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Adaptive Layered Buying Strategy Using Mode and Standard Deviation of Daily Price Range: Evidence from BBRI Indonesia Stock Market

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BBRI;
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Abstract

The Indonesian stock market exhibits substantial price volatility, making fixed-interval averaging strategies less effective under changing market conditions. This study proposes an adaptive averaging strategy based on the historical distribution of daily price ranges. Daily open, high, low, and close (OHLC) price data for Bank Rakyat Indonesia (BBRI), covering the period from November 2003 to July 2026 and comprising 5,602 observations, were analyzed. The adaptive buying interval was estimated using the mode of non-zero daily price ranges combined with two standard deviations. The resulting interval was then used to construct a layered buying strategy with exponential position sizing. Simulation results indicated that the proposed strategy substantially reduced the average acquisition cost while maintaining manageable capital requirements. Under a seven-level buying strategy, total capital deployment reached IDR 23.68 million, assuming purchases began in January 2025. Furthermore, the simulated portfolio generated a positive unrealized return of 59.28% under the historical price scenario. These findings suggest that statistical measures of price volatility provide a practical basis for determining adaptive averaging intervals in long-term equity investment. The proposed framework offers a simple yet robust alternative to conventional fixed-interval averaging strategies.

INTRODUCTION

Over the past two decades, Indonesia's capital market has expanded considerably, supported by rapid advances in digital trading platforms and financial technology that have encouraged greater participation by retail investors. Simplified account registration procedures, lower transaction costs, and broader access to real-time financial information have made equity investing more accessible to the general public. Nevertheless, the Indonesian stock market continues to experience substantial price volatility, driven by both domestic and international factors, including monetary policy adjustments, inflationary pressures, geopolitical developments, and fluctuations in global capital flows. Although these market dynamics create opportunities for investors to achieve attractive returns, they also expose retail investors to considerable downside risk, particularly those with limited experience in portfolio management and risk management (He et al., 2025; Santoso et al., 2025)

Among the various investment strategies adopted by retail investors, Dollar-Cost Averaging (DCA) remains one of the most widely used approaches. Under this strategy, investors purchase a predetermined amount of shares at regular intervals regardless of prevailing market conditions. The primary objective of DCA is to reduce market-timing risk while lowering the average acquisition cost over a long-term investment horizon. Despite its popularity and ease of implementation, DCA follows a fixed investment schedule and therefore does not adapt to changes in market volatility. As a result, investors may miss opportunities to accumulate shares more efficiently during periods of substantial price corrections (Brown, 2023).

Another strategy frequently employed by long-term investors is averaging down, which involves purchasing additional shares after the market price declines to reduce the overall average purchase price. Compared with DCA, averaging down is intended to capitalize on temporary price corrections and improve portfolio recovery when market prices rebound. However, the effectiveness of this strategy depends largely on selecting appropriate price intervals for additional purchases. In practice, many investors determine these intervals using fixed price differences, psychological price levels, or personal judgment rather than objective statistical analysis. Such subjective approaches often overlook the historical distribution of price movements, potentially resulting in excessive capital deployment during periods of high market volatility or inefficient capital allocation when market volatility is relatively low (Jin et al., 2023).

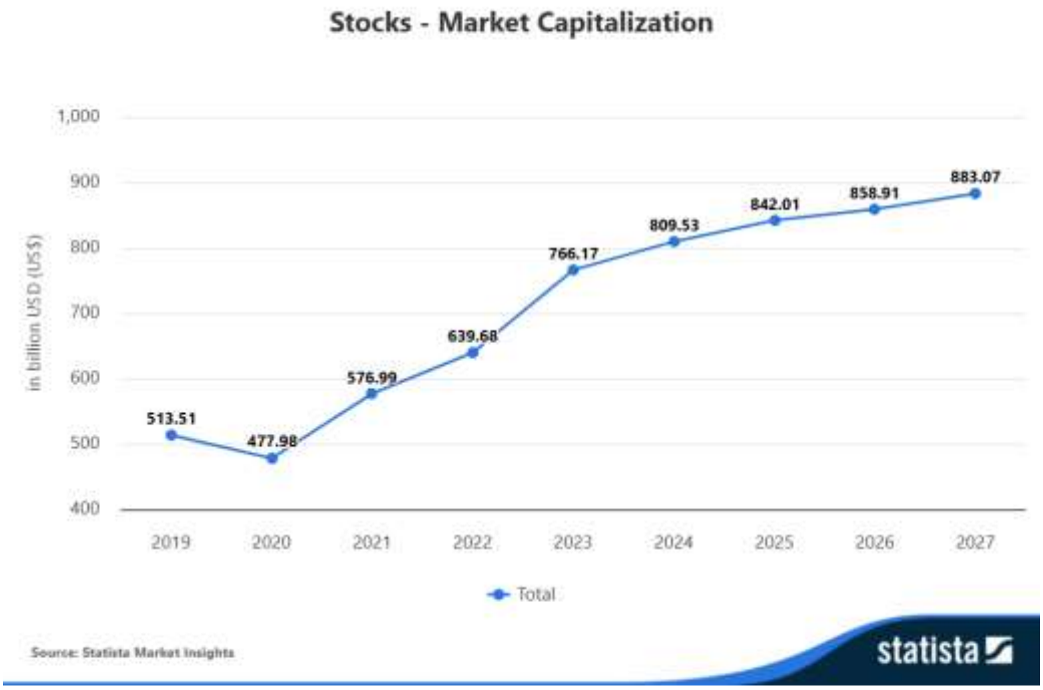

Figure 1. The Growth of Financial Market in Indonesia
Source: Financial Services Authority (OJK), Indonesian Capital Market Statistics, accessed July 2026

The reliance on fixed-interval averaging represents an important practical limitation. Conventional averaging strategies generally recommend purchasing additional shares after the price declines by a predetermined amount, such as IDR 50 or IDR 100, or by a fixed percentage. Although these rules are straightforward to implement, they do not account for the dynamic nature of stock price volatility. During periods of heightened volatility, fixed intervals may trigger excessive buying activity and rapidly exhaust available investment capital. Conversely, during relatively stable market conditions, the same intervals may be overly conservative, reducing the efficiency of capital deployment. Consequently, developing adaptive buying intervals that more accurately reflect historical market behavior has become an important objective in designing more effective averaging strategies.

A wide range of previous studies has focused on technical analysis methods to support investment decision-making. Popular indicators, such as the Moving Average (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands, have been widely used to identify market trends, price momentum, and potential buy or sell signals. Although these methods have proven valuable for market timing, relatively little attention has been devoted to determining statistically derived averaging intervals for layered investment strategies. Existing averaging approaches continue to rely primarily on fixed price intervals or percentage-based thresholds without incorporating the empirical distribution of historical price movements. Consequently, the selection of averaging intervals remains largely heuristic and lacks a rigorous statistical foundation (Almeida & Vieira, 2023; Kamara et al., 2022; Ni, 2024).

This limitation highlights an important research gap. Although previous studies have extensively investigated technical indicators and portfolio optimization methods, few have proposed a statistical framework capable of translating historical market volatility into adaptive buying intervals. Furthermore, there remains a need for approaches that are both computationally efficient and sufficiently practical for implementation by retail investors using publicly available historical market data. A statistically derived interval that reflects both the most frequently occurring daily price range and the variability of historical price ranges may provide a more rational and objective basis for determining successive buying levels than conventional fixed-interval approaches (Dhingra et al., 2024; Melina et al., 2023).

To address this limitation, the present study introduces an adaptive statistical averaging framework based on the historical distribution of daily stock price ranges. The proposed framework calculates the daily trading range as the difference between the daily high and daily low prices, identifies the most representative market movement using the mode of the non-zero daily price ranges, and quantifies market variability using the standard deviation of the range distribution. These statistical measures are then combined to generate an adaptive buying interval that reflects the historical volatility characteristics of the stock. The resulting interval is subsequently incorporated into a layered buying strategy with progressive position sizing to evaluate capital requirements and portfolio performance (Lin & Marques, 2024).

The proposed framework was empirically evaluated using the historical daily stock prices of Bank Rakyat Indonesia (BBRI) from November 2003 to July 2026, comprising 5,602 trading observations. The analysis estimated the statistical characteristics of daily price ranges, constructed adaptive buying intervals, and performed investment simulations under predefined capital constraints. The findings indicate that historical measures of price volatility can be effectively used to generate practical and adaptive buying intervals for long-term equity investment. This study offers several practical benefits. It provides retail investors with a simple, data-driven framework for identifying buying opportunities, reducing emotional bias, and improving investment discipline. By adapting buying intervals to prevailing market volatility, the proposed strategy improves capital deployment, lowers the average acquisition cost, and enhances the potential for portfolio recovery while remaining accessible to individual investors using only publicly available price data and basic statistical techniques. These advantages support more rational, efficient, and inclusive long-term investing in the Indonesian stock market.

This study contributes to both the academic literature and investment practice in three important ways. First, it proposes a statistical interval estimation approach that derives adaptive buying intervals from the empirical distribution of historical price ranges rather than relying on arbitrary fixed intervals. Second, it develops an adaptive averaging framework that integrates descriptive statistical measures into a systematic layered buying strategy capable of adjusting to different market conditions. Finally, it provides a simple, transparent, and practical decision-support framework that can be readily implemented by retail investors in the Indonesian stock market using publicly available historical price data. By combining descriptive statistical methods with an adaptive averaging mechanism, the proposed framework offers a data-driven alternative to conventional averaging strategies while narrowing the gap between traditional investment practices and quantitative decision-making.

METHOD

Research Design

This study adopted a quantitative research approach supported by statistical analysis and simulation to develop an adaptive averaging strategy for equity investment. Historical stock price data were analyzed to estimate statistically derived buying intervals, which were subsequently implemented and evaluated within a layered buying framework. Unlike conventional averaging strategies that rely on predetermined fixed price intervals, the proposed method derived buying intervals from the empirical distribution of historical price volatility, enabling the strategy to adapt to changing market conditions (Zeng et al., 2025).

Data Collection

It utilizes secondary data obtained from Yahoo Finance, comprising the historical daily stock prices of PT Bank Rakyat Indonesia Tbk. (BBRI). The observation period extends from 10 November 2003 to 17 July 2026, yielding a total of 5,602 daily observations. The dataset consists of the standard daily market variables, including the opening price (Open), highest price (High), lowest price (Low), closing price (Close), and trading volume (Volume).

The historical price data were retrieved using the Python yfinance library and subsequently processed with the Pandas library for data cleaning, statistical analysis, and simulation. These data provide the empirical basis for estimating historical price volatility and constructing the adaptive averaging strategy proposed in this study (Achyutha et al., 2022; Albahli et al., 2023).

```
pip install yfinance pandas -qq

Note: you may need to restart the kernel to use updated packages.

import yfinance as yf
import pandas as pd
from datetime import datetime

TICKER     = "BBRI.JK"
START_DATE = "2000-01-01"
END_DATE   = datetime.today().strftime("%Y-%m-%d")

def get_ohlc(ticker: str = TICKER, start: str = START_DATE, end: str =
END_DATE) -> pd.DataFrame:
    df = yf.Ticker(ticker).history(start=start, end=end,
interval="1d", auto_adjust=True)

    df.reset_index(inplace=True)
    df["Date"] = pd.to_datetime(df["Date"]).dt.tz_localize(None)
    df = df[["Date", "Open", "High", "Low", "Close", "Volume"]].copy()
    df.sort_values("Date", inplace=True)
    df.reset_index(drop=True, inplace=True)

    return df

if __name__ == "__main__":
    df = get_ohlc()
    print(df)
    print(f"\nShape : {df.shape}")
    print(f"Periode: {df['Date'].min().date()} –
{df['Date'].max().date()}")

           Date         Open         High          Low        Close  \
0    2003-11-10    38.995785    40.852729    35.281901    36.210373
1    2003-11-11    36.210364    37.138832    35.281892    37.138832
2    2003-11-12    36.210372    38.995785    36.210372    38.995785
3    2003-11-13    38.995785    38.995785    38.067313    38.995785
4    2003-11-14    38.995785    38.995785    37.138841    38.995785
...         ...          ...          ...          ...          ...
5597 2026-07-13  2790.000000  2870.000000  2780.000000  2870.000000
5598 2026-07-14  2800.000000  2890.000000  2800.000000  2800.000000
5599 2026-07-15  2840.000000  2870.000000  2810.000000  2830.000000
5600 2026-07-16  2840.000000  2880.000000  2830.000000  2860.000000
5601 2026-07-17  2860.000000  3000.000000  2840.000000  2970.000000

          Volume
0     5658651738
1     3232466332
2     2203244555
3     1380077610
```

Figure 2. Extraction Daily OHLC Price for BBRI Stocks

Source: Historical daily price data of PT Bank Rakyat Indonesia Tbk. (BBRI) retrieved from Yahoo Finance via the yfinance Python library (period: November 10, 2003 – July 17, 2026).

```
plt.grid(True)

# agar tanggal lebih rapi
plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```

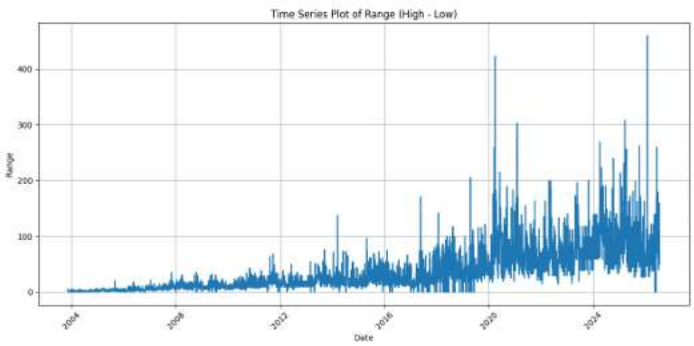

Figure 3. BBRI High-Low Plot Daily

Source: Processed from historical daily BBRI price data obtained from Yahoo Finance (period: 2003–2026)

Research Variables:

Market variables are obtained directly from the daily trading records, whereas the statistical variables are calculated to estimate the adaptive buying interval used in the proposed investment strategy (Albahli et al., 2023; Huang et al., 2024).

Tabel 1. Research Variable

Variable	Description
Open	Daily opening price
High	Daily highest price
Low	Daily lowest price
Close	Daily closing price

Volume	Daily trading volume
Range	Daily price range, calculated as High − Low
Mode	Most frequently observed non-zero value of the daily price range
Standard Deviation	Standard deviation of the daily price range
Adaptive Interval	Buying interval estimated from the statistical properties of the daily price range

Source: Developed based on market variables available from Yahoo Finance and statistical calculations by the authors

The daily price range is calculated as:

$Range_t = High_t - Low_t$ (1), where:

- $Range_t$ = daily price range on day t;
- $High_t$ = highest stock price on day t;
- Low_t = lowest stock price on day t.

Based on the series of daily price ranges, the statistical parameters are estimated as follows. The mode is defined as the most frequently occurring non-zero daily price range:

$\mathbf{Mode = mode(Range_t), \quad Range_t > 0}$ (2)

The standard deviation of the daily price range is calculated as:

$\boldsymbol{\sigma = \sqrt{[(\Sigma(Range_t - \bar{R}ange)^2)/(n - 1)]}}$ (3), where:

- **σ** = standard deviation of the daily price range;
- **R̄ange** = mean daily price range;
- **n** = total number of observations.

The adaptive buying interval is then determined using the following equation:

Adaptive Interval = Mode + 2σ (4)

The resulting adaptive interval represents the price distance between consecutive buy orders in the proposed averaging strategy (Akhtar et al., 2022).

Statistical Analysis:

The adaptive buying interval proposed in this study is estimated from the historical distribution of daily price ranges. The analysis begins by calculating the daily price range for each trading day and constructing its empirical distribution. This distribution is then used to derive statistical measures that characterize the typical magnitude and variability of daily price movements. To represent the most common market movement, the mode of the non-zero daily price ranges is calculated as

Mode = mode(Range). (5)

The exclusion of zero observations ensures that non-trading or unchanged price movements do not bias the estimation of the representative daily price range. Market variability is subsequently quantified using the sample standard deviation of the daily price range, computed as

$\boldsymbol{\sigma = \sqrt{[\Sigma(Range_i - \bar{R}ange)^2/(n - 1)]}}$. (6)

where **σ** denotes the standard deviation of the daily price range, **R̄ange** is the mean daily price range, and **n** represents the total number of observations. The adaptive buying interval is then determined by combining these two statistical measures according to

Adaptive Interval = Mode + 2σ. (7)

This formulation is based on the premise that the mode represents the most frequently observed daily price movement, whereas the standard deviation captures the historical dispersion of price fluctuations. Consequently, the resulting buying interval reflects both the central tendency and the variability of historical market behavior. Unlike conventional averaging strategies that employ predetermined fixed intervals, the proposed approach allows the spacing between successive buy orders to adjust according to the statistical characteristics of the underlying asset. Applying the proposed procedure to the historical daily price data of PT Bank Rakyat Indonesia Tbk. (BBRI) over the sample period produced the following statistical estimates (Pagnottoni et al., 2022).

Table 2. Statistics of Value Calculation

Statistics	Value
Mode (Non-zero Range)	1.948
Standard Deviation	37.642
Adaptive Interval	77.232

Source: Computed from the daily BBRI price data over the 2003–2026 period using equations (Brown, 2023; He et al., 2025; Jin et al., 2023)

Adaptive Layering Strategy

Following the estimation of the adaptive buying interval, the performance of the proposed method is evaluated through a simulation of a layered averaging strategy. The simulation assumes that an initial position of one lot is established at the first purchase. When the market price declines by one adaptive interval from the previous purchase price, an additional buy order is executed. This process continues sequentially as long as the price reaches each subsequent buying level. To accelerate the reduction of the average acquisition cost, the position size is increased geometrically, with the number of shares purchased at each level being twice that of the preceding purchase. Consequently, the cumulative average purchase price decreases as additional positions are accumulated during periods of price decline.

The simulation is conducted using historical daily price data over the entire observation period. At each buying level, the corresponding purchase price, investment amount, cumulative position, total capital invested, and weighted average acquisition cost are recorded. These outputs are subsequently used to evaluate the effectiveness of the proposed adaptive averaging strategy in managing declining market conditions. The simulation parameters adopted in this study are summarized in **Table 3**.

Table 3. Buying Simulation

Parameter	Value
Initial Lot	1 lot
Position Multiplier	2×
Number of Buying Levels	7
Lot Size	100 shares
Initial Capital	IDR 100,000,000

Source: Simulation parameters defined by the authors based on the proposed layered averaging strategy framework.

This approach enables larger positions to be accumulated at lower prices while maintaining a statistically determined spacing between buying levels.

Capital Requirement and Portfolio Performance

The capital allocated at each buying level is determined by multiplying the purchase price by the corresponding number of shares acquired. Accordingly, the capital invested at buying level i is calculated as

$$\mathbf{Capital_i = P_i \times Shares_i}. \qquad (8)$$

where $\mathbf{P_i}$ denotes the purchase price at buying level i and $\mathbf{Shares_i}$ represents the number of shares purchased. The total capital invested throughout the simulation is obtained by summing the capital allocated across all executed buying levels:

$$\mathbf{Total\ Capital = \Sigma\ Capital_i}. \qquad (9)$$

As additional positions are accumulated, the portfolio's acquisition cost is updated using the weighted average purchase price. This measure reflects the average cost per share after considering both the purchase prices and the corresponding investment sizes:

Average Price = $\Sigma(P_i \times Shares_i) / \Sigma Shares_i$. (10)

The unrealized portfolio profit or loss is then estimated by comparing the latest market price with the weighted average acquisition cost:

PnL = (Pcurrent − Average Price) × Total Shares. (11)

where **Pcurrent** is the latest market price, **Average Price** is the weighted average acquisition cost, and **Total Shares** denotes the cumulative number of shares acquired during the simulation. To facilitate performance comparison across different investment scenarios, the portfolio return is expressed as a percentage of the total invested capital:

Return (%) = (PnL / Total Capital) × 100. (12)

The proposed performance measures provide a comprehensive assessment of the adaptive averaging strategy by quantifying the capital required at each buying level, the evolution of the average acquisition cost, and the resulting portfolio profitability. These indicators are subsequently used to evaluate whether the statistically derived adaptive interval improves capital efficiency while reducing the average purchase price under declining market conditions.

Research Procedure

The overall research procedure is illustrated in below flow. The study begins with the acquisition of historical daily stock price data, from which the daily trading range is calculated as the difference between the highest and lowest prices. The resulting time series of daily price ranges is subsequently used to estimate two descriptive statistical measures, namely the mode and the standard deviation, which represent the central tendency and variability of historical price movements, respectively.

Based on these statistical estimates, an adaptive buying interval is determined using the proposed interval formulation. The estimated interval is then incorporated into a layered averaging strategy, whereby additional purchases are executed whenever the stock price declines by one adaptive interval. The simulation records the capital allocated at each buying level, the cumulative investment, the weighted average acquisition cost, and the resulting portfolio performance throughout the investment horizon.

Finally, the effectiveness of the proposed adaptive averaging strategy is evaluated using several performance indicators, including total capital invested, weighted average purchase price, unrealized profit or loss, and portfolio return. This sequential procedure enables the transformation of historical price volatility into statistically derived buying intervals and provides an empirical assessment of their effectiveness in improving capital allocation and reducing the average acquisition cost in long-term equity investment.

Historical Daily Stock Data => Daily Price Range (High − Low) => Mode Estimation => Standard Deviation Estimation => Adaptive Interval (Mode + 2σ) => Adaptive Layered Averaging Strategy => Capital Simulation => Performance Evaluation.

RESULTS AND DISCUSSIONS

Dataset

The empirical analysis was conducted using the historical daily stock prices of PT Bank Rakyat Indonesia Tbk. (BBRI) obtained from Yahoo Finance. The dataset covers the period from **10 November 2003 to 17 July 2026**, comprising **5,602 daily observations**. This extended observation period includes multiple market cycles characterized by expansion, correction, and recovery phases, thereby providing a comprehensive basis for evaluating the proposed adaptive averaging strategy under varying market conditions.

The dataset includes the daily opening, highest, lowest, and closing prices, together with trading volume. From these variables, the daily price range was calculated and subsequently used to estimate the statistical parameters required for determining the adaptive buying interval.

Distribution of Daily Price Range

The empirical distribution of the daily price range provides an overview of the historical volatility characteristics of BBRI. **Figure 2** presents the histogram of the daily price range, while **Figure 3** illustrates its evolution throughout the observation period.

The histogram indicates that the distribution is positively skewed, with most observations concentrated within relatively small daily price movements and a limited number of extreme observations. This finding suggests that typical market movements are substantially smaller than the largest price fluctuations observed during periods of heightened market activity.

The time-series plot further reveals that volatility is not constant over time. Instead, periods of relatively low volatility are followed by episodes of elevated market uncertainty, indicating the presence of **volatility clustering**, a well-documented characteristic of financial time series. During market stress, the magnitude of daily price movements increases considerably, resulting in several extreme observations that contribute to the heavier right tail of the empirical distribution.

These findings indicate that a fixed buying interval may not adequately reflect the changing characteristics of market volatility. Consequently, estimating the buying interval from the historical distribution of daily price movements provides a more data-driven alternative for adaptive investment decisions.

Estimation of the Adaptive Buying Interval

The adaptive buying interval was estimated using the empirical distribution of historical daily price ranges. Two descriptive statistical measures were employed: the mode of the non-zero daily price range and the sample standard deviation. The estimated statistics are summarized in **Table 4.**

Table 4. Statistical Value

Statistic	**Value:**
Mode	1.95
Standard Deviation	37.64
Adaptive Interval (Mode + 2σ)	77.23

Source: Statistical estimates derived from the daily BBRI price data over the 2003–2026 period (identical to Table 2).

The mode represents the most frequently observed daily price movement and therefore provides an estimate of the typical market fluctuation. In contrast, the standard deviation measures the historical dispersion of daily price movements and reflects the level of market uncertainty. By combining these two statistics, the proposed adaptive interval incorporates both the central tendency and the variability of historical price behaviour.

Unlike conventional averaging strategies that employ arbitrarily selected price intervals, the proposed method derives the buying interval directly from historical market data. Consequently, the interval is determined by the statistical characteristics of the asset rather than by subjective investment preferences.

Layered Averaging Simulation

Following the estimation of the adaptive interval, a layered averaging simulation was conducted to evaluate its application in a systematic investment strategy. An initial position was established at the prevailing market price, and additional purchases were executed whenever the stock price declined by one adaptive interval. At each successive buying level, the investment size was doubled, resulting in a progressively lower weighted average acquisition cost. The simulated buying sequence is presented in **Table 5**.

Table 5. Simulation of Lot Sizing for Dollar Cost Averaging

Level	Purchase Price (IDR)	Lot	Capital (IDR)
1	2,970	1	297,000
2	2,815	2	563,107
3	2,583	4	1,033,535

Source: Simulation results of the layered averaging strategy using BBRI historical price data and the estimated adaptive interval

The simulation indicates that completing seven buying levels requires an estimated total investment of approximately **IDR 16.96 million**. This amount remains substantially below the assumed investment budget of **IDR 100 million**, suggesting that the proposed strategy can accommodate considerable market corrections without exhausting the available investment capital.

Portfolio Performance

The substantial reduction in the average acquisition cost demonstrates the effectiveness of the adaptive layering strategy. Because additional purchases are executed only after statistically determined price declines, the portfolio accumulates a larger position at lower prices, thereby reducing the overall average purchase cost. As market prices recover, the lower acquisition cost enables the portfolio to achieve profitability earlier than strategies relying on wider or arbitrarily selected buying intervals.

These results suggest that statistically derived buying intervals may improve capital efficiency while simultaneously enhancing the portfolio's recovery potential following market corrections.

Scenario Analysis

To examine the robustness of the proposed approach, an additional simulation was conducted using an investment starting point in **2025**, representing a substantially higher initial purchase price than the full historical sample. The simulation produced a weighted average acquisition cost of **IDR 1,864.59**, resulting in an unrealized portfolio return of **59.28%** at the latest observed market price.

Although the investment commenced during a period of relatively elevated stock prices, the adaptive averaging strategy continued to produce a positive unrealized return. This finding indicates that the proposed method remains effective under less favourable entry conditions, provided that subsequent price movements allow the strategy to execute additional purchases according to the estimated adaptive interval.

The scenario analysis therefore demonstrates that the proposed approach is not limited to a single historical entry point but exhibits consistent performance under different investment starting periods.

The proposed adaptive averaging strategy differs fundamentally from several commonly employed accumulation approaches, including **Dollar Cost Averaging (DCA)**, **Grid Trading**, and **Martingale**.

Dollar Cost Averaging allocates a fixed investment amount at predetermined time intervals regardless of prevailing market conditions. Consequently, purchasing decisions are driven solely by time rather than by historical price behaviour. Grid Trading, in contrast, executes buy and sell orders at predetermined price intervals. Although the strategy is price-based, the spacing between trading levels is generally selected arbitrarily and remains fixed throughout the investment horizon. Martingale strategies increase position sizes following adverse price movements to reduce the average acquisition cost; however, they typically rely on predefined distance parameters and therefore do not explicitly account for the statistical characteristics of market volatility.

The proposed methodology differs from these approaches by introducing a statistically derived buying interval. Rather than determining **when** investments should be made, the proposed framework determines **where** successive purchases should be executed based on the historical distribution of daily price movements. The buying interval is estimated using the mode and standard deviation of the daily trading range, allowing the spacing between purchase levels to reflect the empirical characteristics of the underlying asset.

This distinction represents the principal methodological contribution of the study. By transforming historical price volatility into an adaptive buying interval, the proposed framework replaces subjective parameter selection with a data-driven statistical procedure. Consequently, the layered averaging strategy becomes responsive to the historical behaviour of the market while preserving a simple and systematic investment mechanism suitable for long-term equity accumulation.

CONCLUSION

This study proposed an adaptive statistical averaging framework for equity investment that used the mode and standard deviation of the daily price range to construct a statistically derived buying interval as an alternative to conventional fixed-interval averaging strategies. Applying the framework to 5,602 daily observations of PT Bank Rakyat Indonesia Tbk. (BBRI) from November 2003 to July 2026, the adaptive buying interval was estimated at IDR 77.23, based on a mode of 1.95 and a standard deviation of 37.64 calculated from the distribution of non-zero daily price ranges.

The layered buying simulation, employing exponential position sizing across seven buying levels, demonstrated that the proposed strategy could accommodate substantial market corrections while requiring relatively modest capital, remaining well within the assumed investment budget. When applied to a scenario beginning in January 2025, the strategy required total capital deployment of approximately IDR 23.68 million and produced a weighted average acquisition cost of IDR 1,864.59, resulting in a positive unrealized portfolio return of 59.28% based on the most recent historical closing price.

These findings indicate that historical price volatility, when translated into statistically derived buying intervals, provides a more objective and adaptive basis for averaging strategies than conventional fixed-interval or arbitrarily determined approaches, such as Dollar-Cost Averaging (DCA), grid trading, or Martingale strategies. By combining the mode and standard deviation of the daily trading range, the proposed framework captures both the typical magnitude and the variability of price movements, allowing buying intervals to adapt dynamically to changing market conditions. The strategy also demonstrated robustness across different investment entry points, maintaining positive unrealized returns even when initiated during periods of relatively elevated market prices.

Overall, the proposed adaptive layered buying strategy offers a simple, transparent, and practical decision-support framework for long-term equity investors, particularly retail investors in the Indonesian stock market, by reducing the average acquisition cost and improving capital efficiency without requiring complex computational techniques. Future research could extend this framework to other stocks or market indices, incorporate additional measures of price volatility, or compare its performance with other adaptive or machine learning-based averaging strategies under different market regimes.

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