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Adaptive Portfolio Optimization using MVF with Machine Learning Forecasting and Regime Switching: Evidence from LQ45 Stocks

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ABSTRACT

This study proposes an adaptive portfolio optimization framework that integrates Random Forest(RF)-based return forecasting into a Mean-Variance-Forecast Error (MVF) model, augmented by a Hidden Markov Model (HMM) for market regime identification. Using weekly historical return data from 40 LQ45-listed stocks spanning January 2014 to January 2025, the framework dynamically adjusts portfolio allocations in response to bull and bear market conditions detected by a two-state HMM. The primary methodological contribution lies in addressing the static limitation of conventional MVF under shifting market regimes. Out-of-sample evaluation over a 138-week test period demonstrates that regime-switching MVF achieves Sharpe ratios above 1.30, substantially lower maximum drawdowns than the MVF-only portfolio, and cumulative returns of 291.96%. Bootstrap-validated 95% confidence intervals confirm the statistical robustness of these improvements. Nevertheless, portfolio turnover remains high during active reallocations. These findings indicate that combining machine-learning-based predictive modelling with adaptive, regime-driven allocation enhances portfolio stability, mitigates extreme losses, and improves risk-return efficiency under dynamic emerging-market conditions.

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1. INTRODUCTION

Portfolio Optimization is a strategic decision-making process that determines the allocation of financial assets to maximize returns and minimize investment risk [1]. The most widely recognized classical approach is the Mean-Variance (MV) model introduced by Markowitz [2]. In its implementation, the classical MV model estimates expected returns using historical averages. However, this method may induce a low-pass filtering effect on stock price dynamics, causing short-term fluctuations to be overlooked. This can result in portfolio strategies that are less responsive to rapid market changes and potentially suboptimal [3].

To address this limitation, subsequent research has integrated return forecasts directly into the optimization objective [4]. Forecasted returns have been shown to improve portfolio decisions compared with historical averages alone [5]. Machine learning models, including Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM), have demonstrated superior ability to capture complex temporal patterns in asset prices [6], [7]. Among these, the Random Forest (RF) algorithm has emerged as a competitive and interpretable alternative for stock return prediction [8]. Building on these developments, Ustun and Kasimbeyli [9] proposed a mean-variance-skewness model incorporating stock predictions; Yu et al. [10] combined ARIMA forecasting models with various classic portfolio optimization models, such as mean-variance (MV), Value at Risk (VaR), and Omega. Ma et al. [11] integrated RF and deep learning predictions with forecast errors into MV and Omega frameworks. Most directly relevant, Huang et al. [12] formalized the Mean-Variance-Forecast Error (MVF) model, which incorporates predicted returns and explicit forecast uncertainty through linear weighting. However, that study was limited to the Chinese equity market and has not been validated in the Indonesian context. The LQ45 index, comprising highly liquid large-capitalization stocks, serves as a critical benchmark for both domestic and international investors in Indonesia [13], making it an important target for testing such frameworks.

Despite its merits, the MVF model remains static across market phases, exposing portfolios to severe drawdowns when market conditions shift from bullish to bearish regimes, or vice versa. Shi and Xu [14] demonstrate that equity prices exhibit discontinuous jumps during regime transitions, not merely ordinary daily fluctuations. Hidden Markov Models (HMM) have been widely applied to identify latent market regimes and facilitate adaptive portfolio weight adjustments [15]. Manjunatha et al. [16] applied a multivariate HMM to sectoral stock indices, demonstrating how latent states connect returns, risk, and volatility within an adaptive allocation framework. Tampouris and Dritsaki [17] introduced an Adaptive Hierarchical HMM to capture structural shifts through latent meta-regimes, enabling portfolio strategies to adapt dynamically to changing market conditions and improving long-term regime identification.

To the best of our knowledge, portfolio optimization, machine-learning-based forecasting, and regime-switching approaches have largely evolved as separate strands of research. While prior studies have incorporated RF-based return prediction into the MVF framework, HMM-driven regime switching has received little attention within this setting. This motivates the development of an adaptive MVF framework that incorporates both RF-based forecasting and HMM-driven market regime detection. This study addresses this gap through the following contributions:

a. Methodological: We propose an integrated framework combining RF return forecasting, MVF optimization, and HMM regime switching, extending the MVF model to operate adaptively across market states.
b. Empirical: We extend the application of the MVF framework to the Indonesian LQ45 equity market, validating the framework over a 138-week out-of-sample period with bootstrap-validated confidence intervals.
c. Practical: The framework offers institutional asset managers a transparent and interpretable alternative to black-box models, enabling dynamic reallocation between risky and risk-free assets in response to detected market regimes.

The central research question is: Does integrating RF-based return prediction with HMM regime switching into the MVF framework reduce portfolio risk and improve risk-adjusted performance for LQ45 stocks relative to a regime-agnostic MVF baseline?

2. RESEARCH METHOD

This section describes the research methodology, covering the experimental workflow, data processing procedures, return forecasting, portfolio optimization, HMM-based regime identification, and evaluation metrics. The overall process is designed to minimize look-ahead bias and ensure all performance assessments are fully out-of-sample.

2.1 Research Methodology Workflow

Figure 1 summarizes the end-to-end research pipeline. The process begins with data collection and preprocessing of historical LQ45 constituent stock prices. A two-state Gaussian HMM is then trained on LQ45 index weekly returns and volatility to infer regime probabilities, classifying each week as bullish or bearish using a 60% probability threshold. In parallel, an RF model is trained on historical stock returns to generate one-week-ahead return predictions. These predicted returns, together with estimated covariance matrices and forecast errors, are combined in the MVF optimization to determine portfolio weights. Portfolio performance is evaluated over a 138-week out-of-sample period and compared across regime-switching and non-regime-switching configurations.

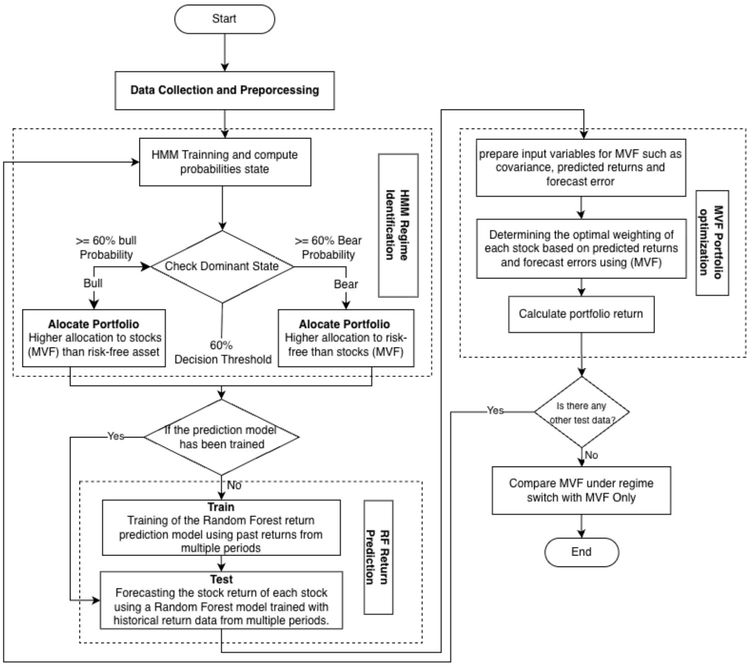

Figure 1. Research Methodology Flowchart

2.2 Dataset and Preprocessing

Historical weekly price data were collected for all LQ45 constituent stocks from January 2014 to January 2025, sourced from Yahoo Finance via the yfinance library (Python). The LQ45 index, maintained by the Indonesia Stock Exchange (IDX), is revised semi-annually based on liquidity-related criteria, including trading volume, market capitalization, and transaction frequency; consequently, all constituents represent highly liquid equities, effectively satisfying the liquidity screening requirement without additional filtering [11]. From all stocks appearing in the LQ45 index during the study period, 40 stocks with uninterrupted price records across the full sample horizon were retained.

These 40 stocks were selected because they consistently dominated LQ45 membership throughout the study period—appearing across multiple consecutive semi-annual revisions—and maintained complete price records, thereby representing the most persistent constituents of the index. This criterion ensures a consistent training and testing universe for the RF model and MVF optimizer without structural breaks caused by stock entry or exit. Although this may introduce mild survivorship bias by excluding delisted or underperforming firms, the trade-off was deemed necessary to preserve temporal consistency and comparability across datasets.

Regarding corporate actions, Yahoo Finance's adjusted closing prices automatically incorporate stock splits and rights issues using backward-adjustment factors, ensuring price continuity. Dividend adjustments are excluded because the study focuses on capital gains rather than total returns; consequently, portfolio performance may be slightly underestimated for high-dividend stocks, although this effect is expected to be moderate within the LQ45 universe. Liquidity considerations are addressed implicitly through LQ45 membership itself, as all constituents meet the minimum transaction value and frequency thresholds set by the IDX.

Missing values were imputed using the forward-fill method, which propagates the most recent observed price to fill isolated gaps. Observations with gaps exceeding five consecutive trading days were removed to avoid stale price effects.

Weekly returns were adopted because they align directly with the one-week-ahead forecasting horizon of the RF model, ensuring consistency between prediction targets and portfolio rebalancing. Weekly data also reduces microstructure noise relative to daily returns while maintaining a practically feasible rebalancing frequency. In addition, the 15-week RF input window captures sufficient recent market information without incorporating structurally distant market conditions.

Weekly returns for each stock i at week t are calculated as:

$$r_{i,t}^{(weekly)} = \frac{p_{i,t} - p_{i,t-5}}{p_{i,t-5}} \tag{1}$$

In Equation (1), where $p_{i,t}$ is the adjusted closing price at the end of week t and $p_{i,t-5}$ is the price five trading days prior. The dataset is split into a training period (January 2014–December 2021) and an out-of-sample testing period (January 2022–January 2025). In addition, the opening and closing prices of the LQ45 index are used to identify market regimes during the research period. The selected stocks are presented in Table 1.

Table 1. Selected stock name of the LQ45 Index.

Stock Name					
AALI	ACES	ADHI	ADRO	AKRA	AMTR
ANTM	ASII	BBCA	BBNI	BBRI	BBTN
BDMN	BMRI	BSDE	CTRA	EXCL	GGRM
HMSP	ICBP	INDF	INDY	INTP	ITMG
JSMR	KLBF	MEDC	MNCN	PGAS	PTBA
PTPP	SCMA	SIDO	SMGR	SMRA	TBIG
TLKM	TPIA	UNTR	UNVR		

2.3 Random Forest

Random Forest (RF) is a non-parametric ensemble method that aggregates predictions from multiple independently grown decision trees, mitigating overfitting through bootstrap aggregation and random feature sub-selection [18], [19]. RF requires no distributional assumptions, accommodates non-linear interactions, and has demonstrated competitive accuracy in stock return prediction tasks [20], [21].

In this study, the RF model is configured with 500 trees, following Breiman [19] guidance that larger ensembles improve stability. Maximum tree depth is set to 20, consistent with Ma et al. [11], to capture non-linear patterns without excessive overfitting. All remaining hyperparameters retain their scikit-learn library defaults. The model is trained using lagged weekly returns as input features. To assess prediction robustness, four input window lengths— 5, 10, 15, and 20 weeks—were evaluated based on out-of-sample MAE and RMSE, with the optimal window selected prior to portfolio construction.

2.4 Mean-Variance-Forecast Error (MVF)

The mean-variance (MV) model provides a mathematical framework to balance expected return and investment risk. This model forms the basis of modern portfolio theory (MPT) and is used to determine the optimal portfolio by measuring return and risk through expected return and variance. The model was later developed into the mean-variance-forecast error (MVF), which allows for optimal portfolio allocation based on predicted returns and prediction error for each stock [10], [11]. Then, MVF is applied using a linear weighting method that combines expected return and forecast error into a single objective function [12].

$$\min_{w} \frac{1}{2}\alpha_1 \sum_{i=1}^{n}\sum_{j=1}^{n} w_i \sigma_{ij} w_j - \alpha_2 \sum_{i=1}^{n} \hat{r_i}\, w_i - \alpha_3 \sum_{i=1}^{n} w_i \bar{\varepsilon_i} \tag{2}$$

$$\begin{aligned} s.t.\quad & \alpha_1 + \alpha_2 + \alpha_3 = 1 \\ & \alpha_1, \alpha_2, \alpha_3 \in [0,1] \\ & \textstyle\sum_{i=1}^{n} w_i = 1 \\ & l_i \le w_i \le u_i, \quad i = 1,2,\ldots,n \end{aligned} \tag{3}$$

Equation (2), where w_i is the portfolio weight of asset i, n is the number of assets in the portfolio, σ_{ij} denotes the covariance between assets i and j, $\hat{r_i}$ is the RF-predicted return for asset i at time t, and $\bar{\varepsilon_i}$ as the average prediction error, calculated as $\bar{\varepsilon_i} = r_i - \hat{r_i}$ where r_i is the actual return of the risky asset i.

Equation (3) requires that several conditions must be satisfied. First, $(\alpha_1, \alpha_2, \alpha_3)$ represent the weights that reflect the investor's preferences for the three key components of the model: risk, expected return, and forecast error, which can be interpreted as abnormal return. These weights must lie within the range of 0 and 1, meaning $\alpha_1 + \alpha_2 + \alpha_3 = 1$. This indicates that the investor must allocate their preferences proportionally among these three factors. Additionally, i refer to the indices of assets in the portfolio, where i = 1,2, ..., n, and n is the total number of assets in the portfolio. Furthermore, the weight of each asset w_i in the portfolio is constrained by the lower bound l_i and the upper bound u_i, which define the permissible range for each asset's allocation.

The classical MV model is a special case of MVF where $\alpha_3 = 0$ and expected returns are derived from historical averages rather than RF predictions. Both models are subject to the same weight constraints and transaction cost assumptions, ensuring a fair comparison.

2.5 Hidden Markov Model (HMM)

An HMM is a doubly stochastic process in which a sequence of hidden states follows a first-order Markov chain, and each state emits an observable output according to a state-dependent probability distribution [22]. This structure is well-suited to financial markets, where latent economic regimes—not directly observable—drive observable return and volatility dynamics [15], [17]. Volatility clustering, a well-documented feature of equity markets [23], [24], further motivates the inclusion of volatility as an HMM input variable.

Mathematically, the HMM is represented by the parameters in Equation (4).

$$\lambda = A, \mu, \sigma, \pi \tag{4}$$

Where in equation (4) A is the state transition probability matrix, μ and σ are the mean and covariance of the Gaussian emission distributions for each state, and π is the initial state probability vector. Parameter estimation employs the Expectation-Maximization (Baum-Welch) algorithm; the most probable state sequence is inferred via the Viterbi algorithm; and state probabilities are computed using the forward algorithm.

A Gaussian HMM from the hmmlearn Python library is fitted to weekly LQ45 index returns and 12-week rolling realized volatility. The number of hidden states was selected using AIC and BIC criteria Table 2, with the two-state specification achieving the lowest information criterion values. The covariance type is set to “full” to permit unrestricted covariance structures, and the EM algorithm runs for a maximum of 150 iterations.

2.6 Model Configuration and Training

The HMM is retrained weekly using a rolling window of the most recent 235 weeks of LQ45 index return and volatility data. After each retraining, the regime probability for the following week is estimated by multiplying the probability vector derived from the current observation by the transition matrix. A 60% probability threshold is applied: if the estimated probability of a given regime exceeds 60%, the portfolio switches to (or remains in) that regime; otherwise, the previous regime assignment is retained. This threshold prevents frequent oscillation between states driven by marginal probability differences.

The RF model is trained on historical data and evaluated on out-of-sample test data. Predicted returns generated for week t use only information available through week $t-1$, ensuring strict forecasting discipline. Forecast errors for MVF are computed as the rolling 15-week mean absolute difference between predicted and realized returns. Covariance matrices for both MVF and MV are estimated over a 400-week expanding window.

MVF portfolio weights are rebalanced weekly over the 138-week test period. Short-selling is not permitted; therefore, all portfolio weights are constrained to non-negative values. Transaction costs of 0.15% per transaction (one-way) are applied to both purchases and sales, consistent with Indonesia Stock Exchange fee structures. No transaction costs are incurred if weights remain unchanged from the prior period.

2.7 Selection of the Number of Hidden States

In this study, the number of states was selected using AIC and BIC criteria to determine the optimal number of states and assess how well the model fits the data. AIC and BIC are calculated using the formulas in Equations (5) and (6). AIC is used to evaluate the model's quality by considering both the goodness of fit and model complexity, while BIC imposes a larger penalty on the number of parameters. Log-likelihood (LogL) measures how well the model fits the observed data. Higher logL values indicate a better fit. However, both AIC and BIC penalize complex models based on the number of parameters. The lower the AIC and BIC values, the better the model, as they reflect a better balance between fit and complexity. In Equation (5), AIC is calculated as :

$$AIC = -2Log\ L + 2k \tag{5}$$

Where Log L represents the log-likelihood of the model, and k is the number of parameters, for BIC, Equation (6) is used :

$$BIC = -2Log\ L + p \times Log\ T \tag{6}$$

Where p is the number of parameters, and T is the number of observations.

Table 2. Model Selection Criteria

Number of states	Log likelihood	AIC	BIC
2 State	-491.62	1009.24	1054.21
3 State	-489.62	1025.23	1104.80

Despite the slightly higher log-likelihood of the three-state model (−0489.62 vs. −491.62), the two-state specification achieves superior parsimony, with AIC and BIC values lower by 15.99 and 50.59 points, respectively. The two-state model's interpretability mapping directly to bull and bear market concepts also facilitates practical implementation. The lower AIC and BIC values reflect a better balance between fit and complexity, as shown in Table 2.

2.8 Regime Classification

Based on the weekly average returns and volatility of the two hidden states identified by the HMM, as shown in Table 3, state 0 exhibits a higher return with moderate volatility, while state 1 shows a negative return with slightly higher volatility. Therefore, the state with positive returns is categorized as the bullish regime, whereas the state with negative returns is categorized as the bearish regime.

Table 3. Regime Analysis and breakdown

Regime	Average Weekly Return	Average Volatility
State 0 (Bull)	0.061864	0.481799
State 1 (Bear)	-0.182474	0.486578

Table 4 shows high persistence in both regimes—the bullish state has a 96.85% probability of remaining bullish, and the bearish state has a 95.18% probability of persisting—consistent with stylized facts about regime duration in equity markets [15]. The low transition probabilities (3.15% bull-to-bear, 4.82% bear-to-bull) confirm that regime switching is an infrequent but economically significant event.

Table 4. State transition probabilities

Regime	Destination Regime	
	Bull	Bear
Bull	0.96849	0.031503
Bear	0.048167	0.951833

2.9 Model Evaluation Metric

Prediction accuracy is assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which evaluate the average magnitude and outlier sensitivity of forecasting errors, respectively [25]. The definitions of these metrics are as follows in Equations (7) and (8):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | r_i - \hat{r}_i | \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - \hat{r}_i)^2} \tag{8}$$

Where r_i and $\hat{r}_i$ respectively represent the actual return and the prediction return at time t. In addition, this study uses four metrics to evaluate the performance of different portfolio optimization models:

$$Cumulative\ Return = \prod_{t-1}^{T}(1 + r_t) - 1 \tag{9}$$

$$Sharpe\ ratio = \frac{R_e}{\sigma} \tag{10}$$

$$Maximum\ drawdown = \max_{t<s}\left(\frac{\mathrm{Netv_t} - \mathrm{Netv_s}}{\mathrm{Netv_t}}\right) \tag{11}$$

$$Standard\ Deviation = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \bar{r})^2} \tag{12}$$

$$Turnover\ rate = \sum_{i=1}^{n} | \mathrm{w_{i,t}} - \mathrm{w_{i,t-1}} | \tag{13}$$

Based on Equation (9), the cumulative return is calculated as the cumulative product of the periodic return r_t, capturing portfolio growth over time while incorporating compounding. Equation (10) defines the Sharpe ratio as a measure of risk-adjusted performance, comparing excess return R_e to standard deviation as a proxy for risk, where a higher value indicates more efficient performance. Equation (11) defines maximum drawdown as the largest decline from peak to trough percentage decline in portfolio net value (NetV). By measuring the worst-case capital loss from a peak ($\mathrm{NetV_t}$) to a subsequent trough ($\mathrm{NetV_s}$), it serves as a key proxy for downside risk. Equation (12) defines the standard deviation as a measure of the portfolio's return volatility, with higher values indicating greater variability in portfolio returns. Equation (13) defines the turnover rate, where $\mathrm{w_{i,t}}$ and $\mathrm{w_{i,t-1}}$ represent the weights of the asset i at time t and t -1, respectively. This formula measures the total absolute change in portfolio composition during the rebalancing process. Additionally, a 95% bootstrap confidence interval is used to validate the robustness of portfolio performance. This method generates 1,000 simulated datasets by randomly sampling historical returns with replacement, ensuring the results are statistically significant rather than due to random chance [26].

2.10 Experimental Design and Implementation

The experimental design comprises two sequential stages. In Stage 1, the RF model is optimized by comparing input windows of 5, 10, 15, and 20 weeks using out-of-sample MAE and RMSE. The selected window is then used in MVF optimization under four investor preference combinations $(\alpha_1, \alpha_2, \alpha_3)$ = (33,33,33), (60,20,20), (70,15,15), and (80,10,10), reflecting progressively more risk-averse investor preferences. The MVF portfolios are benchmarked against the classical MV model using preference combinations. (α_1, α_2) = (50,50), (65,35), (80,20), and (95,05), which also represent progressively more risk-averse preferences. In addition, an Equal Weight and Buy and Hold portfolio is employed as a naive diversification benchmark, where all selected stocks receive identical portfolio weights and are periodically rebalanced to maintain equal allocation proportions.

In Stage 2, the best-performing MVF configuration is augmented with HMM regime switching. Three stock-to-risk-free allocation scenarios are tested under bullish conditions: 79%/21%, 85%/15%, and 95%/5%, with allocations reversed under bearish conditions. Performance is assessed using Cumulative Return, Sharpe Ratio, Maximum Drawdown, Standard Deviation, and bootstrap-validated 95% confidence intervals. In addition, a transaction-cost sensitivity analysis is conducted by re-estimating portfolio performance under transaction cost assumptions of 0.15%, 0.20%, and 0.25%.

3. RESULT AND ANALYSIS

This chapter presents and interprets experimental results, provides structured analysis, and evaluates the performance of the prediction model as well as the portfolio optimization model.

3.1 Identification Market Regime

Figure 2 presents the two-state HMM classification applied to the 138-week out-of-sample period (April 2022–January 2025). Of the 138 weeks, 102 (73.9%) were classified as bullish and 36 (26.1%) as bearish. The bearish periods correspond visually to episodes of sustained LQ45 index decline, confirming the HMM's ability to distinguish strengthening from weakening market conditions. Minor discrepancies during short-lived reversals reflect the model's emphasis on regime persistence rather than immediate reactivity, a deliberate design feature to prevent excessive rebalancing.

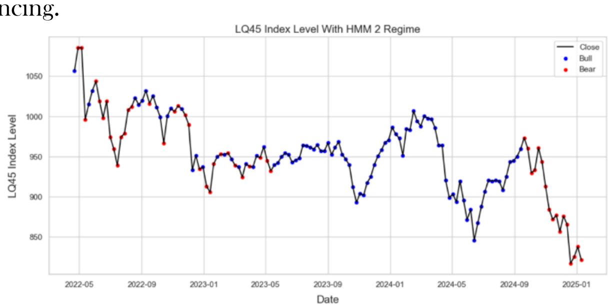

Figure 2. Visualization of HMM for Identifying LQ45 Market Regimes

Visually, it can be observed that the bullish regime dominates most of the observation period, particularly when the LQ45 index is relatively stable. This result indicates that the HMM model can distinguish between strengthening and weakening market conditions. Although the model does not always immediately capture regime changes during short-term fluctuations, the overall classification pattern shows good consistency with the index movement over the total 138 weeks of observation.

3.2 Predictive Model Performance

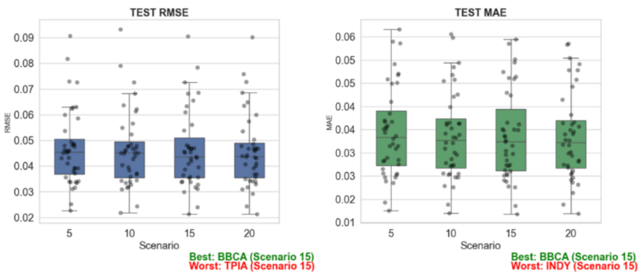

Figure 3. Boxplot RMSE and MAE on the Test Data

Based on Figure 3, the error distributions across historical return length scenarios show differences in the Random Forest model's performance in predicting LQ45 stock returns. The boxplots of RMSE and MAE for the test data show that the 15-period scenario has a more tightly distributed, more stable error distribution than the other scenarios. This indicates that using 15 historical return periods can yield more consistent predictive results. Meanwhile, in the 5-period scenario, the error distribution remains higher, indicating that the historical information used is not yet optimal for supporting the prediction process.

Table 5. Data for Different Return Period Length Scenarios

Period	RMSE	MAE
5 period	0.046977	0.034487
10 period	0.046172	0.033710
15 period	0.045704	0.033410
20 period	0.045745	0.033508

Table 5 shows that the average prediction error is consistent with Figure 3. In the 5-period scenario, the model produced an RMSE of 0.046977 and an MAE of 0.034487. In the 10-period, error decreased to RMSE 0.046172 and MAE 0.033710. The 15-period scenario performed best, with RMSE. 0.045704 and MAE 0.033410, the lowest among all scenarios. In the 20-period scenario, errors increased slightly to RMSE 0.045745 and MAE 0.033508. These results show that 15 historical return periods are the optimal input configuration.

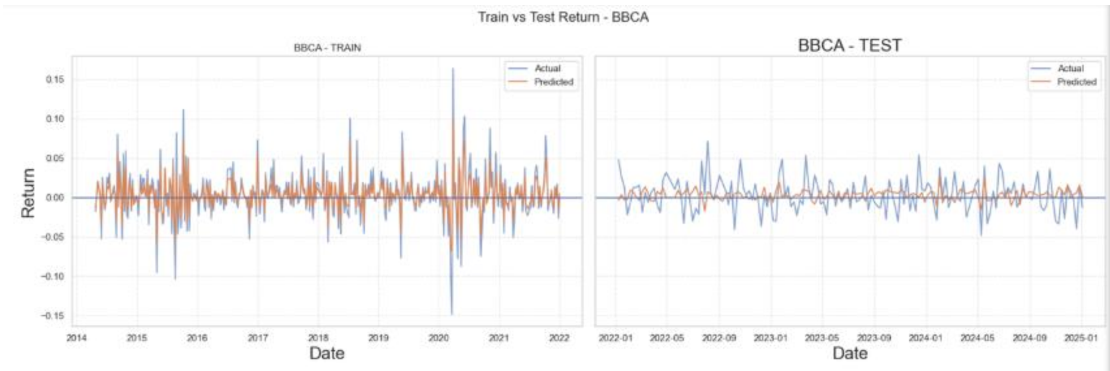

Figure 4. Best Model Prediction Random Forest BBCA

Figure 4 shows the prediction for the BBCA stock, which was selected as a representative because it performed best. In the 15-period historical returns scenario, the Random Forest model consistently follows the trend of actual returns in the training data, though there are small fluctuations that are not fully captured. In the test data, the model still follows the directions of actual returns movements, although there are deviations at the peaks and troughs due to high market volatility. This visualization demonstrates how the model captures the main pattern of BBCA Stock returns, although it should be noted that predicting stock movements is challenging due to the market's high volatility.

Table 6. Data Performance Model Prediction Return BBCA

Dataset	RMSE	MAE
Train	0.0124	0.0084
Test	0.0214	0.0168

Table 6 presents the prediction error for the BBCA stock. In the training data, the RMSE is 0.0124, and the MAE is 0.0084, indicating low prediction errors. In the test data, RMSE increases to 0.0214 and MAE to 0.0168, showing a slight rise in error but still within a low range. This confirms that the model's predictions remain stable and consistent. Overall, the 15-period historical return scenario provides the most optimal prediction result for BBCA stock, although forecasting stock movements remains an inherent challenge.

3.3 Evaluation of MVF and MV Classic Portfolios

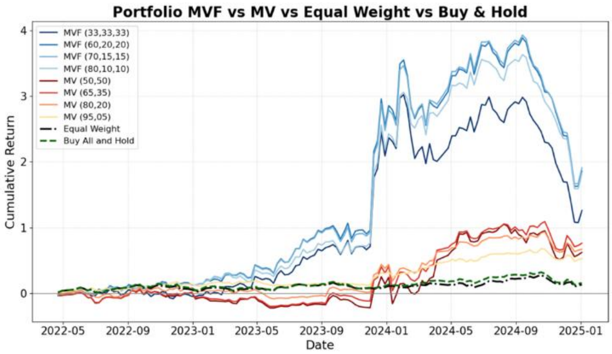

Figure 5. Cumulative Return of MVF and MV

Figure 5 compares portfolio performance for the MVF method, the classical MV method, the buy and hold strategy, and the Equal Weight benchmark. Visually, the MVF portfolios show higher, faster cumulative returns than MV and the benchmark. The MVF scheme (70,15,15) achieves the highest peak return by leveraging a combination of predicted returns and forecast errors to capture abnormal profit opportunities. However, the simultaneous portfolio decline observed around September 2024, along with the high maximum drawdown (-44.02% to – 48.35%), indicates that portfolio performance is still strongly influenced by overall market conditions. This suggests that implementing MVF within a market regime could help adjust portfolio weights in line with prevailing market conditions. Meanwhile, the MV portfolio grows more slowly and steadily, while both Equal Weight and Buy & Hold exhibit similarly low performance.

Table 7. The Performance of MVF Only and MVF Regime

Weight	Standard deviation	Sharpe Ratio	Maximum Drawdown	Cumulative Return	Avg Turnover	Total TC
MVF (33,33,33)	0.5374	0.8550	-48.35%	126.15%	165.48%	34.24%
MVF (60,20,20)	0.5218	1.0345	-46.21%	186.42%	164.11%	33.97%
MVF (70,15,15)	0.5147	1.0533	-45.89%	190.47%	164.22%	33.99%
MVF (80,10,10)	0.5015	1.0447	-44.02%	182.26%	162.36%	33.62%
MV (50,50)	0.4701	0.6727	-32.71%	62.59%	8.53%	1.34%
MV (65,35)	0.4092	0.7817	-26.33%	76.44%	9.96%	1.77%
MV (80,20)	0.2816	0.9135	-17.54%	67.39%	10.02%	1.88%
MV (95,05)	0.1251	1.5553	-11.50%	52.85%	5.05%	1.01%
Equal Weight	0.0899	0.8573	-13.73%	13.33%	6.62%	1.37%
Buy all and hold	0.0939	0.8980	-14.52%	15.58%	-	0.15%

Table 7 presents the portfolio statistics for both methods. MVF portfolios deliver substantially higher cumulative returns (126.15%–190.97%) than their MV counterparts (52.85%–76.44%), confirming the value of integrating RF-predicted returns and forecast errors into the optimization objective. The high cumulative returns are partly attributable to weekly compounding effects and continuous portfolio reallocation driven by changing return forecasts. The MVF (70,15,15) configuration achieves the highest Sharpe ratio among MVF variants (1.0533). Relative to the Equal Weight benchmark, both MV and MVF portfolios achieve substantially higher cumulative returns, indicating the benefit of dynamic portfolio reallocation during the sample period. The Equal Weight benchmark achieves a cumulative return of 13.33% with relatively low turnover (6.62%) and transaction costs (1.37%). The Buy and Hold strategy records a cumulative return of 15.58% with minimal transaction cost exposure (0.15%), reflecting its passive nature. Although these passive benchmarks show lower performance compared to optimized strategies, they provide a reference point for evaluating the value added by active portfolio construction.

However, the extremely high turnover of MVF portfolios (162%–165% average weekly) raises practical implementation concerns, as frequent rebalancing may generate additional trading frictions beyond the transaction costs considered in this study. Total transaction costs of approximately 34% over the test period represent meaningful friction but are fully absorbed within the reported cumulative returns. The transaction cost model includes proportional exchange fees but does not account for slippage or market impact costs, which may reduce realizable performance in practice, particularly under high-turnover strategies. Notably, the extreme risk-averse MV (95,05) configuration achieves the highest Sharpe ratio (1.5553) of any single portfolio, but at a considerably lower absolute return (52.85%), illustrating the inherent trade-off between return and risk. However, this configuration's maximum drawdown of −11.50% confirms that simple risk-aversion without predictive enhancement fails to deliver the growth potential of MVF.

Regarding potential overfitting: the 15-week RF model was selected prior to portfolio construction, avoiding circular optimization. Performance on the 138-week test period—entirely unseen during training—provides an out-of-sample assessment. Nevertheless, the strong performance and high turnover of MVF portfolios suggest that some sensitivity to model specification may remain. Further investigation of retraining windows and feature selection procedures is therefore warranted in future work.

3.4 Evaluation MVF with Regime Switching

To evaluate the effectiveness of applying market regime to the MVF method, Figure 6 and Table 8 present a comparison of portfolio performance between MVF without regime switching and MVF with regime adjustments at various tolerance levels.

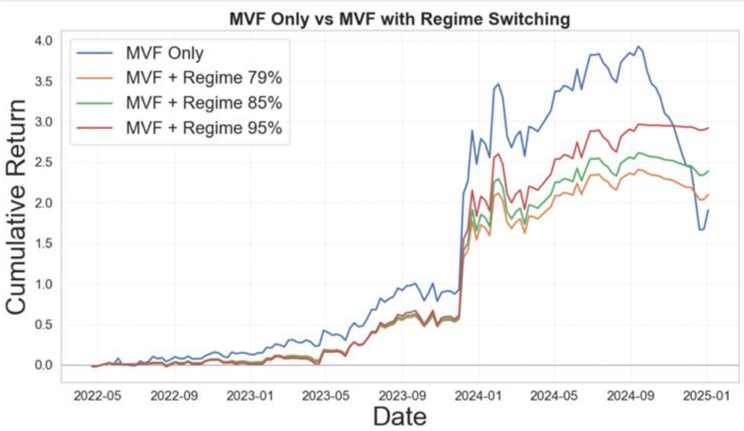

Figure 6. Cumulative Return MVF Only and MVF Regime

Figure 6 shows that the MVF portfolio without regime switching (blue line) achieves high cumulative returns but is highly volatile, with sharp declines, particularly around September 2024. In contrast, MVF with market regime (green, orange, and red lines) produces more stable portfolios and smoother cumulative return curves, demonstrating the ability of this strategy to adjust portfolio weights according to market conditions.

Table 8. The Performance of MVF Only and MVF Regimes

Weight	Standard deviation	Sharpe Ratio	Maximum Drawdown	Cumulative Return
MVF Only	0.5147	1.0533	-45.89%	190.97%
MVF + Regime 79/21	0.3937	1.3072	-15.82%	209.91%
MVF + Regime 85/15	0.4216	1.3225	-17.0%	235.95%
MVF + Regime 96/5	0.4691	1.3415	-18.96%	291.96%

Table 8 presents portfolio statistics, where MVF without regime has a standard deviation of 0.5147, a Sharpe ratio of 1.0533, a maximum drawdown of -45.89%, and a cumulative return of 190.97%. Incorporating regime switching reduces volatility (0.3937-0.4691), increases the Sharpe ratio (1.3072–1.3415), lowers maximum drawdown (-15.82% to -18.96%), and still maintains high cumulative return (209.91%-291.96%). By successfully avoiding severe market crashes, the portfolio preserves its capital, which leads to a much stronger compounding effect. These results confirm that using a Hidden Markov Model (HMM) market regime in MVF can mitigate extreme risks and improve risk-adjusted returns without sacrificing, and instead enhancing, long-term portfolio growth.

Table 9. Robustness of MVF Portfolios to Transaction Cost Variations

Weight	Standard deviation	Sharpe Ratio	Maximum Drawdown	Cumulative Return
MVF Only TC 0.15%	0.5147	1.0533	-45.89%	190.47%
MVF Only TC 0.20%	0.5146	0.9704	-46.68%	159.94%
MVF Only TC 0.25%	0.5146	0.8876	-47.45%	132.19%
MVF + Regime 96/5 TC 0.15%	0.4691	1.3415	-18.96%	291.96%
MVF + Regime 96/5 TC 0.20%	0.4689	1.2747	-19.30%	260.77%
MVF + Regime 96/5 TC 0.25%	0.4687	1.2078	-19.65%	232.04%

Table 9 evaluates portfolio robustness to transaction cost (TC) frictions ranging from 0.15% to 0.25%. Increasing transaction costs reduces performance across all portfolios. Focusing specifically on the top-performing MVF + Regime (96/5) configuration. To maintain analytical conciseness and avoid redundant discussions. For MVF Only, the Sharpe ratio declines from 1.0533 to 0.8876, and cumulative return drops from 190.47% to 132.19%, accompanied by persistently large drawdowns. The MVF + Regime (96/5) portfolio remains more robust, with the Sharpe ratio decreasing from 1.3415 to 1.2078 but still exceeding MVF Only, while cumulative return remains relatively strong (291.96% to 232.04%) and drawdown, although lower, remains notable (−18.96% to −19.65%). However, the performance gap narrows as transaction costs increase, indicating that MVF with regime switching remains sensitive to transaction costs due to relatively high portfolio turnover.

Table 10. Portfolio performance statistics and 95% Confidence Intervals

Weight	Cumulative Return	Sharpe Ratio	Sharpe 95% CI	Maximum Drawdown	Max DD 95% CI
MVF Only	190.97%	1.0533	[0.0, 1.95]	-45.89%	[-58.7%, -18.3%]
MVF + Regime 79/21	209.91%	1.3072	[0.33, 2.33]	-15.82%	[-38.2%, -11.0%]
MVF + Regime 85/15	238.95%	1.3225	[0.39, 2.27]	-17.0%	[-41.7%, -12.0%]
MVF + Regime 96/5	291.96%	1.3415	[0.39, 2.29]	-18.96%	[-41.2%, -10.4%]

The addition of HMM regime switching produces consistent improvements across all performance dimensions. Incorporating regime information reduces portfolio standard deviation by 8.9%–23.5% (from 0.5147 to 0.3937–0.4691), reflecting risk reduction through dynamic allocation toward risk-free assets during bearish periods. The Sharpe ratio increases by 24–27% across all regime-switching variants, with the MVF + Regime (95/05) configuration achieving the highest value of 1.3415.

Maximum drawdown is reduced from −45.89% to between −15.82% and −18.96%—a reduction of 59–65%—indicating that capital preservation during downturns is the main driver of performance improvement. By limiting severe losses, the compounding effect is preserved, which also explains the higher cumulative returns despite partial allocation to risk-free assets during bear regimes.

The economic mechanism is regime-conditioned capital allocation. During the 36 identified bearish weeks, the portfolio allocates a higher proportion of capital to risk-free assets than in bullish periods (5%–21%). This protects capital during downturns and allows faster recovery during subsequent bullish phases. The high regime persistence (Table 4) ensures that switching remains stable and does not generate excessive transaction costs while still capturing major regime shifts.

Bootstrap confidence intervals (Table 10) confirm robustness. The Sharpe ratio lower bound for MVF-Only approaches zero (CI: [0.00, 1.95]), indicating unstable performance under adverse resampling. In contrast, all regime-switching models maintain positive lower bounds (0.33–0.39), indicating more stable risk-adjusted returns. Similarly, the worst-case maximum drawdown is higher for MVF-Only (−58.7%) than for regime-switching portfolios (−38.2% to −41.7%).

3.5 Discussion

The empirical results demonstrate that each layer of the proposed framework contributes meaningfully to performance improvement. The RF-based MVF outperforms classical MV by incorporating forward-looking return predictions and forecast uncertainty, consistent with the broader literature on forecast-integrated portfolio optimization [11], [12]. The integration of HMM regime-switching further improves adaptability to changing market conditions.

The effectiveness of the HMM regime identification is supported by the high regime persistence documented in Table 4 (self-transition probabilities of 96.85% and 95.18%) and the distinct return profiles of the two regimes (mean weekly returns of +0.062 versus −0.183), which justify different portfolio allocations. These findings support the effectiveness of regime-driven portfolio reallocation. The regime-switching mechanism may be particularly valuable during periods of market stress, although extreme disruptions may increase prediction uncertainty and reduce allocation stability.

From a practical standpoint, the high turnover of MVF portfolios (approximately 164% per week) presents a significant implementation challenge. Although the 0.15% transaction cost assumption is consistent with Indonesia Stock Exchange fee structures, actual market impact costs may be higher, particularly for less liquid LQ45 constituents. Lower rebalancing frequencies or turnover penalties may help reduce this friction. Nevertheless, the framework remains computationally feasible and scalable under weekly rebalancing frequencies.

Several limitations should be acknowledged. First, survivorship bias may remain because delisted or removed stocks are excluded to preserve a consistent training and testing universe. Second, dividend returns are excluded, so portfolio performance reflects capital gains rather than total returns. Third, the RF model relies solely on historical return inputs; incorporating macroeconomic, sentiment, or fundamental variables may improve predictive performance. Fourth, the 60% regime threshold and 235-week HMM training window represent design choices that may influence portfolio behaviour under alternative market conditions. Finally, although bootstrap confidence intervals provide an indication of statistical robustness, formal statistical comparison tests such as the Jobson–Korkie, SPA, or Diebold–Mariano tests are not conducted, and a broader set of benchmarks and validation schemes should be examined in future research.

4. CONCLUSION

This study proposes and evaluates an adaptive portfolio optimization framework combining Random Forest return forecasting, Mean-Variance-Forecast Error (MVF) optimization, and Hidden Markov Model (HMM) regime switching for LQ45 stocks listed on the Indonesia Stock Exchange. The main contribution is methodological: to the best of our knowledge, limited studies have integrated these components within a unified portfolio framework in the Indonesian equity market.

The empirical evidence, based on a 138-week out-of-sample evaluation period, yields three main findings. First, within the specific sample observed, the MVF framework with RF-predicted returns outperforms the classical MV model in cumulative returns (190.97% vs. 52.85%–76.44%), although with substantially higher turnover and transaction costs. Second, incorporating HMM regime switching is associated with improved risk-adjusted performance: Sharpe ratios increase by 24–27% (to 1.3072–1.3415), while maximum drawdowns decline from −45.89% to −15.82% to −18.96%. Cumulative returns also range from 209.91% to 291.96% during the evaluation period. Third, bootstrap-validated 95% confidence intervals indicate that these improvements remain statistically robust within the sample period examined. Complementary transaction-cost sensitivity analysis further shows that although regime-based MVF remains superior to MV under higher-cost assumptions, its performance deteriorates as costs increase, highlighting the impact of high portfolio turnover on net returns.

These findings should be interpreted cautiously and within the context of Indonesian market conditions during the study horizon. The approximately three-year test period reflects a specific market environment; therefore, the framework's generalizability to other markets, asset universes, or longer horizons remains uncertain. In addition, the high turnover of MVF portfolios may limit practical implementation without turnover constraints or more comprehensive transaction cost modelling. Survivorship bias and the limited RF feature set represent further limitations.

Future research may address these limitations by: (1) incorporating broader feature sets, including macroeconomic variables, market sentiment, and fundamental indicators; (2) integrating turnover penalties or transaction cost constraints directly into the MVF objective function; (3) conducting sensitivity analyses on the HMM threshold, training window, and rebalancing frequency; (4) comparing the framework against a richer set of benchmarks, including Risk Parity, LSTM-based portfolio forecasting, XGBoost-based forecasting, and cross-sectional momentum strategies; and (5) extending the analysis to other emerging market indices to evaluate cross-market robustness.

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