JUSTEK : JURNAL SAINS DAN TEKNOLOGI
http://journal.ummat.ac.id/index.php/justek
ISSN 2620-5475
Vol. 9, No. 1, March 2026, pp. 1-10

Sugar Price Prediction in East Java Using the Geometric Brownian Motion Model

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ARTICLE INFO

Article History:

Received : 10-12-2025
Revised : 02-03-2026
Accepted : 12-03-2026
Online : 25-03-2026

Keywords:
Geometric Brownian Motion;
MAPE;
Sugar Price

ABSTRACT

Sugar is a national strategic commodity that plays a vital role in Indonesia's economic stability and food security. East Java, as a major sugar producer, faces fluctuating price dynamics due to various factors, including sugarcane production, supply distribution, refined sugar imports, weather conditions, and the needs of the food and beverage industry. To understand the random price movement patterns, the Geometric Brownian Motion (GBM) model is used because it is able to represent price dynamics through log-normal drift and volatility components. This study aims to predict sugar prices in East Java using the Geometric Brownian Motion (GBM) model to provide insight into price uncertainty and volatility. The study population consists of daily sugar price data in East Java in August-November 2025, with August-October 2025 data as training data and November 2025 data as testing data. Sugar price prediction uses a stochastic modeling approach, implementing GBM through multi-path simulations to capture the shift and volatility parameters of sugar price movements. Sugar price prediction using the GBM model is carried out with 50, 500, and 1000 iterations (paths). The results obtained from the GBM model effectively capture the inherent volatility of sugar prices, producing a Mean Absolute Percentage Error (MAPE) value of 0.0846% for 50 trajectories, 0.0659% for 500 trajectories, and 0.0522% for 1,000 trajectories. These results indicate that the GBM can model sugar price fluctuations in East Java and provide accurate probabilistic estimates.

Crossref

A. INTRODUCTION

Sugar is a national strategic commodity that plays a crucial role in maintaining Indonesia's economic stability and food security. East Java, as one of the regions with a substantial contribution to national sugar production, continues to experience fluctuations in sugar prices over time. These price dynamics are influenced by various factors, including sugarcane production levels, supply chain distribution, refined sugar import policies, weather variability, and demand from the food and beverage industry (Badan Pusat Statistik, 2023). Such instability creates significant uncertainty for farmers, agribusiness actors, and local governments, particularly in formulating effective production strategies and designing appropriate market regulation policies (Kementerian Pertanian Republik Indonesia, 2022).

Sugar price forecasting in East Java is of considerable importance due to the pivotal role of sugar in the regional economy and agricultural sector. Given the consistently high demand for sugar particularly during festive seasons and major holidays price fluctuations can substantially affect purchasing power and overall economic stability. Accurate price predictions enable farmers to make informed decisions regarding planting schedules and production planning, thereby minimizing the risk of financial losses resulting from unexpected price volatility.

Numerous studies on sugar-related forecasting have been conducted, including the work of Jaelani et al. (2022), who compared the prediction of Indonesian sugar production using machine learning and classical statistical approaches. Specifically, the study employed the Long Short-Term Memory (LSTM) method and linear regression. The dataset consisted of national sugar production data spanning 52 years, from 1968 to 2020. The results indicated that the linear regression model projected an increasing production trend with an error rate of 8%. In contrast, the LSTM model predicted a decreasing production trend, achieving a training error of 0.069% and a testing error of 0.082%, suggesting superior predictive performance compared to the linear regression approach(Jaelani et al., 2022).

Another study conducted by Chamidah et al. (2021) forecasted international sugar prices using a Fourier series estimator within a nonparametric regression framework. The approach was designed to capture periodic patterns in the data. In this study, the response variable was the international price of white sugar, while the predictor variable was the monthly time index. The estimation results produced a Fourier series model with a Mean Absolute Percentage Error (MAPE) of 3.71% for the in-sample data. However, when comparing the predicted values with the out-of-sample data, the model yielded a MAPE of 18.9%, indicating reduced predictive accuracy outside the training period (Chamidah et al., 2021). In addition to machine learning, linear regression, and nonparametric regression approaches, sugar price forecasting can also be conducted using stochastic process–based models such as the Geometric Brownian Motion (GBM) method, which explicitly accounts for the probabilistic and dynamic nature of price movements.

In the field of commodity and financial asset price modeling, Geometric Brownian Motion (GBM) is one of the most widely utilized methods for representing continuous stochastic processes characterized by inherent volatility. GBM assumes that price movements follow a log-normal distribution driven by two key components: a constant drift, which captures the long-term trend of the price, and a constant volatility, which reflects random fluctuations occurring over time. This model serves as a fundamental framework in numerous financial applications, including derivative valuation**,** market risk assessment, and asset price forecasting (Hull, 2018). In addition to financial markets, several studies have applied GBM to various commodity price dynamics, such as crude oil, gold, and agricultural products. These applications demonstrate that GBM is capable of providing a reasonably accurate representation of price behavior in markets characterized by high uncertainty and volatility (Dixit & Pindyck, 1994; Willmot, 2007).

One study applying the Geometric Brownian Motion (GBM) model integrates a modified Kalman filter to forecast gold prices. The dataset consists of historical daily gold prices obtained from Yahoo Finance for the year 2023. The model was implemented using the Python programming language, and simulations were conducted with 100, 500, 1,000, and 5,000 iterations. The minimum Mean Absolute Percentage Error (MAPE) values obtained for each respective trajectory were 2.80%, 2.27%, 2.17%, and 1.69% (Hunaifi & Maulana, 2024).

Another study examined the implementation of the Geometric Brownian Motion (GBM) model in forecasting crude oil prices during the COVID-19 pandemic. In this research, price predictions were generated using 50, 100, and 1,000 simulation iterations. The findings indicate that the GBM model demonstrated satisfactory predictive performance during the pandemic period, as evidenced by Mean Absolute Percentage Error (MAPE) values below 10% (Seru et al., 2023).

Most research using the GBM model focuses on predicting the prices of financial assets such as stocks and crude oil.Research specifically applying the Geometric Brownian Motion (GBM) model to forecast food commodity prices in Indonesia, particularly sugar, remains relatively limited. Sugar price movements, which are often volatile and influenced by various external factors, render stochastic approaches such as GBM particularly relevant. The GBM model adopts a probabilistic framework based on multi-trajectory simulations, enabling the evaluation of estimate stability and the coverage of potential sugar price distributions. This approach facilitates a more comprehensive assessment of price uncertainty compared to conventional deterministic models, which typically provide only point forecasts without explicitly modeling stochastic dynamics.

B. METHODS

The population of this study consists of all sugar price data in East Java from August to November 2025. The sample comprises daily sugar price data within the same period, which is divided into training and testing datasets. The training data include observations from August to October 2025, while the testing data consist of observations from November 2025. The sugar price data were obtained from the official price monitoring system website managed by the East Java Industry and Trade Office (Disperindag Jawa timur, 2025). This research is quantitative, using the Geometric Brownian Motion model to analyze secondary data. The stages of sugar price prediction using the Geometric Brownian Motion model are shown in **Figure 1** below:

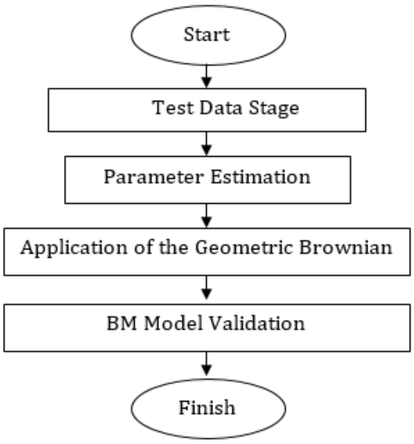

Figure 1. GBM model simulation flowchart

The steps for predicting sugar using the GBM model are as shown in **Figure 1** as follows:

1. Data analysis

At this stage, the sugar price data that has been collected is processed using the following steps:

a. The return values of the sugar price data are calculated using the following formula (Ruppert & Matteson, 2015):

$$R_{\boldsymbol{i}} = \ln\left(\frac{P_i}{P_{i-1}}\right) \quad (1)$$

Where R_i is the return of rice prices at time i, P_i is the actual price of rice at time i, and P_{i-1} is the actual price of rice at time $i-1$.

b. Conduct a normality test on the return values of the historical sugar price data using the Kolmogorov–Smirnov test to ensure that the data is normally distributed.

Hyphotesis:

$H_0 : F(x) = F_0(x)$ (normally distributed)
$H_1 : F(x) \neq F_0(x)$ (not normally distributed)
Test Statistics:

$$D = maks|F_t - F_s| \tag{2}$$

Testing Criteria:

If $D < D_{\alpha,n}$ with $\alpha = 0,05$, then H_0 is accepted, meaning the returns are normally distributed (Ghasemi & Zahediasl, 2012).

2. Parameter Estimation

At this stage, the drift and volatility parameters of sugar prices are estimated using the training data. The resulting drift and volatility values are then used as inputs for forecasting sugar prices using the Geometric Brownian Motion (GBM) model. The formula for finding sugar price volatility is as follows (Tsay, 2010; Willmot, 2007):

$$\hat{\sigma} = \frac{s_r}{\sqrt{t}} \tag{3}$$

Where:

$$\bar{R} = \frac{\sum_{t=1}^{n}(R_t)}{n} \tag{4}$$

$$s_r = \sqrt{\frac{\sum_{t=1}^{n}(R_t - \bar{R})^2}{n-1}} \tag{5}$$

And the formula for drift estimation is (Ruppert & Matteson, 2015; Shreve, 2004):

$$\hat{\mu} = \frac{\bar{R}}{t} + \frac{\hat{\sigma}^2}{2} \tag{6}$$

Where $\hat{\sigma}$ denotes the estimated volatility, s_r represents the standard deviation of rice price returns, t is the time interval, $\bar{R}$ is the mean return of rice prices, and $\hat{\mu}$ is the estimated value of the drift parameter.

3. Application of the Geometric Brownian Motion Model

In this step, sugar prices for the following month are predicted using the Geometric Brownian Motion (GBM) model based on the following equation (Hull, 2018; Joshi, 2008):

$$F_t = F_{t-1}e^{\left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma\varepsilon\sqrt{dt}} \tag{7}$$

Where F_t is the predicted rice price at time t, F_{t-1} is the predicted rice price at time $t-1$, μ represents the drift parameter, and σ represents the volatility parameter.

4. GBM Model Validation

After obtaining the sugar price prediction results using the GBM model, the Mean Absolute Percentage Error (MAPE) is calculated by comparing the predicted sugar prices with the testing data. Calculation of MAPE value using the following formula (Rob J. Hyndman & Koehler, 2006):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|P_t - F_t|}{P_t} \times 100\% \tag{8}$$

MAPE measures the average absolute percentage error between the actual and predicted values. A smaller MAPE value indicates higher forecasting accuracy. In general, the interpretation of MAPE is as follows (Lewis, 1982):

Table 1. MAPE Percentage

MAPE Percentage	Forecasting Accuracy
$< 10\%$	Very good
$10\% - 20\%$	Good
$21\% - 50\%$	Sufficient
$> 50\%$	Not good

C. RESULT AND DISCUSSION

1. Data Pattern Analysis

The data source used in this study is secondary data, specifically white crystal sugar price data. The dataset consists of daily sugar prices in the East Java Province. The data covers a four-month period, with sugar prices from August 1, 2025, to October 31, 2025, used as training data, and prices from November 1 to November 30, 2025, used as testing data.

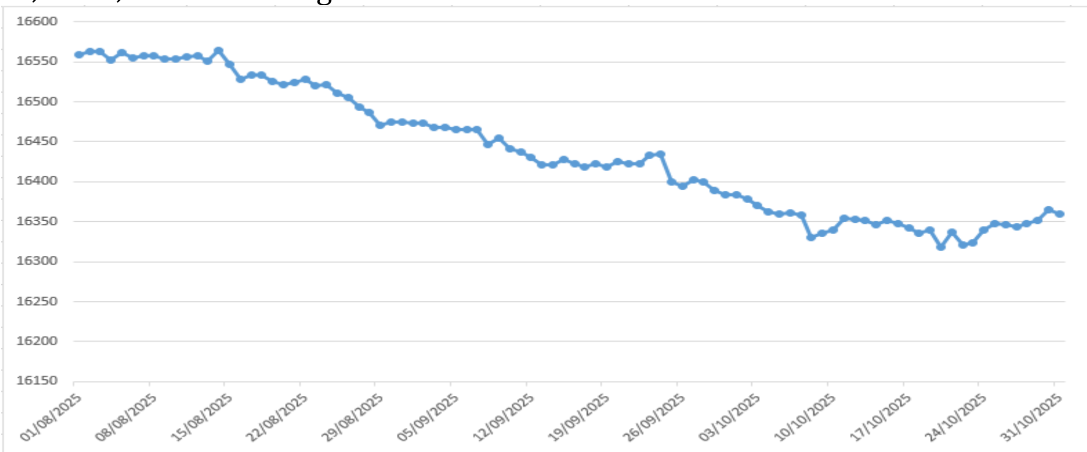

Figure 2. Plot training sugar prices in East Java province

Figure 2 presents the daily prices of crystal sugar from August to October 2025. The graph indicates a gradual downward trend over the observation period, accompanied by relatively stable fluctuations. From early August to the end of October 2025, sugar prices consistently declined without significant volatility, suggesting a systematic decrease rather than abrupt price shocks.

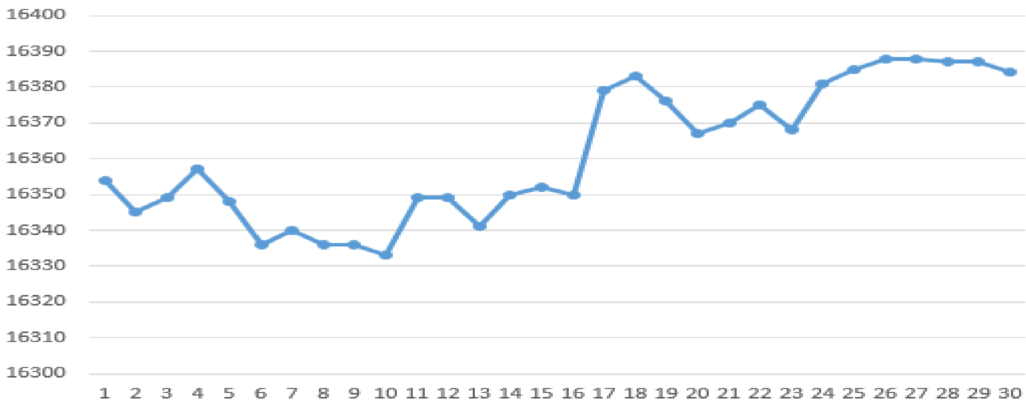

Figure 3. Plot testing sugar prices in East Java province

Figure 3 illustrates the daily sugar prices in November 2025. The graph indicates that the data fluctuated while exhibiting an upward trend toward the end of the observation period. A comparison between Figure 1 and Figure 2 reveals differences in the data patterns between the training and testing datasets, particularly in terms of trend direction and short-term price movements

The stages of sugar price prediction using the Geometric Brownian Motion model are:

2. Test Data Stage

At this stage, the return values of sugar prices are calculated, followed by a normality test using the Kolmogorov–Smirnov test.

a. Calculating the Return Value

Using the price return formula presented in Equation (1), the sugar price returns are obtained as follows:

$$R_i = \ln\left(\frac{P_i}{P_{i-1}}\right)$$
$$R_1 = \ln\left(\frac{P_1}{P_0}\right) = 0{,}0002415$$
$$R_2 = \ln\left(\frac{P_2}{P_1}\right) = 0$$
$$\vdots$$
$$R_{91} = \ln\left(\frac{P_{91}}{P_{90}}\right) = -0{,}000305577$$

The results of the return value calculation are presented in the following figure:

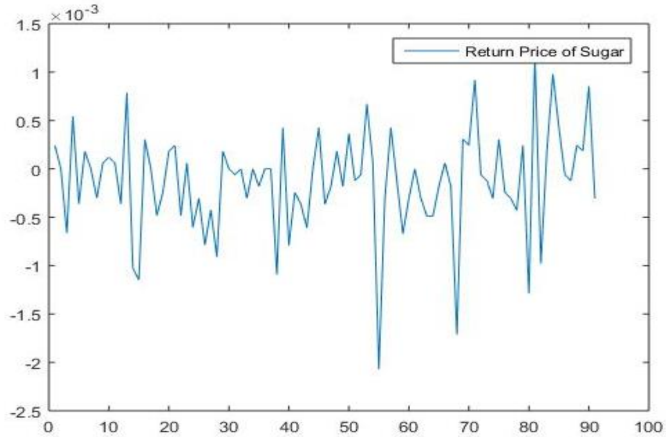

Figure 4. Return price of sugar plot

Figure 4 presents the return series of sugar prices based on the training dataset. The graph shows that the return values fluctuated around zero throughout the observation period. Most movements occurred within a relatively small range (on the order of 10^{-3}), indicating modest daily price changes. This pattern suggests the absence of a systematic trend in the return series, as the values vary randomly around a mean close to zero. However, several extreme negative and positive spikes are observed, particularly around the middle and the end of the observation period. A pronounced negative spike indicates a relatively sharp price decline on a specific day, whereas a positive spike reflects a significant short-term price increase.

b. Kolmogorov-Smirnov

A normality test is conducted to determine whether the data used is normally distributed. The Kolmogorov–Smirnov test is commonly employed to assess normality (Razali & Wah, 2011). In this step, the Kolmogorov–Smirnov test is applied to the sugar price return data.

H_0 : $F(x) = F_0(x)$ (normally distributed)

H_1 : $F(x) \neq F_0(x)$ (not normally distributed)

Test Statistics:

$$D = maks|F_t - F_s|$$
$$= 0{,}122947826$$
$$D_{\alpha,n} = D_{0,05;122}$$
$$= \frac{1{,}36}{\sqrt{92}}$$
$$= 0{,}141789802$$

Testing Criteria:

If $D < D_{\alpha,n}$ with $\alpha = 0{,}05$, then H_0 is accepted, meaning the returns are normally distributed.

3. Parameter Estimation

In this step, the parameters of the Geometric Brownian Motion (GBM) model, namely volatility and drift, are estimated. The mean return and standard deviation are first calculated in order to determine the volatility and drift values using the formula presented in Equation (4)(5), resulting in the following estimates:

$$\bar{R} = \frac{\sum_{t=1}^{n}(R_t)}{n}$$
$$= \frac{\sum_{t=1}^{91}(R_t)}{91}$$
$$= \mathbf{-0,000133}$$
$$\boldsymbol{s_r} = \sqrt{\frac{\sum_{t=1}^{n}(\boldsymbol{R_t - \bar{R}})}{\boldsymbol{n-1}}}$$
$$= 0{,}00053$$

Next, the volatility and drift parameters are estimated using the formulas presented in Equations (3) and (6). The results of the calculations are shown as follows:

$$\hat{\sigma} = \frac{s_r}{\sqrt{t}}$$
$$= 0{,}00053$$
$$\hat{\mu} = \frac{\bar{R}}{t} + \frac{\hat{\sigma}^2}{2}$$
$$= -0{,}000133$$

4. Application of the Geometric Brownian Motion Model

In this step, the sugar commodity prices are forecasted using the Geometric Brownian Motion model using the formulas presented in Equations (7).

$$F_t = F_{t-1}e^{\left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma\varepsilon\sqrt{dt}}$$
$$F_1 = F_0 e^{\left(-0{,}000133 - \frac{1}{2}0{,}00053^2\right)1 + 0{,}00053\varepsilon\sqrt{1}}$$
$$= 16366$$
$$F_2 = F_1 e^{\left(-0{,}000133 - \frac{1}{2}0{,}00053^2\right)1 + 0{,}00053\varepsilon\sqrt{1}}$$
$$= 16353$$
$$\vdots$$
$$F_{30} = F_{29} e^{\left(-0{,}000133 - \frac{1}{2}0{,}00053^2\right)1 + 0{,}00053\varepsilon\sqrt{1}}$$
$$= 16392$$

The results of each run of the Geometric Brownian Motion model using MATLAB vary due to the presence of normally distributed random variables within the Wiener process. Therefore, the GBM model was simulated using multiple trajectories to evaluate the consistency of its predictions. Simulations of the GBM model for forecasting sugar prices using 50, 100, 500, and 1000 trajectories are presented in the figure below:

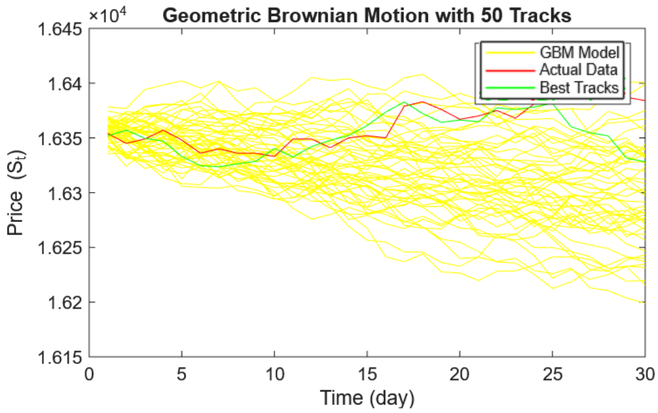

Figure 5. GBM model prediction results for sugar price testing data (50 paths)

Figure 5 presents the results of a Geometric Brownian Motion (GBM) simulation using 50 tracks to model sugar price movements over a 30-day period. The thin yellow lines represent the various possible price paths generated by the GBM model, while the red line depicts the actual price movement. The green line indicates the path with the best prediction performance, characterized by the smallest MAPE value among all simulated paths.

In general, most simulated trajectories remain within a relatively narrow range around the initial price level, approximately 16,300–16,400, suggesting moderate volatility. The simulated paths fluctuate in different directions, reflecting the stochastic characteristics of the GBM model. The actual price series lies within the ensemble of simulated trajectories, indicating that the model is reasonably capable of capturing the underlying price dynamics.

However, not all simulated paths closely match the actual pattern. Some trajectories deviate above or below the observed data, illustrating the range of possible future price scenarios implied by the stochastic process. The presence of a best-fitting trajectory demonstrates that the model possesses adequate predictive capability, although inherent uncertainty remains due to the probabilistic nature of the GBM framework.

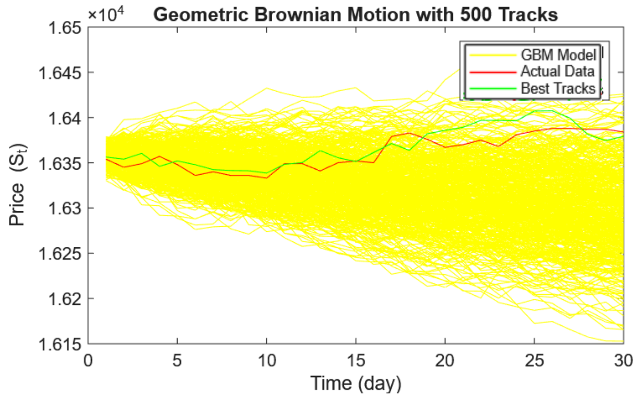

Figure 6. GBM model prediction results for sugar price testing data (500 paths)

Figure 6 illustrates the results of a Geometric Brownian Motion (GBM) simulation using 500 tracks to model sugar price movements over a 30-day period. Compared to the simulation with 50 tracks, the use of 500 tracks produces a denser and more diverse distribution of simulated paths, thereby offering a more comprehensive representation of possible price outcomes. Increasing the number of tracks enhances the visualization of potential price scenarios, including movements that fall below or rise above the actual observed prices. This outcome highlights the stochastic nature of the GBM model, which generates a probabilistic distribution of future price trajectories rather than a single deterministic forecast.

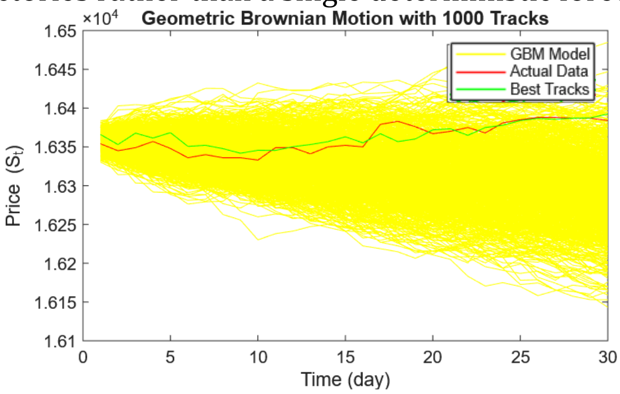

Figure 7. GBM model prediction results for sugar price testing data (1000 paths)

Figure 7 presents the results of a Geometric Brownian Motion (GBM) simulation using 1,000 tracks to model sugar price movements over a 30-day period. Compared to the simulation with 500 tracks, the use of 1,000 tracks generates a denser and more diversified distribution of simulated paths, thereby providing a more comprehensive representation of the probability distribution of possible price outcomes. The graph indicates that increasing the number of tracks enhances the coverage of the simulation and yields a more stable and representative estimate of the uncertainty associated with future price movements.

Table 2. Minimum MAPE Values from the GBM Simulation Results

No.	Paths	Min. MAPE	Mean MAPE	Time (s)
1	50	0,0843%	2,754%	0,193798
2	500	0,0659%	2,745%	0,429391
3	1000	0,0522%	2,769%	0,630714

Table 1. presents the results of the GBM simulations using four different numbers of paths: 50, 500, and 1000. The minimum MAPE value was obtained from the simulation of the testing data. Based on the table, the average MAPE values for all paths fall into the "very good" category; however, increasing the number of simulated paths does not necessarily produce the lowest average MAPE percentage. This condition arises due to the stochastic nature of the Wiener process, which involves normally distributed random variables. In contrast, the computation time tends to increase as more paths are simulated. The prediction results for sugar prices in December are presented in **Figure 8**.

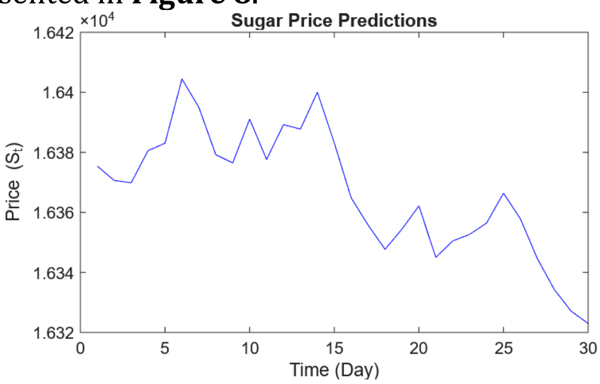

Figure 8. Results of the GBM Sugar Price Prediction Model

According to **Figure 8**, the sugar prices exhibit relatively stable daily fluctuations accompanied by a gradual downward trend.

D. CONCLUSION AND SUGGESTIONS

The forecasting accuracy of the Geometric Brownian Motion (GBM) model for the sugar price testing data based on the minimum MAPE values obtained from the 50, 100, 500, and 1000 trajectory simulations is categorized as very good (MAPE < 10%). This indicates that the GBM model is suitable for predicting sugar prices in the subsequent period.

Suggestions for future research include developing alternative models that better reflect the data trends used for prediction or applying the modeling approach to different research objects.

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