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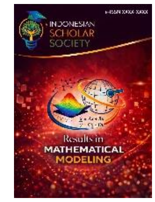


# Stock price forecasting under post-pandemic and normal market conditions using the generalized wiener process

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ABSTRACT

The Covid-19 pandemic significantly altered stock market behavior and increased public participation in short-term trading and investment activities. However, limited analytical knowledge among new investors may increase the risk of inaccurate trading decisions, particularly during volatile market periods. This study evaluates the forecasting performance of the generalized Wiener process in predicting stock prices under two different market regimes: the post-pandemic New Normal period in 2021 and normal market conditions in 2023. Daily adjusted closing prices of two Indonesian mining companies, PT Aneka Tambang Tbk (ANTM) and PT Timah Tbk (TINS), were used as case studies. Historical price data from January to December 2020 were used to forecast stock prices for January–February 2021, while data from January to December 2022 were used to forecast January–February 2023 prices. Two forecasting schemes were compared: forecasts based on real-time reference data and forecasts based on previous predicted values. Forecast accuracy was evaluated using the Mean Absolute Percentage Error (MAPE). The results show that the generalized Wiener process produced more accurate forecasts under normal market conditions than during the post-pandemic period. Real-time reference data consistently generated lower forecasting errors than previous-prediction reference data. For TINS, the MAPE decreased from 5.51% in the 2021 post-pandemic period to 2.73% in the 2023 normal period using real-time reference data. In contrast, using previous predicted values produced substantially higher errors, particularly in 2021, with a MAPE of 27.28%. These findings indicate that the generalized Wiener process is reliable for short-term stock price forecasting when supported by real-time reference data, even under volatile market conditions. The study contributes to financial forecasting by demonstrating the sensitivity of stochastic stock price models to market regimes and reference-data selection.

## 1. Introduction

In recent years, stock investment activities have increased significantly, particularly among young investors and retail traders. This phenomenon became more prominent during the Covid-19 pandemic, when economic instability, layoffs, and work-from-home policies encouraged many individuals to seek alternative income sources through stock trading and short-term investment activities. In Indonesia, the rapid growth of retail investors after 2020 substantially increased daily trading activity in the Indonesia Stock Exchange (IDX). However, the increasing participation of inexperienced investors also raised concerns regarding the lack of analytical understanding in making stock trading decisions [1, 2].

Stock prices are inherently dynamic and stochastic because they are influenced by both internal company performance and external market conditions. Macroeconomic uncertainty, investor sentiment, geopolitical issues, commodity prices, and global crises may cause significant fluctuations in stock prices. The Covid-19 pandemic created one of the most volatile financial market periods in modern history, resulting in abnormal price movements across many sectors, including mining and commodity-related companies [3–5].

Forecasting stock prices has therefore become an important topic in financial mathematics and quantitative finance. Accurate forecasting methods may assist investors in reducing uncertainty and improving buy–sell decision strategies. Various approaches have been developed for stock price prediction, including statistical methods, machine learning techniques, stochastic differential equations, and Monte Carlo simulations. Among stochastic approaches, the Wiener process and its generalized form have been widely applied because they are capable of modeling random stock price movements mathematically [6, 7].

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The generalized Wiener process is a stochastic process that extends the classical Wiener process by incorporating drift and volatility parameters into the stock price movement model. In financial modeling, the drift parameter represents the expected return of stock prices, while the volatility parameter reflects market uncertainty and price fluctuation intensity. This method is closely related to geometric Brownian motion and has been widely utilized in derivative pricing and stock price simulations. One of the advantages of the generalized Wiener process is its ability to represent stock price dynamics under uncertain market conditions through stochastic modeling [8–10].

Previous studies have demonstrated the applicability of stochastic processes in stock forecasting. Siswanto (2013) applied Lévy and Black–Scholes models for stock price prediction and reported acceptable forecasting accuracy based on Mean Absolute Percentage Error (MAPE). Similarly, Asriani (2018) utilized the generalized Wiener process for forecasting stock prices of PT Unilever Indonesia and obtained relatively low forecasting errors. However, most previous studies focused on forecasting performance within a single market condition and did not evaluate the sensitivity of stochastic forecasting models under different market regimes [3, 11].

The transition from the Covid-19 pandemic period to post-pandemic market recovery provides an important opportunity to evaluate the robustness of stochastic forecasting models. Market behavior during the New Normal period in 2021 remained highly volatile due to economic uncertainty, fluctuating commodity prices, and global recovery dynamics. In contrast, stock market conditions in 2023 were relatively more stable and represented a normal trading environment. These contrasting market regimes offer a useful framework for assessing whether the generalized Wiener process remains reliable under both abnormal and normal market conditions [12, 13].

This study focuses on two Indonesian mining companies: PT Aneka Tambang Tbk (ANTM) and PT Timah Tbk (TINS). These companies were selected because they operate in the mining sector and are strongly associated with nickel commodity production, which experienced substantial market attention during the electric vehicle industry expansion. The increasing global demand for nickel as a key battery material influenced stock price movements of Indonesian mining companies, particularly during and after the Covid-19 pandemic. As a result, ANTM and TINS exhibited significant stock price fluctuations, making them suitable case studies for stochastic forecasting analysis [6, 14, 15].

In addition to evaluating different market regimes, this study also compares two forecasting schemes based on different reference-data approaches. The first scheme uses real-time daily stock prices as forecasting references, while the second scheme uses previous prediction outputs as iterative forecasting inputs. This comparison is important because practical stock forecasting often involves recursive predictions where future predictions depend on previously forecasted values rather than actual market observations. Evaluating both approaches may provide insights into the stability and reliability of stochastic forecasting methods in real-world financial applications.

The forecasting performance in this study is evaluated using Mean Absolute Percentage Error (MAPE), which is widely used to assess forecasting accuracy in financial time-series analysis. Lower MAPE values indicate better forecasting performance and closer agreement between predicted and actual stock prices. By comparing MAPE results across different market periods and forecasting schemes, this study aims to identify the most reliable forecasting approach for short-term stock price prediction.

Therefore, the objectives of this study are: (1) to evaluate the forecasting performance of the generalized Wiener process under post-pandemic and normal market conditions, (2) to compare forecasting accuracy between real-time reference data and previous prediction reference data, and (3) to analyze the forecasting behavior of Indonesian mining stocks represented by PT Aneka Tambang Tbk (ANTM) and PT Timah Tbk (TINS). The findings of this study are expected to contribute to the development of stochastic financial forecasting models and provide practical insights for investors, researchers, and financial analysts in understanding stock market behavior under different market conditions.

## 2. Materials and Methods

### 2.1. *Study area*

This study employed a quantitative applied research approach to evaluate the forecasting performance of the Generalized Wiener Process for stock price prediction under different market conditions. The research focused on comparing forecasting accuracy during the post-pandemic New Normal period (2021) and the relatively stable normal market period (2023). The analysis also compared two forecasting schemes: (1) forecasting using real-time reference data and (2) forecasting using previous prediction outputs as recursive forecasting inputs.

The workflow of this research consisted of data collection, statistical preprocessing, stochastic parameter estimation, stock price simulation using the Generalized Wiener Process, Monte Carlo simulation, and forecasting accuracy evaluation using Mean Absolute Percentage Error (MAPE) [4, 16].

### 2.2. *Study objects and data sources*

The study analyzed daily stock price data from two Indonesian mining companies listed on the Indonesia Stock Exchange (IDX):

1. PT Aneka Tambang Tbk (ANTM)
2. PT Timah Tbk (TINS)

These companies were selected because both operate in the mining sector and experienced substantial stock price volatility during the Covid-19 pandemic and post-pandemic recovery periods, particularly due to increasing global demand for nickel commodities associated with electric vehicle battery production [17, 18]. The data used in this study were secondary data obtained from Yahoo Finance (https://finance.yahoo.com). The dataset consisted in Table 1.

**Table 1**
Secondary data of finance in this study

| Dataset | Period | Purpose |
|---|---|---|
| Historical stock prices | January–December 2020 | Model construction for 2021 forecasting |
| Historical stock prices | January–December 2022 | Model construction for 2023 forecasting |
| Validation stock prices | January–February 2021 | Forecast evaluation (New Normal period) |
| Validation stock prices | January–February 2023 | Forecast evaluation (Normal period) |

Noted: The adjusted closing price (Adjusted Close Price) was used because it accounts for corporate actions such as dividends and stock splits.

### 2.3. *Research framework*

This study was designed systematically to evaluate the capability of the Generalized Wiener Process in forecasting stock prices under different market conditions. The research framework illustrates the sequential analytical procedures beginning from raw stock price acquisition to forecasting performance evaluation (Fig. 1). The framework also ensures that each analytical stage is interconnected and scientifically justified [3, 6, 16].

The first stage involved collecting historical stock price data for PT Aneka Tambang Tbk (ANTM) and PT Timah Tbk (TINS) from Yahoo Finance. Daily adjusted closing prices were selected because they provide more accurate representations of stock value after considering corporate actions such as stock splits and dividend distributions. Two historical datasets were prepared: 2020 data for forecasting the New Normal period in 2021 and 2022 data for forecasting the normal market condition in 2023 [19–21].

After data acquisition, preprocessing procedures were conducted. This stage included organizing trading dates, removing incomplete observations, and transforming raw stock prices into logarithmic returns. The logarithmic transformation was important because financial time series data are generally non-stationary and non-normal. Log returns help stabilize variance and reduce heteroscedasticity effects commonly found in stock market data.

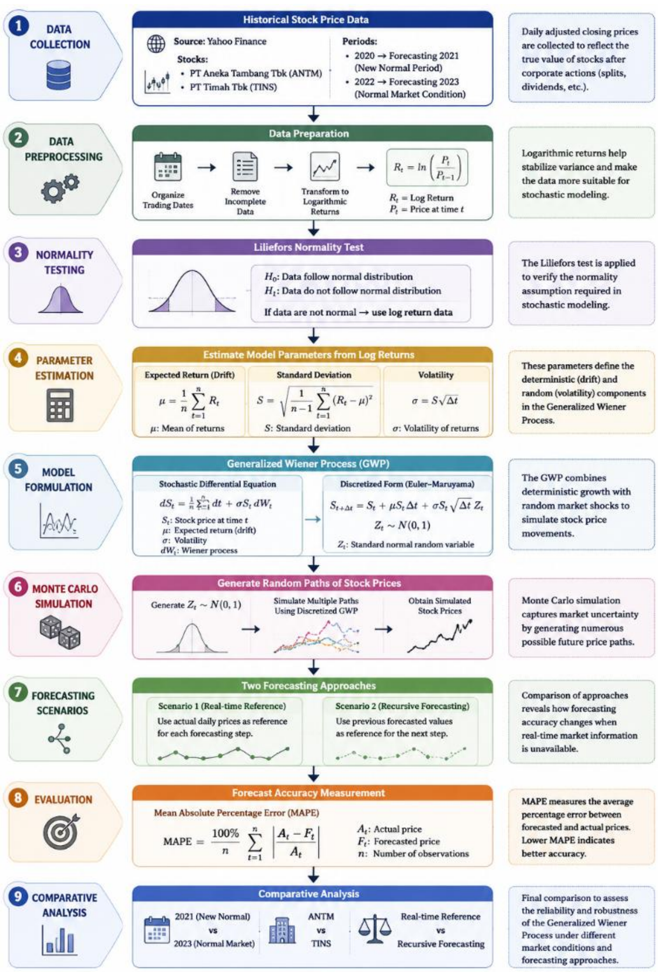


**Fig. 1.** Research framework of stock price forecasting using the Generalized Wiener Process.

The next stage involved conducting a normality test using the Liliefors method. This statistical test was applied to determine whether the return data followed a normal distribution assumption required in stochastic modeling. The test results indicated that the stock return data were not normally distributed in their original form, thus justifying the use of logarithmic transformation before further analysis. Following the preprocessing stage, several statistical parameters required in the Generalized Wiener Process model were estimated. These included the expected return (μ), standard deviation (S), and volatility (σ). The expected return represents the average stock return or drift component in the stochastic process, while volatility measures the intensity of stock price fluctuations. These parameters play critical roles in defining both deterministic and random components of stock price movement [3, 6, 16].

After estimating the statistical parameters, the Generalized Wiener Process model was formulated. This stochastic differential equation combines deterministic growth and random market uncertainty to simulate stock price behavior over time. The model was then discretized into a forecasting equation suitable for daily stock price prediction. To generate future stock prices, Monte Carlo simulation was employed. Random values generated from a standard normal distribution were introduced into the Wiener process to simulate stochastic market behavior. This simulation process enabled the model to capture uncertainty and randomness inherent in stock market movements [7].

Two forecasting scenarios were developed in this study. The first scenario used real-time daily stock prices as forecasting references, while the second scenario used previous forecasting outputs recursively as inputs for future predictions. The comparison between these two approaches was intended to evaluate how forecasting accuracy changes when actual market information becomes unavailable. The forecasting results were then evaluated using Mean Absolute Percentage Error (MAPE). This metric measures the relative difference between predicted and actual stock prices and is widely used in forecasting studies because of its interpretability and effectiveness. Lower MAPE values indicate better forecasting performance [6, 14, 15]. Finally, comparative analyses were conducted between:

- Forecasting results during the New Normal period (2021) and normal market conditions (2023),
- Forecasting performances of ANTM and TINS stocks, and
- Forecasting approaches using real-time references and recursive prediction references.

These comparisons were intended to determine the reliability and robustness of the Generalized Wiener Process under different levels of market volatility and uncertainty.

### 2.4. Data normality test

Before constructing the stochastic forecasting model, the stock return data were tested for normality using the Liliefors normality test. This preliminary statistical test was essential because the Generalized Wiener Process assumes that stock return fluctuations approximately follow a normal distribution. In financial time-series analysis, raw stock price data are typically non-normal due to high volatility, skewness, and extreme market fluctuations, particularly during abnormal market conditions such as the Covid-19 pandemic.

The Liliefors test was selected because it is suitable for testing normality when the population mean and variance are unknown and estimated directly from the sample data. The test was applied to the logarithmic return data of PT Aneka Tambang Tbk (ANTM) and PT Timah Tbk (TINS) for both 2020 and 2022 datasets. The hypotheses used in the normality test are expressed as follows:

$$H_0 = \textit{The stock return data are normally distributed}$$
$$H_1 = \textit{The stock return data are not normally distributed}$$

The decision criteria are: if $L_{calculated} < L_{Table}$ then $H_0$ is accepted, indicating that the data follow a normal distribution. If $L_{calculated} > L_{Table}$ then $H_0$ is rejected, indicating that the data are not normally distributed. The Liliefors test procedure consists of several steps:

1. Transforming stock return observations into standardized values ($z_i$) using equation (1).

$$z_i = \frac{x_i - \bar{x}}{S} \qquad (1)$$

where; $x_i$=Individual stock return, $\bar{x}$ = Mean stock return and $S$ = Standard deviation

2. Calculating the cumulative normal probability distribution using equation (2).

$$F(z_i) = P(Z \le z_i) \qquad (2)$$

3. Computing the empirical cumulative distribution using equation (3).

$$S(z_i) = \frac{Number\ of\ observations \leq z_i}{n} \quad (3)$$

4. Determining the absolute difference using equation (4).

$$|F(z_i) - S(z_i)| \quad (4)$$

5. Selecting the maximum difference value as equation (5).

$$L_{calculated} = max|F(z_i) - S(z_i)| \quad (5)$$

The resulting Lcalculated value was then compared with the critical value Ltable at a significance level of 5%. The normality testing results revealed that all stock datasets were not normally distributed in their original form. Therefore, logarithmic transformation through log-return calculation was required before proceeding to stochastic modeling. This result is consistent with the characteristics of financial market data, which commonly exhibit non-linear and highly volatile behavior. The summary of the Liliefors normality test results is presented in Table 2.

**Table 2**
Liliefors normality test results for stock return data

| Company | Year | ($L_{calculated}$) | ($L_{table}$) | Decision | Distribution |
|---|---|---|---|---|---|
| PT Aneka Tambang Tbk (ANTM) | 2020 | 0.05879 | 0.05695 | Reject (*Ho*) | Not normal |
| PT Aneka Tambang Tbk (ANTM) | 2022 | 0.81634 | 0.05648 | Reject (*Ho*) | Not normal |
| PT Timah Tbk (TINS) | 2020 | 0.65656 | 0.05695 | Reject (*Ho*) | Not normal |
| PT Timah Tbk (TINS) | 2022 | 0.94130 | 0.05648 | Reject (*Ho*) | Not normal |

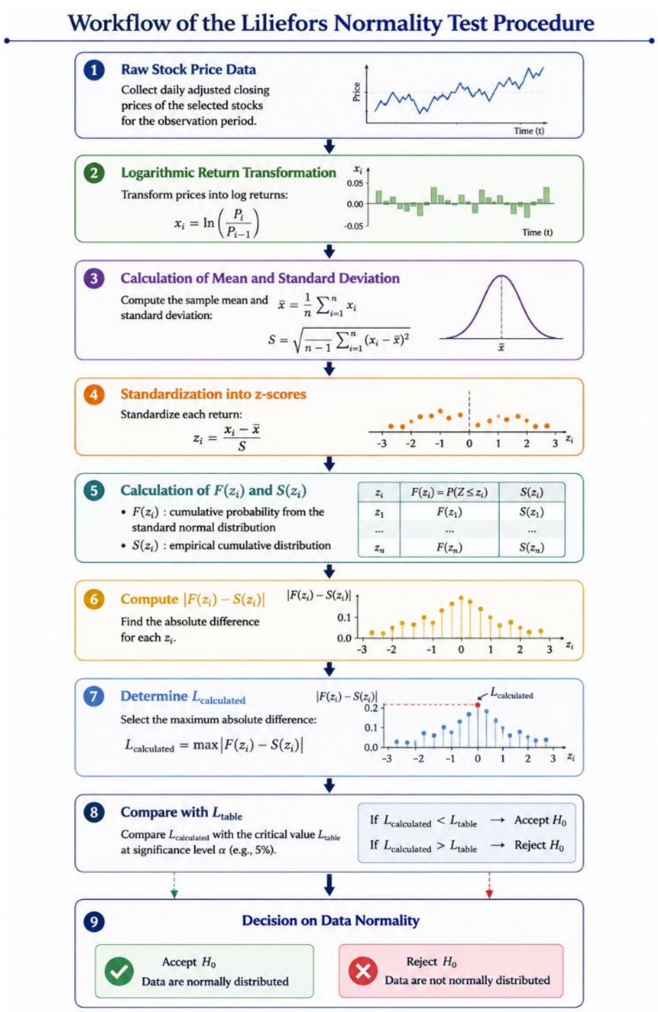


**Fig. 2.** Workflow of the Liliefors normality test procedure applied to stock return data.

The results in Table 2 indicate that all calculated Liliefors statistics exceeded the corresponding critical values. Consequently, the null hypothesis of normal distribution was rejected for all datasets. These findings justify the use of logarithmic returns and stochastic modeling approaches in subsequent forecasting procedures. To provide a clearer illustration of the normality testing process, the methodological workflow of the Liliefors test is presented in Fig. 2. The Fig. 2 illustrates the sequential steps used to evaluate the normality of stock return distributions, including logarithmic return transformation, parameter estimation, z-score standardization, cumulative distribution comparison, calculation of the Liliefors statistic, and hypothesis testing for determining data normality prior to stochastic forecasting modeling.

### 2.5. *Stock return calculation*

Stock return represents the percentage change in stock prices between two consecutive trading periods and is one of the most important indicators in financial time-series analysis. In stochastic stock price modeling, return values are preferred over raw stock prices because returns better describe relative price movements and reduce the effects of scale differences among stocks. In this study, logarithmic returns were used instead of simple arithmetic returns. Logarithmic returns are widely applied in financial mathematics because they possess several desirable statistical properties, including time additivity, variance stabilization, and improved approximation to normal distribution characteristics [19–21]. Furthermore, logarithmic transformation helps reduce heteroscedasticity commonly observed in financial market data, particularly during highly volatile market periods such as the Covid-19 pandemic. The logarithmic stock return was calculated using the following equation (6).

$$x_i = \ln\frac{P_i}{P_{i-1}} \quad (6)$$

where $P_i$ = stock price at time $i$, $x_i$=logarithmic stock return at time $i$, $P_{i-1}$= stock price at previous time, and ln = natural logarithm A positive return value indicates an increase in stock price relative to the previous trading period, while a negative return value indicates a price decline. Returns close to zero represent relatively stable market conditions with minimal price changes. To illustrate the calculation process, a sample calculation for PT Aneka Tambang Tbk (ANTM) stock return is presented below. Suppose the adjusted closing stock prices for two consecutive trading days are:

$$P_{i-1} = 830.08$$
$$P_i = 839.96$$

Then, the logarithmic return is calculated as:

$$x_i = ln\left(\frac{839.96}{830.08}\right)$$
$$x_i = ln(1.01190)$$
$$x_i = 0.01183$$

The positive value indicates that the stock price increased during the observed trading interval. Similarly, if the stock price decreases:

$$P_{i-1} = 874.55$$
$$P_i = 864.67$$

then:

$$x_i = ln\left(\frac{864.67}{874.55}\right)$$
$$x_i = -0.01136$$

The negative return value indicates a decline in stock price from the previous trading day. The stock return calculations were performed for all trading days in 2020 and 2022 for both ANTM and TINS stocks. These return values were subsequently used to estimate the expected return, standard deviation, and volatility parameters required in the Generalized Wiener Process model. A sample of the calculated stock return values is presented in Table 3.

**Table 3**
Sample logarithmic stock returns of ANTM and TINS

| Trading Day | ANTM 2020 | TINS 2020 | ANTM 2022 | TINS 2022 |
|---|---|---|---|---|
| 1 | 0.01183 | -0.01724 | 0.00000 | 0.00682 |
| 2 | 0.04035 | -0.01312 | 0.01204 | -0.02426 |
| 3 | -0.01136 | -0.01777 | 0.01190 | -0.00704 |
| ... | ... | ... | ... | ... |
| Final observation | -0.00515 | -0.01251 | -0.03960 | 0.00428 |

The results indicate that stock returns fluctuate continuously over time, reflecting the stochastic nature of financial markets. The return series of both ANTM and TINS exhibit alternating positive and negative values, indicating dynamic market responses to internal and external economic factors. Furthermore, larger fluctuations were observed during the post-pandemic period, suggesting higher market uncertainty and volatility.

### 2.6. Expected return estimation

After calculating the logarithmic stock returns, the next step involved estimating the expected return of each stock dataset. In stochastic financial modeling, the expected return represents the average tendency of stock prices to increase or decrease over time and is commonly referred to as the drift component in the Generalized Wiener Process. The expected return parameter is particularly important because it describes the deterministic trend of stock price movement within the stochastic differential equation framework. A positive expected return indicates that stock prices tend to increase over time, whereas a negative expected return suggests a downward market tendency. The expected return was estimated by calculating the arithmetic mean of all logarithmic returns using the following equation (7).

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (7)$$

where: $x_i$= logarithmic stock return, $\bar{x}$ = expected return, and $n$= number of observations. In the Generalized Wiener Process model, the expected return is represented as $\mu = \bar{x}$. The $\mu$ is the drift parameter that controls the average direction of stock price movement.

The estimation process was performed separately for each stock and observation period. To illustrate the calculation procedure, an example using PT Aneka Tambang Tbk (ANTM) stock data from 2020 is presented below. Suppose the total logarithmic return from 242 trading observations is:

$$\sum_{i=1}^{242} x_i = 0.83909$$

Then, the expected return is calculated as:

$$\bar{x} = \frac{0.83909}{242}$$

$$\bar{x} = 0.00346$$

Thus, the estimated expected return (drift parameter) for ANTM in 2020 is:

$$\mu = 0.00346$$

This positive value indicates that ANTM stock prices generally exhibited upward movement during the observation period. The same procedure was applied to all datasets for both ANTM and TINS stocks in 2020 and 2022. The estimated expected returns are summarized in Table 4.

**Table 4**
Estimated expected returns (μ) of stock prices

| No | Company | Year | Expected Return ((\mu)) |
|---|---|---|---|
| 1 | PT Aneka Tambang Tbk (ANTM) | 2020 | 0.00346 |
| 2 | PT Aneka Tambang Tbk (ANTM) | 2022 | -0.00080 |
| 3 | PT Timah Tbk (TINS) | 2020 | -0.00060 |
| 4 | PT Timah Tbk (TINS) | 2022 | 0.00242 |

The results in Table 4 indicate that the expected return values vary across companies and market periods. ANTM exhibited a positive drift during 2020 but a slightly negative drift in 2022, suggesting a shift in average market direction between the two periods. In contrast, TINS showed a negative expected return in 2020 and a positive expected return in 2022.

These differences reflect changing market dynamics and investor sentiment under different economic conditions. During the post-pandemic recovery phase, mining-sector stocks experienced fluctuating growth patterns influenced by commodity price volatility, industrial recovery, and global demand for nickel-related products. In the context of the Generalized Wiener Process, the expected return parameter plays a fundamental role because it determines the deterministic component of stock price evolution. Larger positive drift values generally lead to upward forecasting trajectories, while negative drift values may reduce long-term predicted stock prices.

### 2.7. Standard deviation calculation

Following the estimation of expected returns, the next stage involved calculating the standard deviation of stock returns. Standard deviation is a statistical measure used to quantify the dispersion or variability of stock returns relative to their mean value. In financial analysis, standard deviation is widely used to evaluate the degree of market uncertainty and investment risk associated with a stock.

A higher standard deviation indicates that stock prices fluctuate more intensely around their average return, implying greater market volatility and higher investment risk. Conversely, lower standard deviation values indicate more stable stock price movements. Since the Generalized Wiener Process incorporates random market behavior, estimating standard deviation accurately is essential for constructing reliable stochastic forecasting models. The standard deviation of logarithmic returns was calculated using the following equation (8).

$$\boldsymbol{S} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (8)$$

where : $\boldsymbol{S}$= Standard deviation of stock returns, $\boldsymbol{x_i}$= Individual logarithmic return, $\bar{\boldsymbol{x}}$ = Mean return (expected return), and $\boldsymbol{n}$= number of observations. The equation measures the average squared deviation of each return value from the expected return, followed by square-root transformation to obtain the standard deviation in the original return scale.

### 2.8. Volatility estimation

Volatility is one of the most important parameters in stochastic financial modeling because it represents the magnitude of stock price fluctuations over time. In stock market analysis, volatility reflects the uncertainty and risk associated with price movements. Highly volatile stocks tend to experience rapid and large price changes, while stocks with low volatility generally exhibit more stable market behavior [14, 22, 23].

In the Generalized Wiener Process framework, volatility functions as the stochastic component that controls the randomness of stock price evolution. Therefore, accurate volatility estimation is crucial for producing reliable stock price forecasts. In this study, volatility was estimated based on the standard deviation of logarithmic returns. The volatility parameter was calculated using the following equation (9).

$$\boldsymbol{\sigma} = \frac{\boldsymbol{S}}{\sqrt{\boldsymbol{\tau}}} \qquad (9)$$

where :

$$\tau = \frac{1}{n},$$

Thus, the volatility equation can also be expressed as:

$$\boldsymbol{\sigma} = \boldsymbol{S}\sqrt{\boldsymbol{n}}$$

where : $\boldsymbol{\sigma}$= Volatility, and $\boldsymbol{\tau}$= Time interval. The volatility value measures the annualized fluctuation intensity of stock returns. Larger volatility values indicate greater uncertainty and stronger price movements within the market.

### 2.9. Generalized wiener process model

After estimating the expected return and volatility parameters, the next stage involved constructing the stock price forecasting model using the Generalized Wiener Process. The Generalized Wiener Process is a stochastic process widely used in financial mathematics to model asset price movements under uncertainty. This model combines deterministic growth components with stochastic random fluctuations, enabling it to capture the dynamic and uncertain nature of stock market behavior [24].

In financial markets, stock prices are influenced not only by internal company performance but also by external factors such as investor sentiment, commodity prices, economic policies, global market conditions, and unexpected events. Consequently, stock price movements are inherently random and cannot be represented accurately using purely deterministic mathematical models [20, 21, 25]. The Generalized Wiener Process addresses this limitation by incorporating a random diffusion component into the forecasting framework. The continuous-time Generalized Wiener Process is expressed as follows equation (10).

$$\frac{dP}{P} = \mu dt + \sigma dz \qquad (10)$$

where : $P$= Stock price, $\mu$= Expected return (drift rate), $\sigma$= Volatility (diffusion coefficient), $dt$= Small time increment, and $dz$= Wiener process increment.

### 2.10. Monte carlo simulation

The Generalized Wiener Process model, Monte Carlo simulation was employed to generate stochastic stock price forecasts. Monte Carlo simulation is a numerical method widely used in financial engineering and stochastic modeling to simulate random processes through repeated random sampling [16, 26, 27]. In stock price forecasting, this method enables the incorporation of uncertainty and random market behavior into prediction models. The Generalized Wiener Process contains a stochastic term represented by the Wiener increment:

$$dz = \epsilon\sqrt{dt}$$

where

$$\epsilon = N(0.1)$$

Thus, future stock prices depend not only on deterministic growth but also on random shocks generated from a standard normal distribution. Monte Carlo simulation provides a practical approach for generating these random variables computationally.

### 2.11. Forecasting scenarios

To evaluate the forecasting performance of the Generalized Wiener Process under different forecasting mechanisms, two forecasting scenarios were developed in this study. The first scenario used real-time stock prices as daily forecasting references. In this approach, the actual observed stock price of the current trading day was always used as the input for predicting the next trading day. Consequently, forecasting errors did not accumulate over time because each prediction relied on real market information.

The second scenario used previous forecasting outputs recursively as inputs for subsequent predictions. In this recursive forecasting approach, only the initial stock price was obtained from actual market data, while future forecasts depended entirely on previous prediction results. This approach simulated long-term forecasting conditions where real-time market observations are unavailable. The comparison between these two forecasting approaches was intended to evaluate:

- Forecasting stability,
- Error accumulation effects,
- Sensitivity to stochastic fluctuations, and
- Model robustness under different market conditions.

The real-time reference approach is expected to produce higher forecasting accuracy because the model continuously adjusts using actual market prices. In contrast, recursive forecasting tends to accumulate prediction errors over time, particularly during highly volatile market conditions. The forecasting framework comparison is illustrated in Fig. 3.

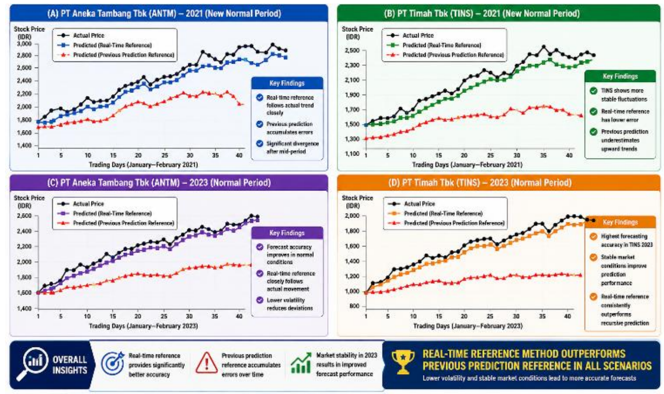


**Fig. 3.** Comparison between actual stock prices and forecasting results generated using the Generalized Wiener Process model with real-time reference data and previous prediction reference data for PT Aneka Tambang Tbk (ANTM) and PT Timah Tbk (TINS) during the New Normal period (2021) and normal market conditions (2023).

### 2.12. Forecast accuracy evaluation using MAPE

The forecasting performance of the Generalized Wiener Process was evaluated using Mean Absolute Percentage Error (MAPE). MAPE is one of the most widely used accuracy metrics in forecasting studies because it expresses prediction errors in percentage form, making interpretation intuitive and comparable across datasets. The MAPE equation (11) is defined as:

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{x_t - f_t}{x_t}\right|}{n} \times 100\% \qquad (11)$$

where: $x_t$=Actual stock price, $f_t$= Forecasted stock price, and $n$= Number of observations. The MAPE value measures the average relative difference between actual and predicted stock prices. Smaller MAPE values indicate higher forecasting accuracy [28, 29]. The interpretation criteria used in this study are presented in Table 5.

**Table 5**
Interpretation criteria for MAPE values

| MAPE Value | Forecast Accuracy |
|---|---|
| < 5% | Very accurate |
| 5–10% | Good |
| 10–25% | Acceptable |
| > 25% | Poor / unacceptable |

## 3. Results and discussion

### 3.1. Data normality test results

The first stage of the analysis involved testing the normality of stock return data using the Liliefors normality test. This test was conducted to determine whether the stock price data followed a normal distribution, which is an important assumption in stochastic modeling and Monte Carlo simulation. The hypotheses used in the test were:

$$H_0 = \textit{The stock return data are normally distributed}$$
$$H_1 = \textit{The stock return data are not normally distributed}$$

The decision criteria are: if $L_{calculated} < L_{Table}$ then $H_0$ is accepted, indicating that the data follow a normal distribution. If $L_{calculated} > L_{Table}$ then $H_0$ is rejected, indicating that the data are not normally distributed. The results of the normality test for PT Aneka Tambang Tbk (ANTM) and PT Timah Tbk (TINS) are presented in Table 6.

The results indicate that all datasets failed the normality test because the calculated Liliefors statistics exceeded the critical values. This finding confirms that raw stock price movements exhibit non-normal characteristics due to high market volatility and stochastic fluctuations. Financial time series commonly demonstrate heavy tails, volatility clustering, sudden jumps, asymmetric movements, and non-linear dynamics.

These characteristics are especially pronounced during unstable economic conditions such as the post-pandemic recovery period in 2021.

**Table 6**

Liliefors normality test results for stock return data

| Company | Year | ($L_{count}$) | ($L_{table}$) | Decision |
|---|---|---|---|---|
| PT Aneka Tambang Tbk (ANTM) | 2020 | 0.05879 | 0.05695 | Not Normal |
| PT Aneka Tambang Tbk (ANTM) | 2022 | 0.81634 | 0.05648 | Not Normal |
| PT Timah Tbk (TINS) | 2020 | 0.65656 | 0.05695 | Not Normal |
| PT Timah Tbk (TINS) | 2022 | 0.94130 | 0.05648 | Not Normal |

Because the stock return data were not normally distributed, logarithmic transformation using equation (6) was applied to stabilize the variance and improve statistical properties for stochastic modeling. The non-normality of the data further justifies the use of stochastic approaches such as the Generalized Wiener Process, which can better represent random market movements compared with deterministic forecasting methods. The distribution patterns of stock returns before and after logarithmic transformation are illustrated in Fig. 4.

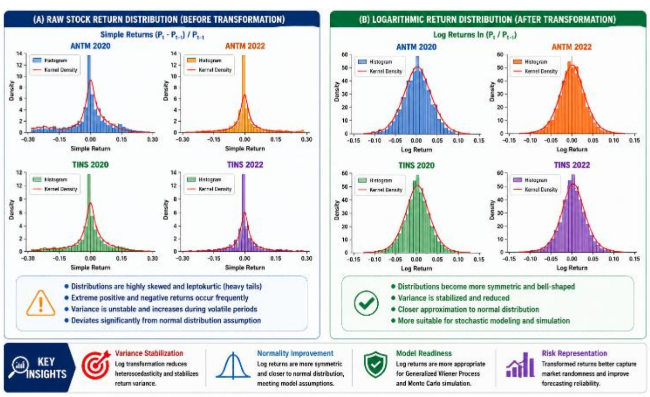


**Fig. 4.** Distribution characteristics of stock return data before and after logarithmic transformation.

## 3.2. *Stock return analysis*

Stock returns were calculated to measure daily percentage changes in stock prices. Return analysis is important because it reflects the profitability and directional movement of stock prices over time. The logarithmic return equation (6). The logarithmic transformation was selected because stabilizes variance, reduces heteroscedasticity, improves distribution symmetry, and simplifies stochastic modeling. Table 7 presents selected examples of daily stock returns.

**Table 7**

Sample stock return calculations

| Trading Day | ANTM 2020 | TINS 2020 | ANTM 2022 | TINS 2022 |
|---|---|---|---|---|
| 1 | 0.01183 | -0.01724 | 0.00000 | 0.00682 |
| 2 | 0.04035 | -0.01312 | 0.01204 | -0.02426 |
| 3 | -0.01136 | -0.01777 | 0.01190 | -0.00704 |
| ... | ... | ... | ... | ... |
| Last Day | -0.00515 | -0.01251 | -0.03960 | 0.00428 |

The results demonstrate that both ANTM and TINS stocks experienced significant fluctuations during the study periods. However, ANTM generally showed larger daily return variability than TINS, indicating higher market volatility. During the New Normal period in 2021, stock prices experienced stronger fluctuations due to:

- Post-pandemic uncertainty,
- Recovery speculation,
- Commodity market instability, and
- Investor sentiment related to electric vehicle industries.

The nickel mining sector became highly attractive during this period because nickel is a major component in electric vehicle batteries. This condition substantially increased speculative trading activity in mining sector stocks.

The larger fluctuations observed in ANTM compared with TINS suggest that ANTM was more sensitive to market information and speculative movements. Consequently, higher volatility may reduce forecasting stability because stochastic deviations become more dominant. Fig. 5 illustrates the comparative stock return fluctuations.

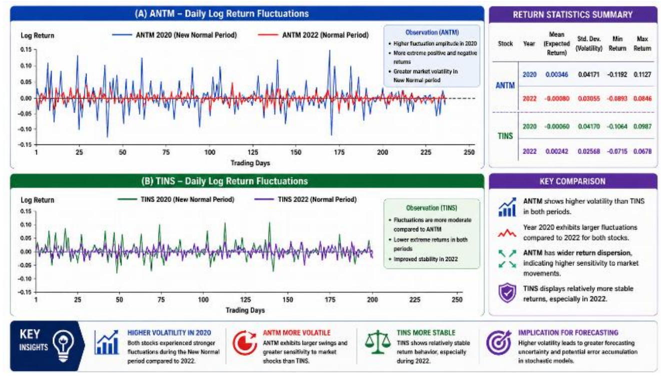


**Fig. 5.** Daily stock return fluctuations of ANTM and TINS stocks.

## 3.3. *Expected return estimation*

The expected return represents the average stock return during the observation period and serves as the drift parameter ($\mu$) in the Generalized Wiener Process model. The expected return was calculated using equation (7). The estimated expected returns are presented in Table 4. Positive expected return values indicate average upward stock movement tendencies, while negative values indicate average declining tendencies during the observation period.

ANTM exhibited a positive expected return in 2020 due to strong investor optimism related to nickel industry expansion and electric vehicle development. However, the expected return became slightly negative in 2022, suggesting a correction phase after excessive market speculation.

Meanwhile, TINS demonstrated a different trend where the expected return improved in 2022, reflecting relatively stronger market performance under more stable economic conditions. The drift parameter plays a critical role in stochastic forecasting because it determines the long-term directional tendency of stock prices. However, because stock markets are highly random, the drift component alone is insufficient to explain stock price behavior. Volatility and stochastic shocks remain dominant contributors to stock movement uncertainty.

## 3.4. *Standard deviation analysis*

Standard deviation measures the dispersion of stock returns from their average values and reflects the variability of stock price movements. The standard deviation equation (8). The calculated standard deviation values are presented in Table 8.

**Table 8**

Standard deviation of stock returns

| Company | Year | Standard Deviation |
|---|---|---|
| PT Aneka Tambang Tbk (ANTM) | 2020 | 0.04171 |
| PT Aneka Tambang Tbk (ANTM) | 2022 | 0.03055 |
| PT Timah Tbk (TINS) | 2020 | 0.04170 |
| PT Timah Tbk (TINS) | 2022 | 0.02568 |

The results indicate that both companies experienced larger return variability during the post-pandemic period compared with normal market conditions. The higher standard deviations in 2020 suggest:

- Stronger market uncertainty,
- Increased investor speculation,
- Unstable commodity prices, and
- Pandemic-related financial shocks.

ANTM consistently exhibited slightly higher variability than TINS, confirming that ANTM stock prices were more volatile and sensitive to market changes. Lower standard deviation values in 2022 indicate improved market stability after the economic recovery phase. The reduction in return variability directly contributed to improved forecasting accuracy in 2023 because stochastic fluctuations became less extreme.

## 4. Conclusion

This study successfully applied the Generalized Wiener Process model to forecast the stock prices of PT Timah Tbk (TINS) and PT Aneka Tambang Tbk (ANTM) during two different market conditions, namely the post-pandemic "new normal" period in 2021 and the relatively stable market condition in 2023. The forecasting process incorporated Monte Carlo simulation and evaluated prediction accuracy using the Mean Absolute Percentage Error (MAPE). The results indicate that stock price forecasting using real-time reference data produced significantly better accuracy compared to forecasting using previous predicted values as recursive inputs. The real-time forecasting approach generated MAPE values below 6% for both companies during the 2021 period and below 4% during the 2023 period, indicating highly acceptable forecasting performance. In contrast, the recursive prediction approach produced larger cumulative errors, particularly during the volatile post-pandemic market condition, where several MAPE values exceeded the acceptable threshold of 25%.

The findings also demonstrate that forecasting performance during the normal market condition in 2023 was more accurate than during the abnormal market condition in 2021. This confirms that high market volatility and uncertainty during the COVID-19 recovery period reduced the predictive stability of stochastic stock price models. Furthermore, PT Timah Tbk (TINS) consistently showed lower forecasting errors compared to PT Aneka Tambang Tbk (ANTM), suggesting that stocks with relatively lower volatility are more suitable for prediction using the Generalized Wiener Process framework. Overall, the study proves that the Generalized Wiener Process model combined with Monte Carlo simulation can serve as an effective short-term forecasting tool for stock trading decision support, particularly when real-time market data are continuously incorporated into the prediction process. However, the model shows limitations for long-term recursive forecasting under highly volatile market conditions due to cumulative stochastic errors.

Future studies are recommended to integrate hybrid stochastic–machine learning approaches, incorporate macroeconomic and sentiment variables, and evaluate longer forecasting horizons in order to improve predictive robustness under dynamic financial market conditions.

## CRediT authorship contribution statement

**Irsal Alfian:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Radhiah:** Writing – review & editing, Investigation. **Rini Oktavia:** Formal analysis, Writing – review & editing, Investigation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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