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RESEARCH ARTICLE

Forecasting Sugar Price Fluctuation In Malaysia Using Geometric Brownian Motion Modelling

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ABSTRACT

A mathematical model known as Geometric Brownian motion has proven to be an effective tool that can be deployed to forecast the price of goods in the future due to the presence of random terms, which represent the stochastic or random fluctuation of prices over a given period of time. The success of this model revolves around the estimation of its governing parameters. To efficiently predict the price of goods, using the Geometric Brownian Motion model (GBM), one needs to determine the value of returns and use the calculated returns to estimate the value of drift as well as volatility. This research used the value of volatility and drift terms obtained from real data of sugar in the months under review. The method has shown to be very reliable in capturing the intelligent trend in the price of sugar in Malaysia. The model was able to stimulate the pattern of the predicted price that shares a great resemblance to the actual price of sugar. The result obtained is very encouraging and places this study with a good note now that the country is just returning to normalcy from the pandemic that has crippled the economies of most developing nations in the world. We used the model to predict the price of sugar for a period of 20 months and the result of our prediction as well as the graph of the predicted prices confirmed the practicability of the model. The obtained values of MAPE and MSE, two of the popular performance metrics, also justified the effectiveness of the GBM in capturing the trend in the data. This model can be classified as a good model that can be deployed to forecast the price of goods that exhibit high volatility.

Keywords: Brownian motion, Drift value, MAPE, MSE, Volatility, Performance metric

1. INTRODUCTION

Price forecasting encompasses any effort or attempt to gain insight into fluctuations in the price of commodities that will benefit the prediction of the price of goods in the future. It could be mathematical models or algorithms built using formulas, relations, logic, or sophisticated paradigms to extract the latent information and knowledge from the dataset of a specified product or commodity within a given time frame and utilise such intuitive, foolproof knowledge to forecast the price of the commodity in the future. Price forecasting is essential over a lengthy time horizon when unforeseen situations force the price of commodities to behave erratically (Jay et al., 2020). A good forecasting model or algorithm is one that generates results that are accurate, reliable, timely, and informative (Hanke & Wichern, 2005 ; Hamdan et al., 2020). One of the appropriate steps towards an efficient price prediction model is credible data that can show an actual trend or pattern in the dataset. A good predictive model is the result of reliable mathematical model algorithms, credible dataset, and high-performance data mining techniques. In the past, researchers have proposed different models to predict the price of goods, but none of them could represent others. Nemes and Butoi (2013) reported that a time series forecasting model that uses statistical methods like moving averages, exponential smoothing, and regression (parametric or non-parametric). ARIMA is one of the best models for predicting the price of goods in business and finance (Madziwa et al., 2022). Data-driven models are effective and dependable when they are properly modelled and response effectively to price changing factors (Nemes & Butoi, 2013).

An Autoregressive Distributed Lag (ARDL) model has been demonstrated to be one of the most proficient techniques in modelling price fluctuations in both long- and short-time frames due to its ability to identify relevant information in datasets when there are irregular changes in the price of goods. The relationship between the trend of prices in the past and present is the backbone of its success as a predictive model, the model presents the price's dependence on its own historical information (Tursoy & Faisal, 2018). Because of ARDL's massive success, many research projects and studies are built on it. Even with a limited or small sample size, the ARDL technique still predicts reliable information (Chirwa & Odhiambo, 2019). The ARDL model stands tall in predicting prices using a variety of dynamic variables. Dynamic multivariable, which could be stationary, non-stationary, or both merged as a model, has amazing applicability in both short- and long-term effects, which is also an amazing quality of the model that adds to its success (Jordan & Philips, 2018).

Neural networks are becoming more popular for predicting prices, and their strong strategies have led to a rise in the number of prediction models. They are now used and adapted based on the desired task. Their high propensity to recognise intricate nonlinear correlations and patterns in data make them popular in price prediction. To use ANN as a price prediction model, historical data and relevant features, such as past prices, volume, technical indicators, economic indicators, news sentiment, or any other relevant information that may influence the price, are collected. These information may be subjected to preprocessing activities, feature engineering, and the processed data is later used in the training the network. The neural network is trained using historical data and target values for supervised learning. It adjusts the internal weights through the training algorithm to minimise loss or error. After training, the network is validated using unseen data, using techniques like cross-validation or time-series validation. After validation, the neural network can make predictions on unseen data, generating predicted prices or movements. The accuracy and performance of these predictions are evaluated using performance metrics like MSE, MAE, or directional accuracy (Rojas et al., 2018).

Data mining, which revolves around unearthing latent knowledge or important patterns from large databases, is the brain behind the success of the neural network in the predictive task (Chang et al., 2021). The functionality of data mining revolves around the classification strength of the data, which is utilised in finding a model that can represent data attributes that can stand alone as attributes of other data (Khashei & Bijari, 2010; Alway et al., 2020). Records have also shown the effectiveness of neural networks in monthly forecasts as well as in particular time frames; ANN outperformed most traditional approaches (Deaconu et al., 2022). Most ANN produce smaller mean square errors (MSE), and the ANN technique is more accurate in projecting the price of goods than the time series method (Shabri, 2001). Shahrour and Dekmak reported that ANN improves real estate valuation by predicting better selling prices, ensuring stability, illustrating property attributes, using appropriate statistical indicators, addressing transparency critiques, and serving valuation reports (Shahrour & Dekmak, 2022).

One of the most significant industrial crops in the world is sugarcane, from which sugar is obtained. Sugar is made up of pure carbohydrate, an important nutrient that supplies energy

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to the human body. Sugar mills and industries, mostly located in rural areas, have substantially created employment opportunities for the rural populace, a gesture that greatly contributes to the rural economy. Recent years have witnessed sudden and unforeseen changes in the global price of sugar. Factors such as supply, demand, stock availability, exchange rates, government policies, interregional differences, climatic conditions, biofuel support policies, and many more (Maitah & Smutka, 2016) have all played significant roles in the contemporary state of fluctuation of the global sugar price. More than 130 countries in the world are regarded as sugar-producing countries. Sugar has experienced a high frequency of price fluctuations, but paradoxically, price volatility is constantly fluctuating in terms of range, from low to high or otherwise (Tukaew et al., 2016). However, the frequency of these fluctuations increases over time, making the sugar market practically unstable. This pattern caused these markets to be unstable, and as profits increased, more speculators, both individual and institutional, got attracted to the sugar market. However, such attractions in total will create more problems in the market in the future (Maitah & Smutka, 2016). Late 2019 and early 2020 witnessed a massive drop in the price of sugar, which can be linked to the COVID-19 epidemic.

During the epidemic, family incomes fell leading to a decline in the demand for sugar. Large industries and small-scale businesses closed down due to the measures adopted by the nation to retard the spread of COVID-19. This study aimed to investigate the fluctuation in the price of sugar in 2021 and make predictions using a mathematical model based on Geometric Brownian motion that can capture the trends in the price of sugar in the specified interval.

2. MATERIAL AND METHODS

2.1. Mathematical Formulation

A mathematical model called Geometric Brownian Motion (GBM) can be used to model the random fluctuation of a price over time. GBM is mostly used in finance to study the behaviour of the price of commodities, its applicability can be extended to other areas of study where randomness dominates the behaviour of the variables. Properties such as log-normal, independent of the price changes relative to the past price change, account for its robustness as a useful price prediction model. It works based on constant volatility, a situation that may not always hold in real-life scenarios. Making GBM not account for market crashes or unforeseen events like war, government policies, and many more may lead to unrealistic predictions (Farida et al., 2018). The Brownian motion, also known as the Wiener process, is a collection of random numbers B_t with $(0 \le t \le T)$, each of which has its own distinct t in the interval.

The collection of B_t is characterised by a continuous time stochastic process, and it begins with $B_0 = 0$, each of the B_t is normally distributed with zero (0) mean and variance of 1, it is the most straight forward Markov process (Debus, 2013). The Markov property implies that each increment of the Wiener process B_t is statistically independent. It is monotone due to its zero mean. In the absence of a discernible trend, the best estimate for the future price is the most recent value of B_t. Price of goods can be modelled as the addition of the deterministic drift and the random number with mean zero (0) and variance (*dt*). Figure 1 depicts the plot of the Wiener process with a value of $n = 500$ and $T = 1$ the graph geometrically justifies the difficulty of using the deterministic calculus method. The Wiener process is an unsmooth function, and it is known to be undifferentiable anywhere.

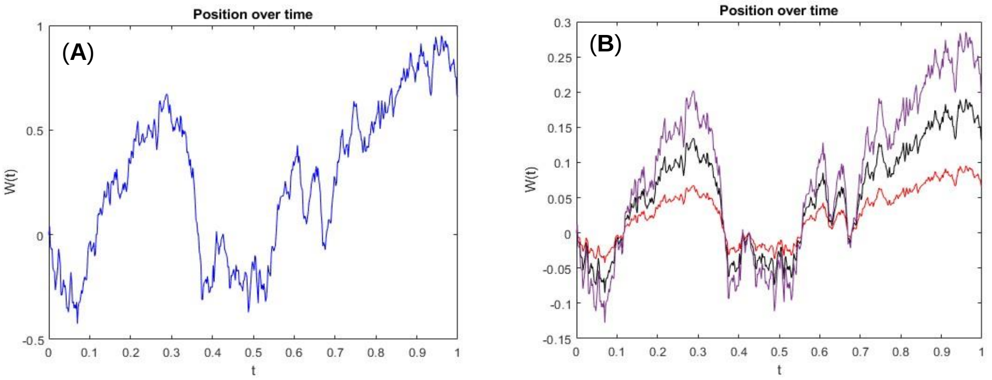

Figure 1. (**A**) Wiener process, (**B**) Generalized Wiener process

Figure 1 (A) is a single Wiener process, which is insufficient to illustrate the dynamics of price, since prices are notorious for exhibiting unpredictable and randomized trends. Therefore, it can be generalized by adding coefficients a and b using the drift and diffusion term to demonstrate a more accurate behaviour. Consequently, the stochastic differential equation (SDE) in equation (1) describes the generalized Wiener process.

$$dS_t = a\mu dt + b\sigma dB_t \tag{1}$$

where, dS_t is the change in the price of sugar at time t, μ is the drift term, dt is the time step, σ is the volatility term, and B_t is Weiner process, while a and b are functions of *S* and *t*.

Figure 1(B) depicts a more generalized Wiener process with drift and volatility terms, even with a more generic model, the continuous drift and variation rates will still pose a degree of difficulty. It can be observed that such unpredictable fluctuation of price follows Markov's process, as such, the next price is independent of other previous prices, and mainly depends on the immediate price. The increment in the price of the goods has nothing to do with the time interval of other price increments. The mathematical model we utilized here can be seen as the temporal emergence of price as a solution to the SDE in Equation (2);

$$\frac{dS_t}{S_t} = \mu dt + \sigma dB_t \tag{2}$$

Equation (2) can be rewritten as Equation(3), which is a stochastic differential equation;

$$dS_t = \mu S_t dt + \sigma S_t dB_t \tag{3}$$

From Equation (3), we can illustrate the application of Itô's formula in stock price movement and SDE for the process *Y* is related to S_t or the solution $(S(t))$ can be obtained. Its partial derivatives are $\frac{\partial G(t,S)}{\partial S} = \frac{1}{S}$, $\frac{\partial^2 G(t,S)}{\partial S^2} = -\frac{1}{S^2}$, $\frac{\partial G(t,S)}{\partial t} = 0$.

According to the Itô's lemma (Hassler, 2016), we have

$$dY(t) = \left(\frac{\partial G(t,\, S)}{\partial t} + \frac{\partial G(\mathrm{t},\, \mathrm{S})}{\partial S}\mu S(t) + \frac{1}{2}\frac{\partial^2 G(t,S)}{\partial S^2}\sigma^2 S^2(t) \right)dt + \frac{\partial G(\mathrm{t},\, \mathrm{S})}{\partial S}\sigma S(t) dB_t \tag{4}$$

Substituting the obtained partial derivative above into Equation(4) gives

$$dY(t) = \left(\mu - \frac{1}{2}\sigma^2 \right)dt + \sigma dB_t \tag{5}$$

We can calculate the stochastic integral on the right hand side of the Eq. (6)

$$\mathrm{Y}(t) = \mathrm{Y}_0 + \int_0^t (u - \frac{1}{2}\sigma^2)dt + \int_0^t \sigma dB_t \tag{6}$$

Simplifying it further and evaluate yields Equation(7)

$$\mathrm{Y}(t) = \mathrm{Y}_0 + (\mu - \frac{1}{2}\sigma^2)\mathrm{t} + \sigma B_t \tag{7}$$

Since $\mathrm{Y}(t) = \ln S(t)$, the solution of as $S(t)$ can be presented as shown in Equation (8);

$$\ln S(t) = \ln(\mathrm{S}(0)) + (\mu - \frac{1}{2}\sigma^2)\,\mathrm{t} + aB_t \tag{8}$$

which can be written as;

$$S(t) = S(0)e^{(\mu - \frac{1}{2}\sigma^2)t + aB_t} \tag{9a}$$

or equivalently

$$S(t) = \mathrm{e}^{\ln \mathrm{S}_0 + (\mu - \frac{1}{2}\sigma^2)\mathrm{t} + aB_t} \tag{9b}$$

where B_t is the standard Wiener process, Equation (9a) has the similar structure of a generalized Wiener process in equation (1) , with constant drift coefficient of $a = \mu - (\sigma^2 / 2)$ and a constant diffusion factor $b = \sigma$. Consequently, $G(\mathrm{t}, \mathrm{S}(\mathrm{t}))$ the increments can be written as normally distributed log returns $\ln S_T - \ln S_0$ with a mean of $\left(\mu - \left(\sigma^2 / 2\right)\right)T$ and a variance. We can also present $\ln S_T$ as

$$\ln S_T \sim \phi\left[\ln S_0 + \left(\mu - \frac{\sigma^2}{2}\right)T, \sigma^2 T\right] \tag{10}$$

From Equation(10), the natural logarithm of the variable $\ln S_T$ is normally distributed, which implies that S_T a must be lognormally distributed. This assumption is intuitive, since the stock price must be positive, which is also an important property of the lognormal distribution. Dmouj (2006) and Agustini et al. (2018) have shown that the variable B_t can be obtained as $\varepsilon\sqrt{t}$ where ε is a noise. Hence, Equation(9a) can be rewritten as

$$S(t) = S(0)\,\mathrm{e}^{(\mu - \frac{1}{2}\sigma^2)\mathrm{t} + a\varepsilon\sqrt{t}}, \varepsilon \sim N(0,1) \tag{11}$$

where, Equation(11) is the model to be used to predict the price of sugar in Malaysia within the specified interval and the values of the parameters μ and σ are calibrated from the real data of sugar price.

2.2. Data Acquisition

The historical daily sugar price was downloaded from indexmundi.com. The raw data taken was strictly for the sugar prices within the specified period, the events of prices before this period were not considered in this research. Exploring and investigating how sugar prices have changed in the Malaysian sugar market in the context of the development of the economy is the main aim of this research. The Malaysian sugar price is examined in light of its fluctuation in 2021, when the nation is just beginning to recover from the COVID-19 incident that has gripped the entire world in fear. The analysis shows how prices have changed in Malaysia. The analysis of sugar pricing is done in light of short-term fluctuations.

Table 1. The monthly sugar price in Malaysia from January 2021 to December 2021*

Month	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**June**	**July**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Price	1.37	1.46	1.40	1.48	1.57	1.57	1.64	1.82	1.79	1.75	1.79	1.80

*Data extracted from indexmundi.com

2.3. Parameter Computation

Table 2 shows the actual price of sugar ranging from January 2021 to December 2021. The monthly price was computed from the daily price for each month. The prices were extracted from indexmundi.com for sugar prices. The computation of the required parameters was carried out using Microsoft Excel.

Table 2. The computation of parameters used in the research

Month	Real Price	Drift Components	Volatility Components
Jan 2021	1.37	0.036252	0.00122027
Feb 2021	1.46	0.037243	-0.1011389
Mac 2021	1.40	0.035552	-0.0208491
Apr 2021	1.48	0.035941	0.10364042
May 2021	1.57	0.039635	0.09498836
Jun 2021	1.57	0.043197	-0.0152824
Jul 2021	1.64	0.043936	0.03167698
Aug 2021	1.82	0.045937	-0.0537832
Sep 2021	1.79	0.045729	0.00147178
Oct 2021	1.75	0.046978	0.06303271
Nov 2021	1.79	0.049889	-0.0127263
Dec 2021	1.80	0.050872	-0.1293102

We computed monthly price returns from January, 2021 to December, 2021, and we adopted the same relation used in (Abidin & Jaffar, 2014) which is given as

$$R_t = \frac{S_t - S_{t-1}}{S_{t-1}} \tag{12}$$

where R_t denotes the price returns at time t, S_t and S_{t-1} a represent price at time, t and time $t-1$ respectively. Using Equation (12), we computed the value of the drift (μ) using Equation(13) which gives as

$$\mu = \frac{1}{n\delta t}\sum_{t=1}^{n} R_t \tag{13}$$

where μ is the drift, R_t as defined above, n is the number of price returns and δt is the time step. However, with known value of drift, we need to compute the volatility value with the formula in Equation(14)

$$\sigma = \sqrt{\frac{1}{(\mathrm{n}-1)\delta t}\sum_{t=1}^{n}(R_t - \bar{R})^2} \tag{14}$$

where σ a denotes volatility and $\bar{R}$ a represents the price return

Table 3. Values of parameters obtained from our sugar price dataset

	Parameter	Value
1	Initial Sugar Price (S_t)	1.370000000
2	Drift (μ)	0.026461040
3	Volatility(σ)	0.050579719
4	Time step δt	1.000000000

3. RESULTS AND DISCUSSION

Forecasting prices of sugar using Geometric Brownian Motion (GBM) encompasses utilising the stochastic process to estimate future price fluctuations based on historical data with the assumption that price returns follow a normal distribution. It is also presumptive that there won't be any notable price spikes or sudden changes in the price of sugar within the research period. Using the price information of the sugar price in Table 1, we can compute the

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volatility (σ) and the drift coefficient (μ) from the data using Equations (13) and (14). The obtained parameter values are then substituted into Equation (11), with the initial price of sugar set as $S(0)$. Future price of sugar is simulated using the calculated drift and volatility. This involves generating random numbers from a standard normal distribution to serve as the random part of the equation, the random numbers are then multiplied by the square root of the time increment (δt) and the volatility to simulate the random increment (dB_t). From Table 4, it is apparent that the price of sugar has fluctuated randomly and is increasing dramatically over the aforementioned period. The rate of price rise and, in particular, the frequency of variations and extremes that have occurred on the sugar market throughout its historical evolution after the Covid-19 pandemic call for urgent attention. The period coincides with the moment that all companies that depend heavily on sugar as one of their main raw materials are returning to operation. Similarly, small-scale business and households that engage in direct consumption of sugar stopped being economical in their sugar consumption. Such excess demand might be responsible for the surge in the price of sugar in Malaysia, which forced it to go higher or fluctuate frequently and randomly.

Table 4. Comparison of the predicted prices and actual prices of sugar

Month	Real price	Predicted Price
January, 2021	1.37	1.4074719
February, 2021	1.46	1.3435762
March 2021	1.40	1.3582796
April, 2021	1.48	1.4978615
May, 2021	1.57	1.6324848
June, 2021	1.57	1.6603997
July, 2021	1.64	1.7360126
August, 2021	1.82	1.7281661
September, 2021	1.79	1.7753670
October.2021	1.75	1.8853777
November,2021	1.79	1.9225405
December, 2021	1.80	1.8441027

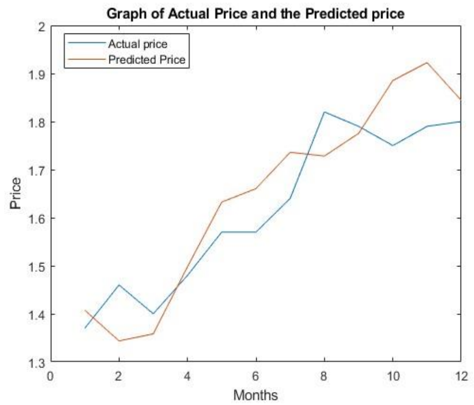

Figure 3. Graph of the actual prices and predicted prices

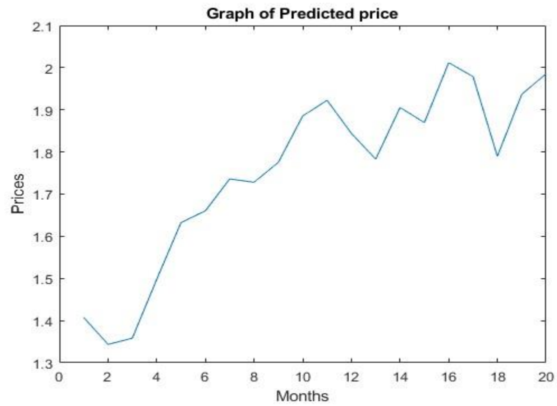

Figure 4. Graph of predicted prices from January 2021 to August 2022

Figure 3 shows a comparison of the predicted price of sugar and the actual price of sugar. This shows how well the model is able to capture the trend in the data. We further deployed the model to predict the price for an additional eight (8) months, ranging from January 2021 to August 2022. The predicted prices for 20 months were shown in Table 5, while Figure 4 shows the graph of the predicted price of sugar until August 2022, information that may be used for decision-making by the stakeholders in the sugar business.

Table 5. The predicted price of sugar for 20 months

Month	Predicted Price	Month	Predicted Price
January, 2021	1.4074719	November,2021	1.9225405
February, 2021	1.3435762	December, 2021	1.8441027
March 2021	1.3582796	January, 2022	1.782970
April, 2021	1.4978615	February, 2022	1.9052942
May, 2021	1.6324848	March 2022	1.8696106
June, 2021	1.6603997	April, 2022	2.0116607
July, 2021	1.7360126	May, 2022	1.9788275
August, 2021	1.7281661	June, 2022	1.7895731
September, 2021	1.7753670	July, 2022	1.9366739
October.2021	1.8853777	August, 2022	1.9854496

3.1. Error Analysis and Performance Metric

We investigated the performance of the prediction, which is made up of the actual price of sugar and the predicted sugar price under review, using two of the most popular performance metrics, namely, mean Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE), which are computed using the Equation(15) and (16), respectively.

$$MSE = \frac{1}{N}\sum_{i=i}^{m}(A_i - P_i)^2 \tag{15}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{m}\left|\frac{A_i - P_i}{A_i}\right| \tag{16}$$

where A_i is the actual sugar price at time i, P_i is the predicted sugar price at time i, and N is the number of stimulations.

Table 6, shows the computation of the Mean Square Error (MSE) and Mean Average Percentage Error (MAPE) for the dataset and model.

$$MSE = \frac{1}{N}\sum_{i=i}^{m}(A_i - P_i)^2 = \frac{1}{12}(0.0848) = 0.007100$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{m}\left|\frac{A_i - P_i}{A_i}\right| = \frac{1}{12}\left(0.539424\right) = 0.044952$$

Table 6. Performance metrics for the actual and predicted price

	A_t	P_t	$\lvert A_t - P_t\rvert$	$(A_t - P_t)^2$	$\lvert A_i - P_i\rvert / A_i$
1	1.37	1.407472	0.0374719	0.001404	0.027352
2	1.46	1.343576	0.1164238	0.013555	0.079742
3	1.40	1.35828	0.0417204	0.001741	0.029800
4	1.48	1.497862	0.0178615	0.000319	0.012069
5	1.57	1.632485	0.0624848	0.003904	0.039799
6	1.57	1.660400	0.0903997	0.008172	0.057579
7	1.64	1.736013	0.0960126	0.009218	0.058544
8	1.82	1.728166	0.0918339	0.008433	0.050458
9	1.79	1.775367	0.014633	0.000214	0.008175
10	1.75	1.885378	0.1353777	0.018327	0.077359
11	1.79	1.922541	0.1325405	0.017567	0.074045
12	1.80	1.844103	0.0441027	0.001945	0.024502
			Total	0.084800	0.539424

4. CONCLUSION

In this research, we used Geometric Brownian Motion (GBM) to investigate sugar price fluctuations in Malaysia within a specified period of time and then used the observed pattern to forecast future sugar prices for another period of time. Similarly, we deployed Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE), two popular performance metrics, to assess the performance of GBM model. Our findings showed that the GBM model was able to capture the fluctuation in sugar prices effectively, allowing us to make predictions for another period of time, Surprisingly, the acquired results of both performance metrics showed low error rates less than 10% for both MAPE and MSE, this validates the precision of our projections and demonstrated the GBM model's sturdiness in capturing the trends in sugar price fluctuation. With the use of GBM, we were able to accurately record and decipher the intricate price swings in sugar, providing stakeholders in the sector insightful information.

Our study highlighted GBM's potential as a useful technique for forecasting sugar prices in the future. Individuals and stakeholders in the sugar sector may use this information to streamline decision-making and create efficient plans for controlling price variations and earn more profits. The limits of our study must be understood. It is assumed that sugar prices would behave in the same stochastic manner as shown in the historical data in order for our forecasts to be accurate in the future. Future pricing may be influenced by outside factors, such as modifications in market circumstances, changes in supply and demand, and unforeseen occurrences. Summarly, this research offers a convincing proof that Geometric Brownian Motion is a vital technique for capturing and forecasting the fluctuation in sugar prices in Malaysia. The use of MAPE and MSE as performance indicators highlights the precision and dependability of our forecasts. For stakeholders in the sugar sector, our results provide insightful information that may help with strategic planning and well-versed decision-making.

Declaration of Interest
I declare that there is no conflict of interest.

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