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BetaSutte: Applying Novelty in Data Forecasting with the Modified Trend-Augmented α-Sutte Indicator, A Case Study on Bank Mandiri (BMRI) Stock Prices

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Abstract

This study assesses the effectiveness of the BetaSutte forecasting model, an enhanced version of the α-Sutte Indicator, dubbed the Modified Trend-Augmented α-Sutte Indicator, in forecasting the stock prices of Bank Mandiri (BMRI). Data from investing.com, spanning January 2018 to December 2023, was divided into training and testing subsets to both develop and validate the forecasting model, ensuring it performs well across unseen data. BetaSutte builds on the foundational α-Sutte by integrating advanced trend analysis, mitigating the influence of outliers, and utilizing automatic parameter optimization to boost forecasting precision. The efficacy of BetaSutte is evaluated against well-established models such as SVR, XGBoost, and ARIMA. ARIMA was chosen for its detailed management of time-series data via autoregressive, differencing, and moving average components. In contrast, SVR and XGBoost are recognized for their strong predictive performance. The performance of these models was gauged using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These metrics shed light on the extent of forecasting errors and the percentage of relative errors, respectively, providing a comprehensive view of each model's predictive accuracy for BMRI stock prices. The results demonstrated that BetaSutte outstripped the other models in terms of RMSE and MAPE, highlighting its enhanced ability to accurately reflect the dynamics of BMRI's stock prices with greater precision and dependability. This establishes BetaSutte as a formidable tool in financial forecasting, particularly valuable in environments characterized by volatile market conditions and unpredictable data patterns.

Keywords: BetaSutte, α-Sutte Indicator, SVR, XGBoost, ARIMA, stock prices.

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1. Introduction

In the Indonesian capital market landscape, Bank Mandiri (BMRI) stands out as a significant player influencing the national economic scene. The fluctuations in BMRI's stock prices are not only indicators of the bank's internal performance but also respond to complex external factors like macroeconomic conditions, government policies, and market sentiments (Adaramola et al., 2023; Bats et al., 2020). Recent studies have highlighted the increasing challenges in forecasting financial markets due to the unpredictable nature of global and domestic events, such as the COVID-19 pandemic and fluctuating commodity prices. Consequently, a profound understanding of these dynamics is vital for investors and stakeholders to make well-informed investment decisions regarding BMRI stocks and the broader banking sector (Gyawali, 2022; Malchev & Lazarevska, 2023).

Stock price movements are key to assessing a company's standing in the capital market. For Bank Mandiri, these fluctuations offer insights into its financial health and growth prospects. However, deciphering the factors influencing stock prices involves considering a multitude of elements, including the bank's financial reports, inflation rates, Bank Indonesia's benchmark interest rate, and government fiscal and monetary policies (Kusumawati, 2023; Bagastio et al., 2023).

Given the prevailing global and domestic economic uncertainties, especially those spurred by the COVID-19 pandemic, there is an escalated demand for analytical tools that can deliver precise stock price forecasts, aiding investors in making

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more confident investment decisions. As such, this study aims to explore novel forecasting methodologies like BetaSutte that can more effectively adapt to market volatility and economic shocks. Thus, the development of sophisticated forecasting methodologies is crucial for navigating the complexities of financial market volatility, particularly for pivotal entities like Bank Mandiri (Choi et al., 2023; Satria, 2023).

Various forecasting techniques have been developed, including ARIMA (Autoregressive Integrated Moving Average), SVR (Support Vector Regression), XGBoost (Extreme Gradient Boosting), α-Sutte Indicator, and the SutteARIMA (Singh et al., 2021). Despite the progress in forecasting models, challenges like parameter tuning, outlier management, and handling abrupt market shifts still remain, which BetaSutte specifically aims to address. Each of these methods offers unique benefits and challenges when applied to the historical data of specific asset values (Gu, 2023; Konur et al., 2024).

For instance, the ARIMA model is a traditional approach valued for its effectiveness with data that exhibits seasonal patterns or trends, although it struggles with outliers and abrupt market shifts—scenarios common in the financial sector when unexpected events like global economic crises or government policy changes occur (Nugroho et al., 2020; Wang, 2023).

Conversely, SVR provides a nonlinear approach that captures complex input-output relationships without presupposing data distribution, but it is sensitive to parameter settings, necessitating intricate tuning to achieve optimal outcomes (Kristiono, 2024; Rawlin & Pakalapati, 2022). XGBoost is renowned for its robustness in handling large, complex datasets through its boosting techniques, yet its "black box" nature makes it difficult to interpret compared to traditional methods (Handri et al., 2024; Kiplangat, 2024).

Meanwhile, the α-Sutte Indicator, focusing primarily on trends and residuals, offers a fresh perspective by not heavily relying on standard statistical assumptions such as stationarity or linear relationships. Previous research has shown that α-Sutte is effective in managing outliers, but its application can be improved by addressing parameter optimization and providing more adaptive trend handling, which BetaSutte does. This method has demonstrated efficacy in managing outliers in past research (Ahmar et al., 2018).

To enhance predictive accuracy and address existing limitations, the BetaSutte: Modified Trend-Augmented α-Sutte Indicator was introduced. BetaSutte refines the α-Sutte methodology by incorporating automatic parameter optimization and more flexible handling of market shifts, making it particularly useful in volatile market conditions. BetaSutte excels in managing trend components through an automatic parameter optimization mechanism, adapting seamlessly to the specific characteristics of a dataset without losing vital information due to outliers or noise. This feature is invaluable for financial analysts attempting to decipher stock price behaviors during volatile periods like economic crises or global pandemics, which continue to impact economies, including Indonesia's.

Moreover, BetaSutte's selective outlier handling mechanism ensures robust performance against extreme market fluctuations, a key attribute for financial analysts who need to understand stock price behaviors during unpredictable times (Ginting & Sussanto, 2024; Kusumawati, 2023). In terms of interpretability, BetaSutte provides substantial advantages over other complex models, as it allows for the separate analysis of each model component. This feature is particularly beneficial in financial decision-making, as it enables investors and portfolio managers to justify their choices based on solid empirical data rather than relying on opaque models. This clarity is especially beneficial for investors and portfolio managers who must justify their investment decisions to stakeholders based on solid empirical data rather than mere intuition (Kallah-Dagadu et al., 2022; Kristiono, 2024).

With these benefits, the study of BetaSutte's application in forecasting Bank Mandiri stock prices is especially relevant, offering significant insights for both the academic community and financial industry practitioners eager to explore cutting-edge methodologies and gauge their effectiveness against traditional methods within the dynamic Indonesian capital market.

2. Methods

This study aims to forecast the stock prices of Bank Mandiri (BMRI) using a novel forecasting method known as BetaSutte. The dataset comprises monthly stock prices from January 2018 to December 2023, sourced from the investing.com website. The dataset will be divided into training and testing subsets, with 85% of the data used for training and the remaining 15% for testing to ensure the model generalizes well to unseen data. The data will be segmented into training and testing subsets; the former will be used to develop the forecasting model, and the latter to assess its accuracy. This segmentation is crucial to verify that the model generalizes well beyond the training data.

Upon employing the BetaSutte forecasting technique, its effectiveness on the testing data will be evaluated against the results from the SVR, XGBoost, and ARIMA. ARIMA is selected for its prevalent use in time series forecasting, leveraging autoregressive, differencing, and moving average components. Conversely, the Holt-Winters method is tailored to address seasonal variations through adjustments in level, trend, and seasonality.

The study will utilize two metrics to measure the accuracy of these methods: Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). RMSE quantifies the magnitude of the forecasting errors in the data's original units, while MAPE provides a relative error percentage, offering a comprehensive view of each model's predictive ability regarding BMRI's stock prices.

Additionally, the steps involved in analyzing the data for forecasting BMRI's stock prices using the BetaSutte method are outlined as follows:

- *Data Collection*: Compile monthly stock price data for Bank Mandiri spanning January 2018 to December 2023 from investing.com.
- *Data Preprocessing*: Adjust the data format as needed, for example, modifying the date format to suit time series analysis requirements.
- *Data Division*: Divide the data into training (85% of the total) and testing (15%) sets. The training data will be used to develop the forecasting model, while the testing data will verify its accuracy.
- *Descriptive Analysis*: Undertake a descriptive analysis to understand data characteristics like the mean, median, standard deviation, and price range. Use visualizations such as line charts to depict stock price trends over time.
- *Forecasting Method Application on Training Data*: Apply the BetaSutte method to the training data to create the forecasting model, optimizing parameters for accuracy and conducting residual analysis to ensure robustness.
- *Comparison with Other Methods*: Implement SVR, XGBoost, dan ARIMA methods on the training data to develop comparative forecasting models. Calculate and compare the forecasting outcomes of all three methods using the training data.
- *Model Evaluation*: Evaluate the accuracy of the three forecasting models using the testing data by computing RMSE and MAPE metrics. Determine the most effective model based on these results.
- *Future Forecasting*: Utilize the most accurate model to predict BMRI stock prices for the next five periods, presenting the forecasts in both tabular and graphical forms for clarity.

Table 1. The stock prices of Bank Mandiri (BMRI) on 2018-2023

Month	2018	2019	2020	2021	2022	2023
January	4.075	3.725	3.775	3.288	3.738	4.975
February	4.150	3.563	3.638	3.075	3.850	5.000
March	3.838	3.725	2.340	3.075	3.950	5.163
April	3.563	3.863	2.230	3.088	4.475	5.175
May	3.525	3.838	2.235	3.000	4.250	5.050
June	3.425	4.013	2.475	2.950	3.963	5.200
July	3.325	3.988	2.900	2.850	4.138	5.725
August	3.450	3.625	2.975	3.050	4.425	6.025
September	3.363	3.488	2.480	3.075	4.713	6.025
October	3.425	3.513	2.888	3.588	5.275	5.675
November	3.700	3.488	3.163	3.500	5.263	5.850
December	3.688	3.838	3.163	3.513	4.963	6.050

3. BetaSutte: Modified Trend-Augmented α-Sutte Indicator

BetaSutte, also known as the Modified Trend-Augmented α-Sutte Indicator, represents an advanced version of the α-Sutte Indicator. It has been specifically developed to address the shortcomings of the original α-Sutte by integrating robust trend analysis, minimizing the effects of outliers and extreme data fluctuations, and employing automatic parameter optimization to elevate forecasting precision. Based on the modified, the advantages of BetaSutte model:

- *Superior trend handling*: BetaSutte is meticulously designed to detect and quantify trend components within the data. Its proficiency in handling data with distinct trend patterns makes it exceptionally effective.
- *Effective outlier management*: The model incorporates a selective outlier handling mechanism that ensures it remains stable in the face of extreme data variations, without distorting the underlying data patterns.
- *Interpretability*: Unlike complex “black box” models such as XGBoost, BetaSutte offers greater interpretability. Its individual components, such as trend and residual, can be examined separately, providing clear insights into the factors driving the predictions.
- *Adaptive parameters*: The model features adjustable shrinkage factors and β coefficients, which can be finely tuned to align with the specific characteristics of the dataset. This adaptability allows BetaSutte to deliver highly accurate forecasts tailored to the unique dynamics of the data it analyzes.

The derivation of the formula from α-Sutte Indicator to BetaSutte is presented as follows.

The basic equation of the standard α-Sutte is:

$$X_t^{\alpha-Sutte} = \left(\frac{1}{3}\right)\cdot\left(\alpha\cdot\frac{2(\alpha-\delta)}{\alpha+\delta}+\beta\cdot\frac{2(\beta-\alpha)}{\beta+\alpha}+\gamma\cdot\frac{2(\gamma-\beta)}{\gamma+\beta}\right) \tag{1}$$

Where:

$\delta = X_{t-4}$
$\alpha = X_{t-3}$
$\beta = X_{t-2}$
$\gamma = X_{t-1}$

From (1), we define the changes between periods:

$$\Delta x = \alpha - \delta = X_{t-3} - X_{t-4} \tag{2a}$$

$$\Delta y = \beta - \alpha = X_{t-2} - X_{t-3} \tag{2b}$$

$$\Delta z = \gamma - \beta = X_{t-1} - X_{t-2} \tag{2c}$$

And the midpoint values for each pair of data:

$$d_1 = \frac{\alpha + \delta}{2} = \frac{X_{t-3} + X_{t-4}}{2} \tag{2d}$$

$$d_2 = \frac{\beta + \alpha}{2} = \frac{X_{t-2} + X_{t-3}}{2} \tag{2e}$$

$$d_3 = \frac{\gamma + \beta}{2} = \frac{X_{t-1} + X_{t-2}}{2} \tag{2f}$$

with the variable changes in equations (2a)-(2f), we can restructure (1) as:

$$X_t^{\alpha-Sutte} = \left(\frac{1}{3}\right)\cdot\left(\alpha\cdot\left(\frac{\Delta x}{d_1}\right)+\beta\cdot\left(\frac{\Delta y}{d_2}\right)+\gamma\cdot\left(\frac{\Delta z}{d_3}\right)\right) \tag{3}$$

BetaSutte adds shrinkage to reduce the influence of extreme changes. First, we calculate the median change:

$$median_{change} = median(|\Delta x|, |\Delta y|, |\Delta z|) \tag{4a}$$

Then we apply shrinkage with parameter s:

$$\Delta x_{adjusted} = \left\{\begin{array}{cc} \Delta x, & if\ |\Delta x| \le median_{change} \\ sign(\Delta x)\cdot\left(median_{change} + (1-s)\cdot\left(|\Delta x| - median_{change}\right)\right), & if\ |\Delta x| > median_{change} \end{array}\right\} \tag{4b}$$

$$\Delta y_{adjusted} = \left\{\begin{array}{cc} \Delta y, & if\ |\Delta y| \le median_{change} \\ sign(\Delta y)\cdot\left(median_{change} + (1-s)\cdot\left(|\Delta y| - median_{change}\right)\right), & if\ |\Delta y| > median_{change} \end{array}\right\} \tag{4c}$$

$$\Delta z_{adjusted} = \left\{\begin{array}{cc} \Delta z, & if\ |\Delta z| \le median_{change} \\ sign(\Delta z)\cdot\left(median_{change} + (1-s)\cdot\left(|\Delta z| - median_{change}\right)\right), & if\ |\Delta z| > median_{change} \end{array}\right\} \tag{4d}$$

Replacing Δx, Δy, and Δz in (3) with the shrinkage-adjusted versions from (4b), (4c), and (4d):

$$X_t^{\alpha-Sutte-shrinkage} = \left(\frac{1}{3}\right)\cdot\left(\alpha\cdot\left(\frac{\Delta x_{adjusted}}{d_1}\right)+\beta\cdot\left(\frac{\Delta y_{adjusted}}{d_2}\right)+\gamma\cdot\left(\frac{\Delta z_{adjusted}}{d_3}\right)\right) \tag{5}$$

BetaSutte adds a trend component T_t estimated through linear regression:

$$T_t = a + b \cdot t \tag{6a}$$

where a and b are regression parameters:

$$b = \frac{\Sigma(i=1)^k\left(t_i-\bar{t}\right)\left(X_{t-i}-\overline{X}\right)}{\sum_{i=1}^{k}\left(t_i-\bar{t}\right)^2} \tag{6b}$$

$$a = \bar{X} - b \cdot \bar{t} \tag{6c}$$

the final BetaSutte equation combines α-Sutte with shrinkage from (5) and the trend component from (6a) using a weight parameter λ:

$$X_t^{BetaSutte} = \left(1-\lambda\right)\cdot X_t^{\alpha-Sutte-shrinkage} + \lambda\cdot T_t \tag{7}$$

by substituting (5) and (6a) into (7), we obtain:

$$X_t^{BetaSutte} = \left(1-\lambda\right)\cdot\left(\frac{1}{3}\right)\cdot\left(\alpha\cdot\left(\frac{\Delta x_{adjusted}}{d_1}\right)+\beta\cdot\left(\frac{\Delta y_{adjusted}}{d_2}\right)+\gamma\cdot\left(\frac{\Delta z_{adjusted}}{d_3}\right)\right)+\lambda\cdot\left(a+b\cdot t\right) \tag{8}$$

and by substituting the values of $\alpha, \beta, \gamma, d_1, d_2, and\ d_3$, we get the final BetaSutte equation:

$$X_t^{BetaSutte} = \left(1-\lambda\right)\cdot\left(\frac{1}{3}\right)\cdot\left(X_{t-3}\cdot\frac{2\Delta x_{adjusted}}{X_{t-3}+X_{t-4}}+X_{t-2}\cdot\frac{2\Delta y_{adjusted}}{X_{t-2}+X_{t-3}}+X_{t-1}\cdot\frac{2\Delta z_{adjusted}}{X_{t-1}+X_{t-2}}\right)+\lambda\cdot\left(a+b\cdot t\right) \tag{9}$$

The (9) involves division by midpoint values (d_1, d_2, and d_3). To prevent division by zero, we need to apply special handling:

$$d_1 = \frac{X_{t-3} + X_{t-4}}{2} \tag{10a}$$

$$d_2 = \frac{X_{t-2} + X_{t-3}}{2} \tag{10b}$$

$$d_3 = \frac{X_{t-1} + X_{t-2}}{2} \tag{10c}$$

if any of these midpoint values approaches zero, we apply the following rule:

$$d_1 = \max(|d_1|, \varepsilon) \cdot sign(d_1) \tag{10d}$$

$$d_2 = \max(|d_2|, \varepsilon) \cdot sign(d_2) \tag{10e}$$

$$d_3 = \max(|d_3|, \varepsilon) \cdot sign(d_3) \tag{10f}$$

where ε is a small value (e.g., 1e-6) and $sign(x)$ is a function that returns the sign of x:

$$sign(x) = \begin{cases} -1, if\ \ x < 0 \\ 0,\ if\ \ x = 0 \\ 1,\ if\ \ x > 0 \end{cases} \tag{10g}$$

by substituting these rules into equation (9), we get BetaSutte with special case handling:

$$X_t^{BetaSutte} = \left(1-\lambda\right)\cdot\left(\frac{1}{3}\right)\cdot\left(X_{t-3}\cdot\frac{2\Delta x_{adjusted}}{\max\left(\left|d_1\right|,\varepsilon\right)\cdot sign\left(d_1\right)}+X_{t-2}\cdot\frac{2\Delta y_{adjusted}}{\max\left(\left|d_2\right|,\varepsilon\right)\cdot sign\left(d_2\right)}+X_{t-1}\cdot\frac{2\Delta z_{adjusted}}{\max\left(\left|d_3\right|,\varepsilon\right)\cdot sign\left(d_3\right)}\right)+\lambda\cdot\left(a+b\cdot t\right) \tag{11}$$

BetaSutte has two main parameters that need to be optimized:

- Shrinkage parameter (s) that controls the degree of reduction of extreme changes

- Trend weight parameter (λ) that controls the balance between the α-Sutte component and the trend component parameter optimization is done by minimizing prediction error:

$$\{s^*, \lambda^*\} = argmin_{s,\lambda} \sum_{t=t_0}^{n} \left(X_t - X_t^{BetaSutte} \right)^2 \tag{12a}$$

where:

- t_0 is the initial evaluation time (typically after the training period)
- X_t is the actual value at time t
- $X_t^{BetaSutte}$ is the BetaSutte prediction at time t using parameters s and λ

Parameter constraints:

$$0 \le s \le 1 \tag{12b}$$

$$0 \le \lambda \le 1 \tag{12c}$$

Optimization can be performed using grid search, where various combinations of s and λ values are evaluated to find the pair that produces the smallest prediction error:

- Define the range of s and λ values to be evaluated
- For each combination (s, λ), calculate the BetaSutte predictions
- Calculate the prediction error (e.g., MSE) for each combination
- Select the combination (s*, λ*) that yields the smallest error

By combining all the components —basic α-Sutte equation, shrinkage, trend component, special case handling, and parameter optimization— we obtain the complete BetaSutte model, which is a modification of the standard α-Sutte:

$$X_t^{BetaSutte} = (1-\lambda^*) \cdot \left(\frac{1}{3}\right) \cdot \left(X_{t-3} \cdot \frac{2\Delta x_{adjusted}}{\max\left(|d_1|, \varepsilon\right) \cdot sign\left(d_1\right)} + X_{t-2} \cdot \frac{2\Delta y_{adjusted}}{\max\left(|d_2|, \varepsilon\right) \cdot sign\left(d_2\right)} + X_{t-1} \cdot \frac{2\Delta z_{adjusted}}{\max\left(|d_3|, \varepsilon\right) \cdot sign\left(d_3\right)} \right) + \lambda^* \cdot (a + b \cdot t) \tag{13}$$

where:

- $\Delta x_{adjusted}$, $\Delta y_{adjusted}$, and $\Delta z_{adjusted}$ are the period-to-period changes after applying shrinkage with the optimal parameter s*
- d_1, d_2, and d_3 are midpoint values with special case handling
- a and b are trend parameters estimated through linear regression
- λ* is the optimal weight parameter that controls the relative influence of the α-Sutte component and the trend component
- s* is the optimal shrinkage parameter that controls the degree of reduction of extreme changes

The (13) is the final BetaSutte model that can be used for time series prediction with higher accuracy compared to the standard α-Sutte, especially for data with outliers and clear trends.

4. Results and Discussion

4.1. Results

4.1.1. Descriptive Analysis

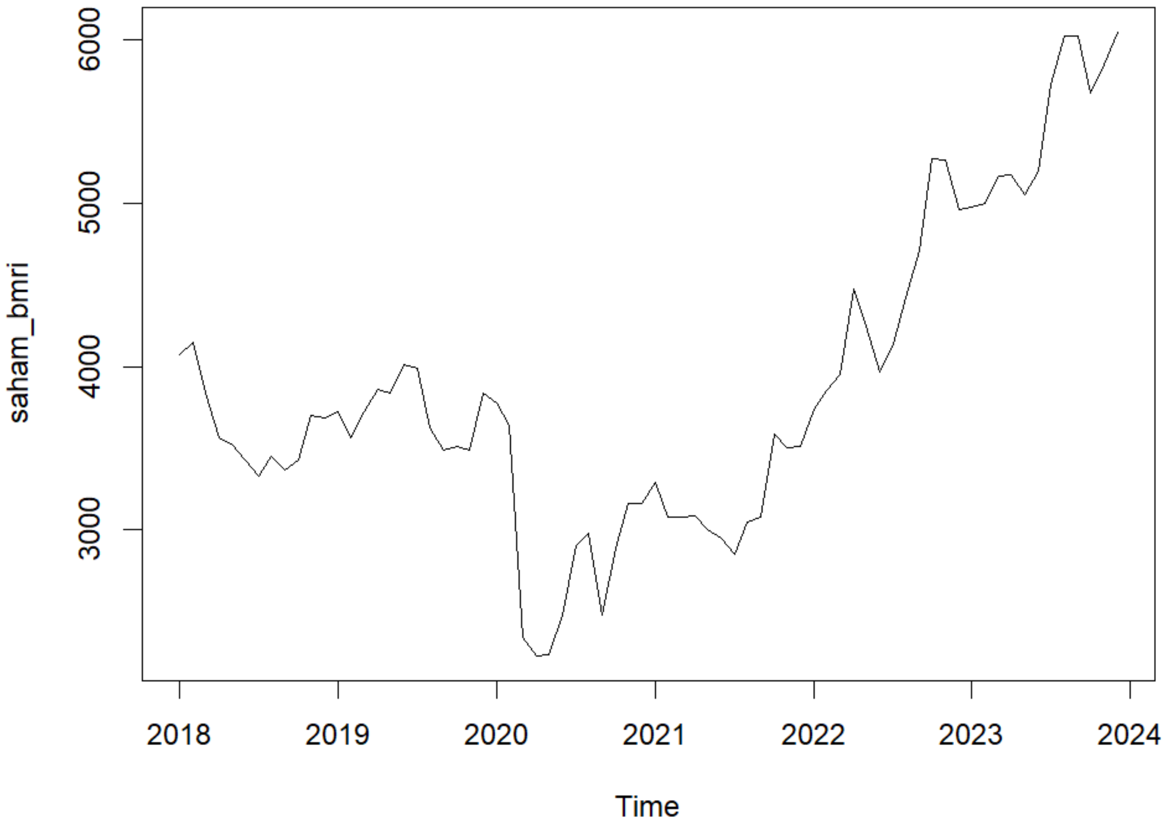

Figure 1. The plot time serios of the stock prices of Bank Mandiri (BMRI)

The figure 1 show the stock prices of Bank Mandiri (BMRI) from January 2018 to December 2023. The data reveals a general upward trend, with prices starting around 3,000 and rising to approximately 6,000 by the end of the observed period. Notably, there is a significant dip in early 2020, likely reflecting market reactions to external economic factors such as the COVID-19 pandemic. This downturn indicates heightened volatility during that time as investors reacted to uncertainty in global markets. Following this decline, BMRI's stock price demonstrates a robust recovery and consistent growth trajectory. From mid-2020 onwards, the stock shows more stability and gradual increases in value, suggesting improved investor confidence and positive performance indicators for Bank Mandiri. The overall pattern indicates resilience in its market position despite earlier challenges. Additionally, minor fluctuations can be observed throughout the years; however, these do not detract from the overarching upward trend.

4.1.2. Forecast Analysis

To see the characteristics of the data, a decomposition was carried out which is presented in Figure 2. The figure 2 presents a decomposition of the additive time series for Bank Mandiri's stock prices from January 2018 to December 2023. The analysis reveals four key components: the original data, trend, seasonal effects, and remainder. The original data shows fluctuations in stock prices over the observed period. There are noticeable peaks and troughs, indicating volatility in the market. This variability suggests that external factors may have influenced price movements significantly during certain periods.

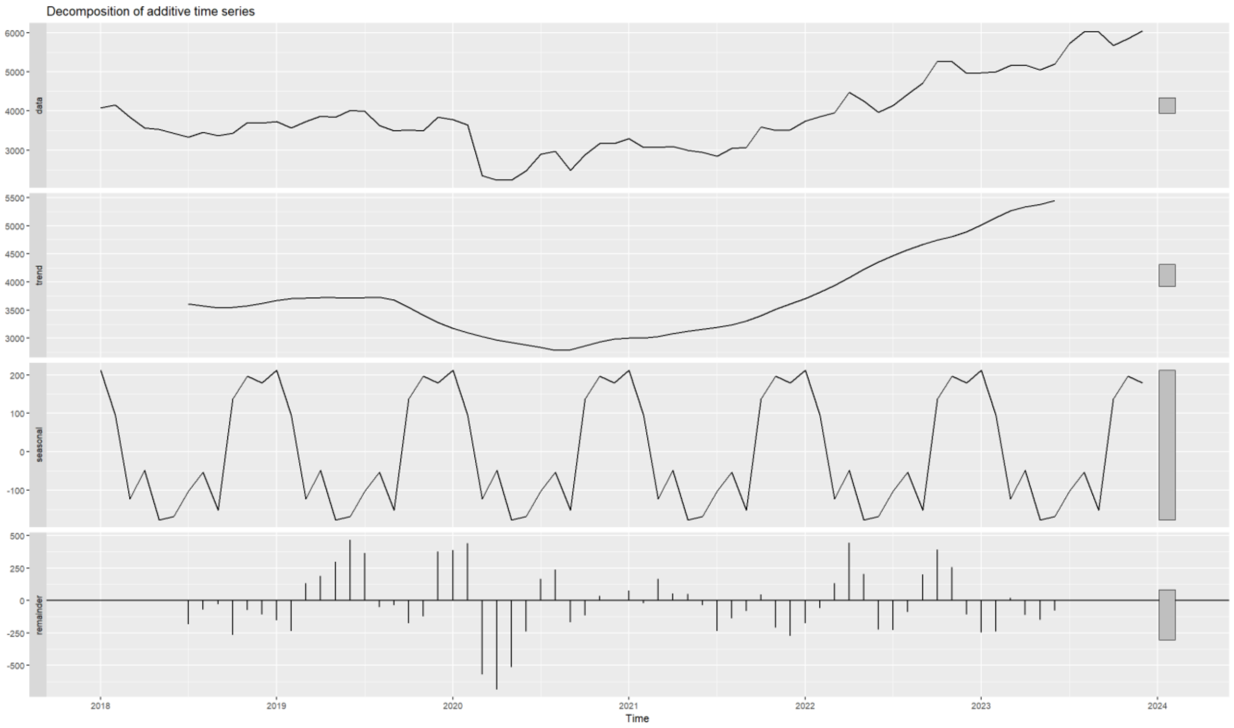

Figure 2. The decomposition of time series of the stock prices of Bank Mandiri (BMRI)

The trend component illustrates a gradual upward trajectory in stock prices over time. Despite some fluctuations, there is an overall increase, suggesting positive long-term growth for Bank Mandiri's shares. This upward trend could be attributed to various factors such as improved financial performance or favorable market conditions. The seasonal component highlights recurring patterns within the data. It indicates that certain times of the year consistently show higher or lower stock prices, reflecting seasonality in investor behavior or business cycles specific to Bank Mandiri’s operations. Lastly, the remainder component captures irregularities not explained by either trend or seasonality. This section displays spikes and dips that may correspond to unexpected events such as economic shifts or company-specific news impacting investor sentiment. Overall, this decomposition provides valuable insights into both predictable patterns and unpredictable variations in Bank Mandiri's stock prices.

The next stage is to forecast the testing data using the training data to obtain the forecasting model. This forecasting is done using 4 methods, namely BetaSutte, SVR, XGBoost, and ARIMA.

The results of analysis data show on the output of R software.

```
Test Metrics Summary:
             Model     RMSE      MAE     MAPE
1 Modified α-Sutte 247.2762 203.9968 3.646170
2              SVR 663.3706 531.5087 9.145640
3          XGBoost 661.8916 526.6642 9.025161
4            ARIMA 694.8492 564.8182 9.712179

$test_data
   Time Actual ModifiedAlphaSutte      SVR  XGBoost ARIMA
1    62   5000           4965.511 4841.505 5016.077  4975
2    63   5163           4979.361 4916.488 5016.077  4975
3    64   5175           5097.411 5158.146 5016.077  4975
4    65   5050           5235.193 5209.777 5016.077  4975
5    66   5200           5507.188 5104.684 5016.077  4975
6    67   5725           5702.585 4967.190 5016.077  4975
7    68   6025           5814.720 4875.251 5016.077  4975
8    69   6025           5965.929 4924.692 5016.077  4975
9    70   5675           6092.658 5081.561 5016.077  4975
10   71   5850           6252.980 5190.322 5016.077  4975
11   72   6050           6393.464 5141.343 5016.077  4975
```

The summary of test metrics assesses the efficacy of four distinct forecasting models based on performance indicators such as RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error). According to the data, the BetaSutte model outperforms the others, achieving the lowest RMSE of 247.2762, MAE of 203.9968, and MAPE of 3.646170. These figures suggest that the Modified α-Sutte model has the most accurate error rate in predicting actual values.

On the other hand, the ARIMA model displays the highest RMSE of 694.8492, MAE of 564.8182, and MAPE of 9.712179, indicating it as the least accurate among the evaluated models. The SVR and XGBoost models show similar performances, with RMSE values closely aligned—663.3706 for SVR and 661.8916 for XGBoost—and MAPEs of 9.145640 and 9.025161, respectively, pointing to a comparable level of forecasting capability between the two, yet both are still not as effective as BetaSutte.

Additionally, test data tracks how each model forecasts values across times 62 to 72, where actual values fluctuate between 5000 to 6050. Notably, the BetaSutte model consistently yields predictions nearest to the real figures, exemplified at time 67 with a prediction of 5702.585 against an actual value of 5725. In contrast, the ARIMA, SVR, and XGBoost models tend to provide static predictions such as 4975 and 5016.077 throughout the test period, lacking the variability to match the actual value changes.

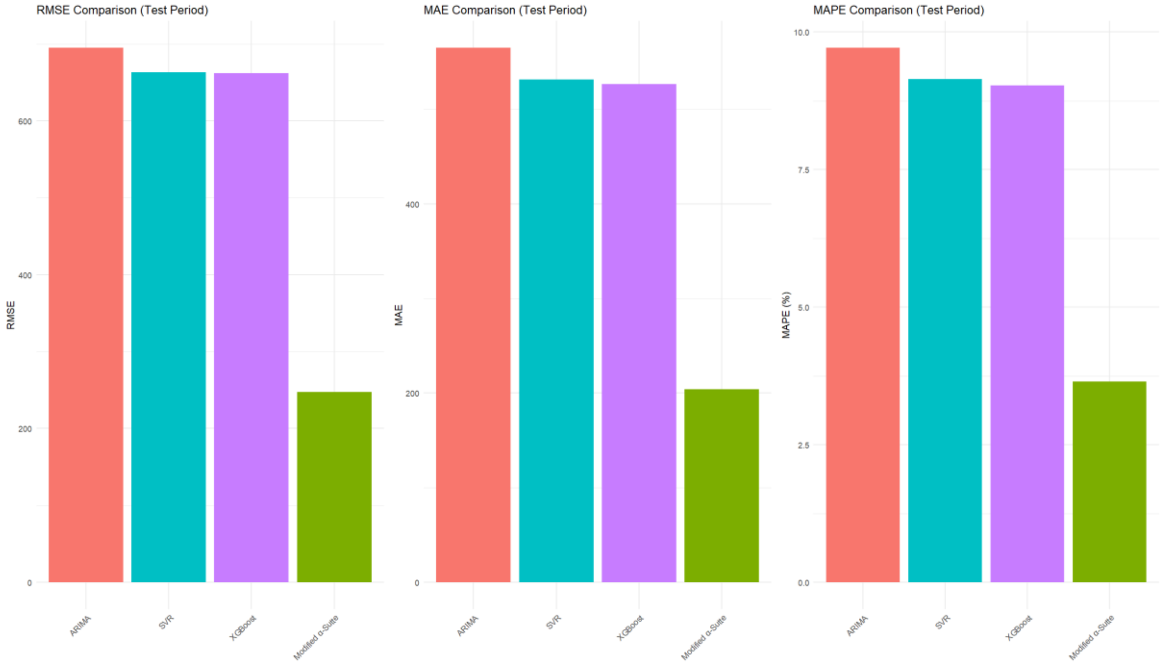

Figure 3. The barchart of RMSE, MAE, and MAPE comparison of Testing Period

To see more of the performance, Figure 3 show the comparison of performance indicators. The Figure 3 presented offers an in-depth comparison between four different forecasting models using three crucial evaluation metrics: RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error). This analysis is vital for assessing the relative performance of each model in the context of forecasting, focusing on the accuracy of the predictions they provide.

Firstly, in the RMSE barchart, which measures the average squared errors between predicted values and actual values, BetaSutte significantly outperforms the other models with a substantially lower RMSE value. This indicates that the predictions made by BetaSutte are closer to the actual values, demonstrating smaller prediction errors compared to the other models. Conversely, ARIMA and XGBoost show the highest RMSE values, indicating that these models are less accurate in their predictions compared to BetaSutte and SVR.

Next, in terms of MAE, which measures the average absolute errors between predictions and actual values without considering the direction of errors, BetaSutte again shows superior performance with a much lower MAE compared to the other models. This reaffirms the superiority of BetaSutte in producing accurate predictions, significantly reducing prediction errors. Although the MAE of SVR is also relatively low, the values produced by BetaSutte are still better.

Finally, in the MAPE category, which measures errors as a percentage and provides an understanding of relative errors in predictions, BetaSutte displays much lower values compared to the other three models. This reveals that proportionally, the prediction errors of BetaSutte relative to the actual values are smaller, indicating higher effectiveness in the conditions of the data used for this analysis.

The performance analysis of the BetaSutte model compared to four distinct forecasting models reveals notable strengths, particularly in its handling of trends, outliers, and parameter adaptability. The reported results show that the BetaSutte model yields the lowest values for root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), indicating superior predictive capabilities. Such findings echo the research conducted by Chen et al. (2016), where effective integration of trend components is deemed crucial for enhancing accuracy in economic forecasting.

Overall, this analysis proves that BetaSutte not only excels in providing accurate predictions but also consistently surpasses other forecasting models in all measured aspects. This demonstrates that the integration of features such as better trend and outlier handling, as well as automatic parameter optimization in BetaSutte, provides significant advantages in forecasting. Its ability to efficiently produce accurate predictions makes it an exceptionally attractive choice for predictive analysis in various application fields, particularly in stock price prediction where accuracy is key to investment success.

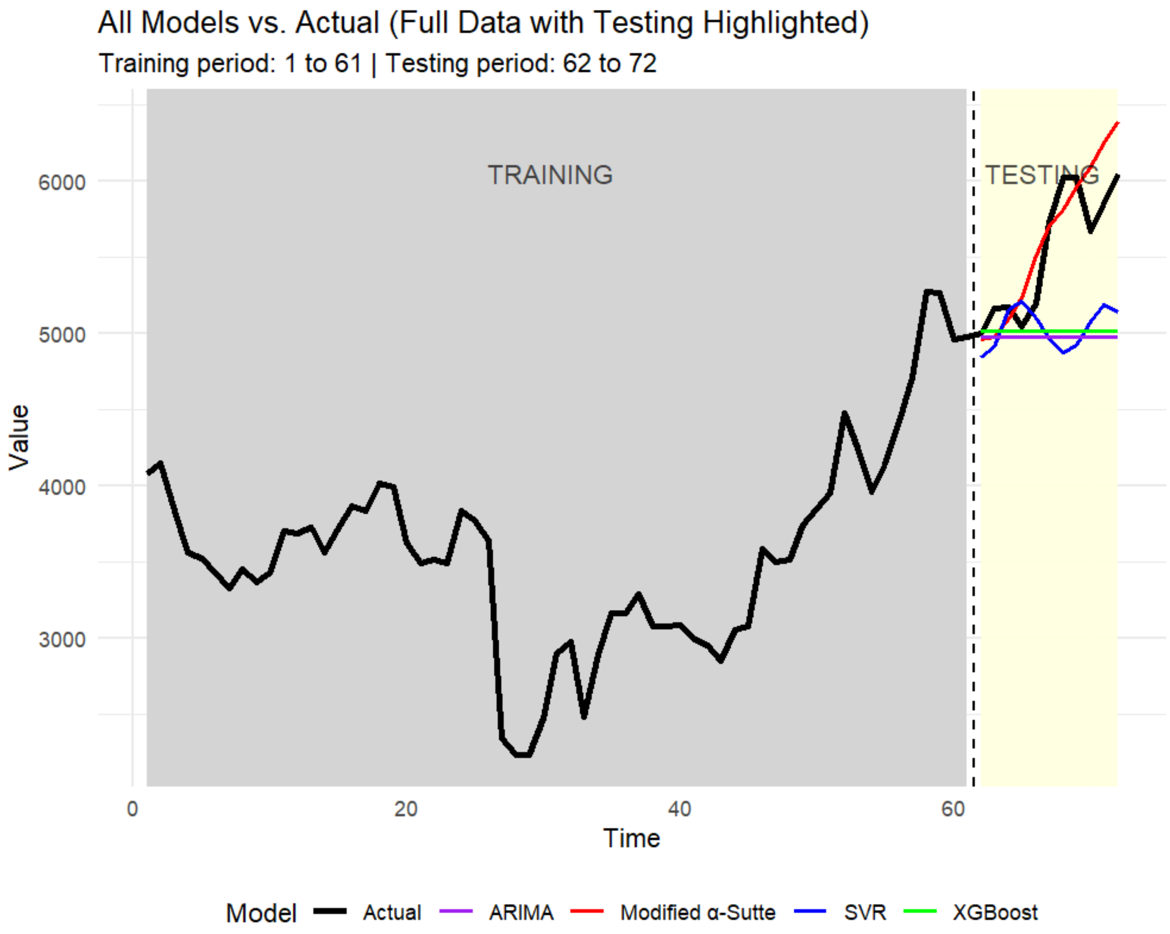

Figure 4. The result of all models with actual data on Testing Period

From the Figure 4, it is observable that the actual data (depicted with a thick black line) experiences a decline followed by a sharp rise around time 60, marking a significant change that models must anticipate. During the testing period, the figure shows that BetaSutte (red line) has the most accurate tendency to follow the movements of the actual values, especially in capturing the peaks and troughs of the value fluctuations. This model appears more responsive to sudden changes in the data and closely approximates the actual values with considerable precision.

Conversely, ARIMA (purple line), SVR (blue line), and XGBoost (green line) display variations in their success rates in capturing market dynamics. ARIMA and XGBoost seem to be less responsive to the peaks and troughs, particularly in responding to changes that occur towards the end of the training period and the beginning of the testing period. They tend to produce flatter predictions compared to BetaSutte. SVR, while performing slightly better than ARIMA and XGBoost, still does not achieve the level of accuracy of BetaSutte. Overall, the figure demonstrates the significant advantage of BetaSutte in providing predictions that are closer to market realities, which is extremely valuable for data-based decision-making.

4.2. Discussions

The significance of managing outliers in forecasting cannot be overstated, as highlighted by Huyghues-Beaufond et al. (2020). Their research underscores that neglecting outliers can severely degrade the forecasting models’ performance. The outlier-handling mechanism embedded in the BetaSutte model is selective, allowing it to maintain the fundamental data patterns while mitigating distortions caused by aberrant values. This selective filtering is consistent with the findings of Ertl (2022), which elucidates how appropriately mitigating the impact of outliers in financial forecasting markedly boosts consistency. Thus, the BetaSutte model's deliberate approach to handling outliers forms a compelling argument in favor of its predictive precision.

Another pivotal aspect of the BetaSutte model's superiority is its interpretability, an area highlighted in the study by Leung et al. (2016). Their findings argue for the advantages inherent in models that offer straightforward analysis and understanding. The BetaSutte model's transparent methodologies facilitate better comprehension of its predictive decisions, ultimately aiding practitioners in making informed choices. Such interpretability is crucial in financial applications, where transparency can enhance trust among stakeholders and inform risk management strategies. Such interpretability stands in contrast to more opaque models, or “black boxes,” that often obfuscate underlying processes—an issue promptly noted by Leung et al. Therefore, the capacity of the BetaSutte model to render its decision-making process accessible significantly underscores its utility in practical applications.

Parameter adaptability, a critical element in dynamic forecasting, further distinguishes the BetaSutte model. The flexibility to adjust model parameters in real-time, as described by Prakash et al. (2025), allows it to effectively respond to the shifting characteristics of financial markets and other data environments. This adaptability enables practitioners to achieve enhanced stability and accuracy in their forecasts. In environments characterized by volatility and rapid change, such as financial markets, the agility of the BetaSutte model can serve as a key competitive advantage.

In terms of comparison with other models, the findings from Elveny et al. (2024) support the observation that while support vector regression (SVR) is competent in managing non-linear relationships, it may falter in contexts dominated by trends and outliers—two areas where BetaSutte excels. Furthermore, Carriero et al. (2024) discuss the advantages of XGBoost in analyzing larger datasets fraught with complex patterns, yet they caution against the potential pitfalls regarding interpretability and computational efficiency when set against the simplicity and clarity offered by the BetaSutte model.

An evaluation of the ARIMA model by Güney et al. (2020) reveals its strengths in autoregressive data but highlights a notable deficiency in managing outliers or abrupt trends, limitations that BetaSutte effectively addresses. This finding reiterates the notion that while established models possess their virtues, the adaptability and robustness of the BetaSutte model render it a stronger candidate under diverse analytical challenges.

The findings articulated here substantiate that the selection of an appropriate forecasting model should be contingent on the specific attributes of the dataset and the analytical needs of the practitioner. The BetaSutte model's commendable performance—grounded in its adeptness at managing trends, outliers, and parameter adaptability—positions it as an invaluable resource for practitioners seeking reliable and interpretable forecasting solutions. Future research should continue to explore BetaSutte's performance in varying datasets and its scalability across different sectors to further establish its utility in diverse real-world applications.

5. Conclusion and Future Research

Based on the analysis and discussion, it is evident that the BetaSutte model offers substantial advantages in managing trends and outliers, and it provides more accurate and interpretable predictions compared to the SVR, XGBoost, and ARIMA models. Utilizing BetaSutte for forecasting Bank Mandiri's stock prices has proven highly effective in adapting to market fluctuations and delivering reliable predictions, which are vital for enabling investors to make well-informed investment choices.

A key strength of the BetaSutte model in analyzing Bank Mandiri's stock prices lies in its enhanced ability to accurately predict stock price trends. This adaptability allows it to generate predictions that are more resilient to unexpected shifts in market conditions, offering investors a strategic advantage during volatile periods. This capability provides a crucial edge to investors aiming to refine their trading strategies based on more precise and dependable forecasts. The model helps pinpoint potential investment opportunities or flags potential depreciation risks with greater accuracy, thereby reducing uncertainty and increasing the potential for profitability.

Moreover, the model's robust outlier management ensures that the predictions remain stable and are not disproportionately affected by sudden market changes or unforeseen events. This robustness makes BetaSutte an ideal tool for navigating market turbulence, which is crucial for mitigating risks in a fast-moving financial environment. This attribute is particularly valuable in volatile market conditions, where outliers can lead to costly prediction errors. The implementation of BetaSutte in analyzing Bank Mandiri's stock prices and similar financial contexts is likely to lead to significant enhancements in the accuracy and reliability of financial predictions. This improvement can substantially benefit investment decision-making and stock market risk management, providing a strategic advantage in navigating the complexities of the financial markets.

Given the outcomes observed from utilizing the BetaSutte model in this study, several potential avenues for future research emerge to broaden the understanding and application of this model in forecasting. First, further testing of BetaSutte across diverse data scenarios, such as different economic sectors or datasets with varying levels of volatility, will help ascertain its reliability in varied forecasting environments. This could involve experimenting with larger or more noise-complex datasets to evaluate how well the model adjusts to new challenges.
Second, enhancing the algorithm for automatic parameter optimization in BetaSutte could lead to significant gains in model efficiency. Integrating machine learning techniques or heuristic approaches to fine-tune model parameters could provide real-time adjustments, improving forecasting accuracy even further. This advancement might include the incorporation of sophisticated techniques like machine learning or heuristic methods that dynamically refine model parameters based on insights from past forecasting results.

Third, combining BetaSutte with other forecasting models such as ARIMA or XGBoost could create a hybrid methodology that capitalizes on the strengths of each model. Such hybrid approaches could better handle datasets with both linear and nonlinear characteristics, thereby enhancing predictive performance across a broader range of applications. Such an integrated approach could effectively address the inherent limitations of individual models, providing a more comprehensive solution for complex forecasting tasks.
Fourth, investigating the application of BetaSutte in the realms of big data analysis and real-time forecasting presents a promising research direction. By adapting BetaSutte for real-time data processing, its application could expand to sectors like high-frequency trading or real-time market sentiment analysis, further demonstrating its versatility and scalability. As the availability of large data sets increases, the demand for models that can process and analyze data in real-time is growing. Adapting BetaSutte to support these capabilities could expand its applicability in broader contexts.

Fifth, conducting a thorough evaluation of how BetaSutte's outlier handling and trend adaptation mechanisms affect result interpretation is crucial. This research could refine the model's output to ensure that the predictions it generates are not only accurate but also meaningful in practical terms, enhancing decision-making for stakeholders. This research could contribute to refining the model to ensure that it not only yields accurate predictions but also produces results that are meaningful and actionable for users.

By pursuing these research initiatives, the capabilities and limitations of BetaSutte can be more fully understood, potentially enhancing its practical effectiveness and utility in future forecasting applications.

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