never find a model that perfectly describes the derivatives market. The big challenge is that there is only one actual crude oil futures price path during a period. Because of that, the crude oil futures price path can be seen as a non-repeatable experiment, as it is impossible to replicate all the initial conditions. Crude oil futures prices prediction and the hedge are exciting topics for everyone who wishes to invest in derivatives. That's why there are various models built for security price prediction, and the hedge, here test model known as the Geometric Brownian Motion (GBM). The purpose of this research study is to determine whether the Geometric Brownian Motion (GBM) model can be used in the Indian Multi Commodity Exchange (MCX). In this research study, the validity of the GBM model was tested using daily crude oil futures prices per barrel in the MCX from February 9, 2005, to December 31, 2020. Researchers used the Mean Absolute Percentage Error (MAPE) to determine the accuracy of this model's application. With MAPE values ranging from 0% to 11%, the GBM model accurately forecasts crude oil futures prices on the MCX in India. The GBM model was created to predict security price behaviour and then used to trade securities. After that, the simulated or forecasted prices were compared to actual crude oil futures prices. The results revealed that in far more than 80% of cases, the model correctly forecasts crude oil futures price behaviour. There is also a way to examine the security's probabilistic distribution mathematically. This research study aims to assist investors and other stakeholders in making judgments concerning crude oil futures trading, notably on the MCX's derivatives market. Furthermore, future researchers will be able to improve these models by focusing on additional derivatives markets with different underlying assets due to this research.

Keywords: Crude Oil Futures, Geometric Brownian Motion Model (GBM), India, Simulation

Jel Classification: C22, E6

1. INTRODUCTION

Crude oil prices are fluctuating wildly these days. However, Asia's (India and China) oil demand continues to be the largest. In 2020, the coronavirus negatively impacted the economy, ending in a deep recession. This, however, resulted in a fast economic and price recovery. A drop in crude oil prices should reduce the cost of transportation and fuel for businesses. Customers like the lower transportation and fuel prices. When oil prices fall, customers can successfully increase their profits by switching their fees to a lot for alternative products. Crude oil is the most traded commodity and has a considerable impact on international transportation costs; therefore, it is projected to generate inflation and stimulate economic growth.

On the other hand, Crude oil prices frequently drop due to investor concerns about an expected economic recession. In March-April 2020, oil prices dropped to their lowest levels in several years, potentially arise to a drop in crude prices. Meanwhile, in April 2020, WTI crude prices fell to unfavourable levels for a brief while. Due to the value loss in March-April 2020, its value has dropped to its lowest in several years.

Consequently, each economy must simulate crude oil pricing on a worldwide scale. As a result, the purpose of this research is to look at how GBM may be used to describe the stochastic evolution of crude prices concerning oil price changes affecting Indian derivatives. Because there is no futures market in Sri Lanka, India is the world's third-largest crude oil importer with a derivatives market.

The National Commodity and Derivatives Exchange (NCDEX) and the MCX are India's two major commodity exchanges. In non-agricultural commodities like bullion, crude oil, and industrial metals, the MCX is the market leader; in agricultural commodity trading, the NCDEX is the market leader. The competition will increase because the NSE and the BSE have already turned their attention to commodities trading. However, because NSE and BSE have only lately entered the commodity trading market, NCDEX and MCX remain the market leaders. The focus of this research was on crude oil that had nothing to do with agriculture. As a result, our research is based on MCX crude oil futures (BRCRUDEOIL, CRUDEOIL, CRUDEOILM).

In Mumbai, MCX was founded in 2003. MCX is India's most well-known and first publicly traded commodity derivatives exchange, providing a platform for price discovery and risk management by facilitating the online trading of commodity derivatives contracts. The Forward Markets Commission (FMC) once regulated the MCX; on September 28, 2015, the FMC was merged with the SEBI. Nonferrous metals, energy (crude oil), bullion, and a few agricultural commodities such as mentha oil, crude palm oil, cotton, cardamom, and other agri-commodities are all available for trade on the MCX. The price of crude oil futures was the subject of this study.

Futures are derivatives because they are contracts that are traded in the future. Derivatives are complex tools with a wide range of uses. A derivative is a contract between two or more parties in which the price is determined by the underlying asset, which is a financial asset, index, or security. Futures contracts, forward contracts, options, swaps, and warrants are commonly traded derivatives.

The derivative's value changes in lockstep with the underlying asset's price. Derivatives have no relevance without an underlying asset. The underlying asset, crude oil, determines the value of a crude oil futures contract, for example. In this case, the derivatives market prices were generated from the spot or cash market price of crude oil, the underlying asset. The primary purpose of these instruments is to give price commitments for future dates to safeguard against adverse changes in future costs and reduce the magnitude of financial risks. A futures contract is an agreement to buy or sell a specific commodity, asset, or security at a predetermined price on a specified date in the future. Futures contracts are standardized in terms of quality and quantity to be traded on an exchange. When futures contracts expire, the purchasers are responsible for purchasing and receiving the underlying asset. Futures contract sellers are obligated to produce and deliver the underlying quality by expiration.

2. LITERATURE REVIEW

In recent years, significant price fluctuations in crude oil have pressured both exporters and importers. As a result, each country must reliably forecast crude oil prices against them. Even though many quantitative studies have been conducted on crude oil prices, forecasting crude oil price movements is challenging due to the difficulty in constructing a forecasting model. Traditional linear forecasting methodologies may also fail to account for nonlinearity in the crude oil price time series, resulting in inconclusive evidence. Policymakers and academics have used the Vector Auto-Regressive (VAR) models, GARCH, and its derivatives to estimate crude oil prices accurately in short to medium term because they are easier to predict future crude oil prices than another forecasting model, the Geometric Brownian Model the most widely used model in the literature.

Simulating the security price requires creating a price path that the security could take in the future. Because future crude oil prices are stochastic, researchers used Monte Carlo Simulation to simulate them. In financial services, strategic planning, cost, and other modelling techniques, Monte Carlo Simulation is one of the approaches used to analyze the impact of risk and uncertainty. It aids in the visualization of the majority, if not all, of the possible outcomes so that the risk associated with a decision can be better understood. (Sengupta, 2014). Crude oil is a crude petroleum product composed of hydrocarbon deposits and other naturally occurring organic components.

A GBM is a continuous-time stochastic technique in which a Brownian motion with drift is escorted by the logarithm of the randomly varying extent. Brennan and Schwartz (1985) depicted the trajectory of oil prices as a GBM. Bachelier's famous work from a century ago was followed by Black and Scholes' interpretation a few decades later, and this model has since been widely applied in various sectors. Concurrently, the GBM model for stock prices has been widely applied to model the evolution of stock price levels and returns in emerging and developed markets.

According to Fama (1995), GBM is a popular hypothesis in corporate finance for explaining time series variables and asset price behaviour. Brownian motion was discovered by biologist Robert Brown while watching pollen particles floating in water under a microscope in the eighteenth century. Brown thought the pollen particles were 'alive' because they moved swiftly. According to Albert Einstein, water molecules move randomly under the right conditions, who discovered this in 1905. Brownian motion is a widely held belief in the financial markets, where asset prices routinely fluctuate by significant amounts. This strategy has resulted in a slew of models based on opposing viewpoints.

Technical analysis theory and quantitative analysis are two extensively utilized methods for estimating the value of securities. According to technical thinkers, history repeats itself, and historical pricing trends will repeat in the future. Fundamental analysis assumes that each commodity has an intrinsic value based on its potential earnings at any given time, indicating whether a security is overvalued or underpriced. Many others believe that security prices follow a random path. The random walk theory states that security will take an unusual and unexpected course that will outperform the market while offering no additional risk. This theory casts serious doubt on other ways to characterize and forecast security price behaviour. Because of its unpredictability and the assumption that asset prices are fixed over time, the GBM model, which employs random walks to determine security costs, is based on the concept of insecurity pricing.

According to substantial assessment errors, a GBM proxy will not produce. Furthermore, both the level and slope of the oil price are stochastic. Pindyck (1999) makes the less realistic assumption of an isoelectric demand function, which permits the integral to converge.

The GBM model, according to Sengupta (2004), suggested the following features for security prices:

- The companies are a going concern, and their security prices are continuous in time and value.
- Securities follow a Markov process, meaning only the current security price is relevant for predicting future prices.
- The proportional return of securities is log-normally distributed.
- The continuously compounded return for securities is normally distributed.

According to Sengupta (2004), The longer an investor wants to keep an asset, the more they get concerned about the security's eventual price, i.e., the greater the likelihood that the actual final price will differ significantly from the predicted final price. The longer an investor plans to hold a stock, the more confident they are in achieving the predicted rate of return. Although they appear different, Sengupta has shown why they aren't and the GBM assumption.

According to Sengupta, the critical assumption about security prices is that they are continuous in time and value, suggesting that security prices can be observed at all times and vary continuously. However, this isn't entirely accurate. Markets are closed on nights and weekends, and securities prices can only fluctuate in whole cent increments. Nonetheless, this reasonable assumption makes calculating security prices much more accessible.

The second assumption is that security prices follow a Markov process, practically identical to the poor version of the efficient market hypothesis, which asserts that future prices cannot be anticipated based on previous prices.

Marathe and Ryan established the Brownian motion theory in 2005, and it allows them to infer that the structure for detecting whether a particular dataset follows a GBM process or not can be used to several data types. Because of regularity and independence requirements, the GBM algorithm may be suitable for particular data sets. However, the GBM process distribution hypothesis may not be appropriate for some data sets. As a result, exercising caution while concluding that a data set follows any particular model's GBM process is advised. According to the researchers, the number of data points utilized to examine cellular phone data and Internet host data could affect the study's results. As a result, additional data points for the example type indicated must be collected.

Data linked to service consumption from diverse industries may or may not satisfy the GBM technique's criteria, according to Marathe and Ryan (2005). Services that fail one or more of Marathe and Ryan (2005)'s tests are in newer industries that may still be classified as emergent. Data on how people use the services indicated in the report is also harder to come by. The early and well-established electric generation and aeroplane transportation services suit the GBM assumption better after deseasonalization. After determining that the model is good enough for deseasonalized data, a forecast of future demand may be obtained from the GBM model with the fitted parameters by re-inserting the seasonal components. How seasonal pattern decision-making influences the application; capacity decisions, for example, are frequently based on peak demand during the season. Generalization into the future does not ensure accuracy when a model appears to match previous data closely.

According to Brewer et al. (2012), the uncertain component of the GBM model is described as a function of the stock's volatility and a stochastic notion described as the Weiner process, which combines random fluctuations and a time interval. Brewer et al. (2012). Kumar et al. (2015) analyzed the path followed by modelled prices and closing prices to see how well the GBM behaved on the price of SBI stocks.

The feasibility of representing the stochastic movement of oil prices using GBM was examined by Nwafor and Oyedele (2017). According to academics, choosing a stochastic strategy for forecasting oil prices is essential. The results show that the GBM approach outperforms the conventional strategy in nearly every forecast evaluation statistic. The Monte Carlo simulation with the GBM model can simulate oil price behaviour in oil-rich emerging countries using simple technology tools. The researchers showed that the Monte Carlo simulation, representing oil prices as a GBM, is a fair proxy for oil price evolution.

3. METHODOLOGY

The validity of the GBM Model in the Indian derivatives market was investigated in this study, which used readily available secondary data (daily crude oil futures' prices) acquired from the MCX to simulate daily crude.

The population in this study analyzed daily crude oil futures prices in the Indian derivatives market from 2005 to 2020 (16 years) (BSE, NSE, NCDEX, MCX). The

BSE offers two types of crude oil futures: OMCRUDE and BRCRUDE. On the other hand, those crude oil futures have been traded since 2020. Since 2019, only BRENT CRUDE OIL futures have been traded on the NSE. Only agricultural commodities are listed on NCDEX. As a result, NCDEX makes no addition to the population. There are four different forms of crude oil futures on the MCX: BRCRUDEOIL, CRUDEOILM, MESCRUDEOIL, and CRUDEOIL. From 2005 to 2016, BRCRUDEOIL futures were traded, followed by CRUDEOILM futures from 2015 to 2019, MESCRUDEOIL futures from 2015 to 2019, and CRUDEOIL futures from 2005.

The sample size for the GBM Model in this research study includes daily crude oil futures prices in the MCX from 2005 to 2020. (16 years). Secondary data from the MCX was used in this study, and data presentation tools included Microsoft Excel and descriptive statistics. The research design GBM Model is a model for determining risk value in which the random variable quantity's logarithm follows a Brownian Motion with drift. It's known as the Wiener Process. By solving the stochastic differential equation below (1), the stochastic process S_t follows GBM.

$$dS_t = \mu S_t \, dt + \sigma S_t dW_t \qquad (1)$$

Where μ is the percentage drift, σ is the percentage volatility, and the Wiener Process abbreviated as W_t is a mathematical method for calculating the (GBM). Both are constants in this situation. On the other hand, this research project uses Excel to simulate future crude oil futures prices. As a result, for the discrete-time example, the preceding equation should be modified as follows:

$$\Delta S_t = S_{t-1}(\mu\Delta t + \sigma\varepsilon\sqrt{\Delta t}) \quad (2)$$

In the above equation (2), ΔS_t represents the crude oil futures price change per unit of time, Δt represents the time interval (one day), and ε represents the standard average random number. The previous day's crude oil futures price allowed the parenthesis words to drift and shock. When studying equation (2), it's important to remember that the GBM is a Markov process because tomorrow's price is determined only by today's price, not the past.

Because the price ratios are lognormal, GBM can be considered a lognormal diffusion process. That means the crude oil futures will have a lognormal, continuously compounded periodic return ($ln\ (S_t / S_{t-1})$). This lognormal random approximately usually distributes a variance $\sigma^2 t$ and mean $(\mu - (\sigma^2/2))t$. To present that in this research study following equation has been formulated. Where α indicates the deterministic component (drift), $z_t\sigma$ indicates the stochastic component where z_t generate random variables for the crude oil futures price, which its corresponding stochastic volatility at t will scale.

$$\ln\left(\frac{S_t}{S_{t-1}}\right) = \alpha_t + z_t + \sigma_t \quad (3)$$

The initial value of the crude oil futures price should be considered as S_0 and volatility as σ_1 before starting the simulation.

The random shock (stochastic component) in this research study is a function of random crude oil futures price and random volatility, allowing the stochastic process to take various pathways every time. The data presentation tool in the GBM model in Excel and the following inputs and procedures should be increased.

Expected Daily Drift

In one cell, the estimated return of the security should be stated. The daily drift is then determined by dividing the annual drift by 252. Finally, subtract 1/2 of the variation at period *t* from this daily drift to get an "expected" daily drift.

Expected Daily volatility

Set the value of the security's annual volatility in one cell, then divide the annual volatility by the square root of 252 trading days to get the value of the security's initial daily volatility. Use a custom Excel function called NORMSINV (RAND () to produce the regular normal random number. The probability between 0 and 1 is obtained using RAND, and the inverse standard normal cumulative distribution is obtained using NORMSINV.

Generated random variable for the security price

To create random variables, utilize the NORMSINV (RAND ()) excel function once more. It should normally get a value between -3 and 3 here.

Gathering Daily closing prices per barrel of the crude oil futures in MCX

Use the MCX website or Publicity available data about the daily closing price for the period and copy it to the excel worksheet.

Periodic Daily Returns

The following excel formula should be applied to calculate daily return.

=LN (Today's Closing Price/Yesterday closing prices) (4)

Then, using the periodic daily return mean in Excel, locate and calculate variance and standard deviation. In Excel, use the "AVERAGE" function to compute Mean (Range of periodic daily returns), "VAR.P" for calculating variance (Range of periodic daily returns), and "STDEV.P" for calculating Standard Deviation (Range of periodic daily returns) (Range of periodic daily return).

Application of GBM Model formula

$$\Delta S_t = S_{t-1}(\mu\Delta t + \sigma\varepsilon\sqrt{\Delta t}) \quad (5)$$

To present the GBM application, consider the equation above. There are two parts to this. One is certain, while the other is uncertain. Those two components should be calculated as follows.

1. Certain Variable (Drift Variable) = Average-(variance/2)
2. Uncertain variable = Previous day security’s price* EXP (Drift+ S.D* NORMSINV (RAND ()))

The following equation (6) is the combination of the above two variables.

Change Security Price = Average-(variance/2) + Previous day security's price* EXP (Drift +S.D* NORMSINV (RAND ())) (6)

The chi-square test, which examines the "goodness-of-fit" between observed and projected security price values, can be used to test the hypothesis under GBM. This test detects a significant difference between expected (forecast) and actual security prices. Consider the equation below (7).

$$X = \frac{(Observed-Expected)}{Expected} \qquad (7)$$

The probability that the observed value changes from the expected value purely due to chance should be compared to 0.05. When the probability value falls below 0, the null hypothesis is rejected.

In GBM, data analysis is done with the Microsoft Excel data analysis suite. The Mean Absolute Percentage Error determines the model's forecast accuracy.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A-F}{A}\right| \qquad (8)$$

F and A = The forecasted values and actual values.

n = the number of observations.

The MAPE Judgment of forecast accuracy indicates the value <11% - Highly accurate, 11% to 20% - Good accurate, 21% to 50% - Reasonable forecast, and >50% - Inaccurate forecast.

4. FINDINGS AND DISCUSSIONS

It analyzes crude oil futures prices and simulates them in MCX using the GBM model by applying 16 years of daily crude oil futures prices across India's four derivatives marketplaces (BSE, NSE, MCX, NCDEX). From February 9, 2005, until December 31, 2020, secondary data was collected from the MCX website. The annual volatility was calculated using an excel formula utilizing 2005 and 2020. The application of the GBM model yielded the following result. The average, variance, standard deviation, and drift are shown in Table 1, which are statistical test values of daily crude oil futures prices at the MCX from February 9, 2005, to December 31, 2020.

Table 1: Statistical test value

Average	Variance	Stand Deviation	Drift
0.0001	0.0098	0.0990	-0.0047

The findings of the February 2020 simulation are shown in Table 2.

Table 2: Sample of actual prices and simulated prices in MCX

Day	Actual Crude Oil Futures Price	Daily Return	Simulated Crude Oil Futures Price
1-Feb-20	3678	-0.0156	3118
3-Feb-20	3665	-0.0033	3864
4-Feb-20	3622	-0.0119	4043
5-Feb-20	3637	0.0041	4424
6-Feb-20	3648	0.0031	3570
7-Feb-20	3630	-0.0050	3445
10-Feb-20	3574	-0.0155	3795
11-Feb-20	3590	0.0043	3256
12-Feb-20	3650	0.0165	3965
13-Feb-20	3658	0.0023	3512
14-Feb-20	3711	0.0143	3544
17-Feb-20	3723	0.0031	4054
18-Feb-20	3676	-0.0127	3666
19-Feb-20	3783	0.0287	3306
20-Feb-20	3887	0.0272	4146
21-Feb-20	3830	-0.0147	3426
24-Feb-20	3707	-0.0327	4565
25-Feb-20	3692	-0.0042	3508
26-Feb-20	3572	-0.0328	3173
27-Feb-20	3398	-0.0500	3940
28-Feb-20	3287	-0.0330	3526

Figure 1 depicts the changes in MCX crude oil futures prices from 2005 to 2020. (16 years). The horizontal axis in this graph depicts current crude oil futures prices per barrel in Indian Rupees, while the vertical axis depicts days. It means that daily crude oil futures prices varied between 2005 and 2020.

On August 17, 2005, the MCX recorded the lowest actual crude oil futures price. The price was Rs 823. In April 2020, the second and third lowest prices were recorded. They were Rs 955 and 957, respectively. This is a situation that has occurred in the recent past. The decline in WTI crude oil prices was documented as a historical note. In August and September 2013, the MCX recorded its three highest actual crude oil futures prices. They were Rs 7571, 7402, and 7365, respectively.

Actual crude oil futures prices in the MCX rose at the start of 2005. It is clear, however, that there are variations over time. Between 2009 and the middle of 2013, there was a significant increase in prices, as shown in this graph. Between the middle of 2013 and 2016, the MCX's actual crude oil futures prices dropped significantly. It was at a low point in 2009, 2016, and 2020. Actual crude oil futures prices on the MCX have dropped dramatically between 2009 and 2020. Actual crude oil futures prices increased moderately between 2016 and the middle of 2018. From 2009 to 2011, 2012 to 2013, and 2019 to 2020, the MCX attempted to keep actual crude oil futures prices stable. However, that commitment didn't exactly work out.

Figure 1: Actual crude oil futures price for MCX from 2005 to 20

The GBM model was used to determine simulated crude oil futures price movements in the MCX from 2005 to 2020 (16 years). The horizontal axis in this diagram depicts simulated crude oil futures prices per barrel in Indian Rupees, while the vertical axis depicts days. It means daily crude oil futures prices modelled from 2005 to 2020 fluctuated.

On August 18, 2005, the MCX recorded the lowest simulated crude oil futures price. The price was Rs 823. In April 2020, the second and third lowest prices were recorded. They were Rs 917 and Rs 1124, respectively. The GBM model also identified a decline in WTI crude oil prices. In August and September 2013, the MCX recorded three of its highest simulated crude oil futures prices. Rs 5306, Rs 7870, and Rs 7266 were the amounts.

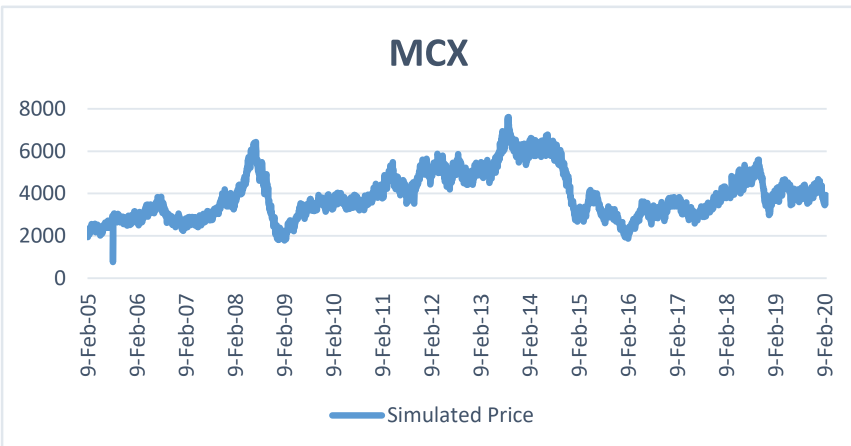

Figure 2: Simulated crude oil futures price for MCX from 2005 to 2020

Simulated crude oil futures prices in the MCX rose at the start of 2005. However, just like real-world prices, there are variations throughout time. Between 2009 and the middle of 2013, this graph shows a significant increase in simulated pricing. From the middle of 2013 to the middle of 2016, MCX's simulated oil futures prices have dropped significantly. In 2009, 2016, and 2020, it reached a breaking point. The simulated crude oil futures prices on the MCX significantly dropped in 2009, 2014, and 2020. From 2016 through the middle of 2018, simulated crude oil futures prices have increased moderately. In the middle of 2009 to 2011, 2012 to the middle of 2013, and 2019 to 2020, the MCX aimed to keep simulated crude oil futures prices stable. However, the commitment usually doesn't work out like actual crude oil futures prices.

Figure 3 shows the actual and simulated changes in MCX crude oil futures prices from 2005 to 2020 on the same graph (16 years). It means that daily crude oil futures prices changed between 2005 and 2020. Both systems go opposite to one another. It shows simulated crude oil futures prices following the actual crude oil futures prices line and does not indicate further changes with actual crude oil futures prices over long time horizons, using the highly accurate GBM model in the MCX. That's why the blue line appears to obscure the red line entirely. If fewer years are utilized to construct simulated crude oil futures prices, the results will differ from figure 2.

The correctness of the GBM model can be determined by looking at Figure 3. The most important aspect is that it has been utilized for an extended time to collect daily data. Using a long period of data, such as this simulated crude oil futures price, will provide reliable forecasts.

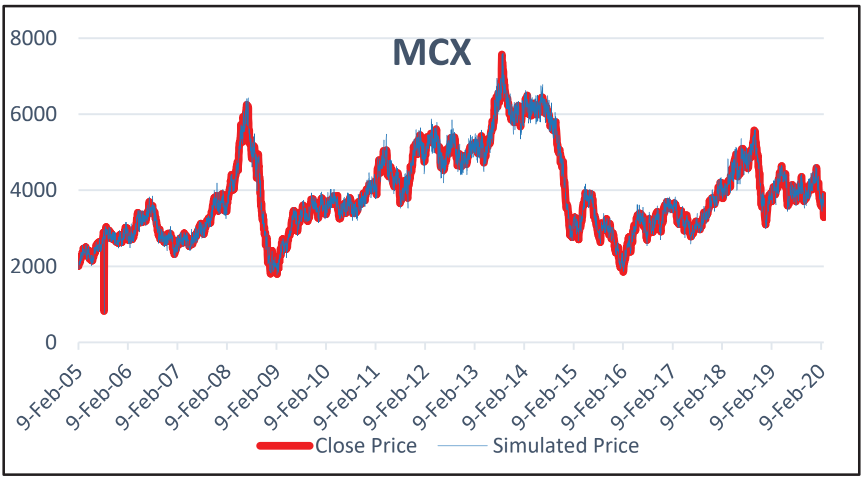

Figure 3: Comparison of actual crude oil futures prices vs crude oil futures prices

The crude oil futures prices obtained from India's Mumbai Commodity Exchange (MCX) were studied using Microsoft Excel data analysis software with constant parameters as in the GBM model. Additionally, 95 per cent confidence interval crude oil futures prices were generated and compared to actual crude oil futures prices. The model's forecast accuracy is calculated using the Mean Absolute Percentage Error. This metric depicts the difference between projected and actual crude oil futures prices, as seen in table 3.

Table 3: MAPE Table

Derivatives Market	MAPE
Multi Commodity Exchange	0.1016535

The GBM model accurately predicts crude oil futures prices on the MCX in India since the MAPE values are between 0% and 11%. The chosen MCX (10.16535%) indicates that the results will be highly accurate.

5. CONCLUSION

The GBM model is a frequently used price prediction model in several countries when it comes to modelling security prices. In the Indian derivatives market, however, there are no widely observables for crude oil futures. As a result, the primary goal of this study is to determine whether or not the GBM model is accurate.

To achieve this goal, the researchers used daily crude oil futures prices from the MCX from February 9, 2005, to December 31, 2020, to test the GBM model's validity. Researchers used Mean Absolute Percentage Error to determine the accuracy of those models' applications (MAPE). With MAPE values ranging from 0% to 11%, the GBM model accurately forecasts crude oil futures prices on the MCX in India. The GBM model was created to predict security price behaviour and then used to trade securities. After that, the simulated or forecasted prices were compared to actual crude oil futures prices. The results revealed that in far more than 80% of cases, the model correctly forecasts crude oil futures price behaviour. There is also a way to examine the security's probabilistic distribution mathematically. This research study aims to assist investors and other stakeholders make informed decisions on crude oil futures trading, notably on the MCX's derivatives market. Future researchers will be able to improve these models by focusing on various derivatives markets with other underlying assets due to this research.

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