Portfolio Optimization Under Varying Market Regimes: A Comparative Study Using ANN Forecasts on MAI Stocks

Pema Sonam Yangchen
School of Management Technology
Sirindhorn International Institute of Technology, Thammasat University
Pathum Thani, Thailand
6422790335@g.siit.tu.ac.th

Rujira Chaysiri
School of Management Technology
Sirindhorn International Institute of Technology, Thammasat University
Pathum Thani, Thailand
rchaysiri@siit.tu.ac.th

***Abstract*—This paper explores the effectiveness of integrating Artificial Neural Network (ANN) based return forecasts into three portfolio optimization frameworks: Equal-Weight (EW), Mean-Variance (MV), and Black-Litterman (BL), under varying market regimes, using 67 stocks listed on Thailand's Market for Alternative Investment (MAI) as a case study. Portfolios are constructed using ANN predictions and tested across pre-COVID stable conditions (2019) and a volatile period (2020–2024), with an additional evaluation of rebalanced portfolios on 2024 data. Results indicate that BL achieves the highest risk-adjusted returns under stable conditions, while EW outperforms significantly during high volatility, driven largely by outlier stock performance during the COVID-19 recovery. Rebalancing with updated ANN forecasts did not guarantee improved performance, highlighting both the promise and limitations of machine learning-enhanced optimization in emerging markets.**

Keywords*— *Portfolio Optimization, Black-Litterman, Mean-Variance, Equal-Weight, Artificial Neural Networks, MAI Stocks

I. Introduction

Portfolio Optimization has been a major aspect of investment decisions, enabling investors to allocate assets in a way that maximizes return while minimizing risk. This is the concept of modern portfolio theory (MPT), which was first introduced by Markowitz in 1952, also known as Mean-Variance (MV) portfolio theory [1]. A key advantage of this concept is that it allows diversification of assets by combining assets of different correlations, providing a systematic and data-based methodology for achieving a portfolio with an optimal return-risk tradeoff [2].

While the MV theory does provide a solid foundational framework for portfolio optimization, it is still heavily dependent and sensitive to the accuracy of expected return estimates, which can lead to unstable or often unintuitive portfolio weights if inaccurately estimated [2]. To address this limitation, Black and Litterman came up with another theory that extends the existing MV framework, known as the Black-Litterman (BL) model [3]. This model incorporates investor views with equilibrium market returns as an additional insight to the MV model. BL model stabilizes the portfolio weights and supports a more practical and intuitive way of allocating assets, especially because investors often have additional information or forecasts to guide their financial decision-making [4].

Traditional methods in MV models rely solely on implementing historical averages as expected returns, which fail to capture non-linear patterns and complex variations in financial markets, leading to suboptimal investment portfolios. In recent research, integrating machine learning forecasts such as Artificial Neural Network (ANN) has demonstrated strong predictive capabilities by capturing non-linear patterns in time series data of the assets [6] [7]. By leveraging historical price data as training data, an ANN model can help identify the patterns that can predict future trends, offering a more improved and accurate return forecast over the simple traditional methods [8]. Integrating forecasts into portfolio optimization frameworks such as MV and BL models can enhance the quality of return estimation, leading to better risk-adjusted returns for the investment [9].

Despite this, there is still limited research that compares the integration of ANN prediction within MV and BL against the Equal-Weight (EW) model. Especially in emerging markets like Thailand's Market of Alternative Investment (MAI) stocks [10], where volatility and shifts are more common, making it a valuable case for testing portfolio optimization frameworks. This gap raises an important question: Can the integration of machine learning-based forecasts with traditional optimization models effectively enhance portfolio performance under real market conditions and during periods of heightened volatility, such as the COVID-19 crisis? How do these integrated models compare with a simple equal-weighted portfolio, which is frequently employed as a benchmark by investors?

This paper can contribute to the literature in three key ways: First, it demonstrates integration of ANN machine learning with important traditional optimization models and provides benchmark comparisons with the basic EW model. Second, it evaluates the performance and robustness of these models between both volatile and a more stable period, providing insights into their consistency in different market regimes. Lastly, it explores a less-studied emerging market by using real-world MAI stock data, showing how data-driven methods can help investors and researchers in this market build better portfolios.

The rest of this paper is structured as follows. Section II covers previous research on portfolio optimization and the use of machine learning for return forecasting. Section III describes the data and explains the methods used in this study, including how the ANN model was set up, how portfolios were built using MV and BL frameworks, and how these models were compared with equal-weighted portfolios across different market conditions. Section IV presents and discusses the results obtained from the experiments. Finally, Section V concludes the paper with a discussion on its key findings, limitations and suggestions for future research.

II. LITERATURE REVIEW

Recent research on financial portfolio optimization has focused on improving the quality of return forecasts in order to enhance the performance of the optimization models in a practical setting. One direction has been towards refining traditional optimization models, especially BL model, while the other is towards exploring more enhanced integration of machine learning to improve forecasting of returns inputs for these portfolio optimization models.

The BL model, for example, has been implemented to address the shortcomings of the MV model by blending investors' views with market returns. Studies have proven this practical usage in real markets, including in areas of global asset allocation and risk management [3] [4]. While the initial BL model provided a theoretical framework for integrating investor views with market equilibrium returns [3], Idzorek [4] offered proper practical guidelines for implementing the model. His study explains the use of key parameters and provides clear examples of the techniques for portfolio managers. Additionally, Meucci [11] extended the BL framework further by providing an extension of the practical implementation steps, such as handling multiple views and confidence levels. This makes the BL model more adaptable for real-world portfolio optimization. Together, their contributions in this study helped bridge the gap between theory and practice, making BL model more accessible to all for constructing stable portfolios.

In parallel to model refinements, there has also been a rise in the usage of machine learning models, such as deep learning methods, which have shown potential in capturing complex patterns from historical financial data and providing improved inputs for the models. Lopez de Prado [8] has highlighted how the implementation of machine learning in financial strategies by improving predictive abilities and adapting to non-linear relationships in market data has provided better insights into investments. Fischer and Krauss [7] applied Long Short-Term Memory (LSTM) networks for stock data prediction, which demonstrated a stronger predictive accuracy in comparison to conventional models. Another study by Zhang [6] has explored hybrid methods of combining a linear time series model (ARIMA) with a non-linear model (ANN), which can improve forecasting accuracy for time series data. This method outperformed the traditional approaches, demonstrating the adaptability of the hybrid approach to changing market conditions.

These studies indicate how machine learning adds practical value to the forecasting components of portfolio optimization, especially during periods of heightened volatility. The justification for using ANN models in return forecasting lies in their ability to capture non-linear patterns within financial data [6], which traditional models are often missing. As the accuracy of return forecasts increases, the effectiveness of portfolio optimization frameworks also increases; therefore, using ANN-based forecasts is one of the common ways we can enhance the inputs used within MV and BL models [8].

In the context of Thailand, its emerging markets pose a unique challenge as well as opportunities for portfolio optimization due to its ever-changing economic structure and volatility compared to developed markets. The Stock Exchange of Thailand (SET) and MAI have growth potential while also experiencing fluctuations, making them valuable samples for testing the robustness of portfolio strategy. The World Bank classifies the Thai market as upper-middle income and an emerging economy [10], making it attractive for investment research. Chaweewanchon and Chaysiri [12] proposed a hybrid approach that integrates machine learning models with the Markowitz MV framework by using CNN-BiLSTM predictions to preselect high-return stocks before portfolio optimization. Their experiment on Thai SET50 stocks demonstrated that machine learning-based stock preselection improves the effectiveness and simplicity of MV optimization, resulting in higher returns and Sharpe ratios. This confirms the practical benefits of incorporating advanced predictive models into portfolio construction.

Financial markets are prone to unpredictable structural changes all the time, particularly in emerging markets where integration with global markets can amplify volatility [5]. Such an example is during the period of COVID when the market was highly volatile, which can affect the risk and returns of portfolios significantly [13]. Relying solely on historical data outputs to optimize a portfolio may lead to suboptimal performance during market changes. This highlights the importance of periodically reevaluating and updating portfolio allocations with changing times [14]. Testing models under different regimes can provide valuable insights into how robust a portfolio is and how practical they are in real market conditions. This creates the need to assess whether ANN-enhanced MV and BL frameworks can maintain improved risk-adjusted returns under varying conditions while also highlighting the need for investors to remake or rebalance portfolios as markets evolve.

III. METHODOLOGY

A. Data Collection and Preprocessing

Daily Open, High, Low, Close, and Volume data for MAI-listed stocks were collected from SET official website [15] and Yahoo Finance for 2014-2024 period. Stocks delisted during this period were excluded, resulting in a final dataset of 67 continuously listed MAI stocks.

In this study, we developed a feedforward ANN price prediction model to generate next-day prediction prices for each stock in the dataset.

The ANN model utilized:

- Features: opening price, previous day's high, previous day's low, previous day's volume, and the last seven-day average closing price.
- Architecture: a single hidden layer with 10 neurons (ReLU activation) and an output layer for price prediction.
- Training: 50 epochs using the Adam optimizer with mean squared error as the loss function.

We used the same ANN architecture and hyperparameters without per-stock hyperparameter tuning to ensure a methodical, scalable implementation across all 67 stocks. With 5 input features and 1 output node in our model, 10 neurons were selected as a reasonable middle-ground that balances model complexity and generalization, preventing overfitting on limited financial time series. While we acknowledge that individual MAI stocks exhibit different volatility profiles, applying a uniform architecture ensures methodological consistency and avoids overfitting individual stock characteristics. This approach also aligns with prior studies that have employed straightforward ANN structures for systematic stock return forecasting [16].

B. Preparation of Inputs for Portfolio Optimization

Following ANN prediction, prices were converted into predicted daily log returns using formula (1) as the expected return estimates. The mean predicted return for each stock was computed and ranked to select the top 20 stocks for portfolio construction. This preselection allows the portfolio construction to focus on high expected return stocks while also having a manageable number of assets for effective diversification [12]. The covariance matrix was then calculated from actual daily returns of the selected 20 stocks, serving as the risk input for both MV and BL models.

$$r_{\{i,t\}} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \quad (1)$$

where:

$r_{i,t}$ is the log return of stock i, at time t,

$P_{i,t}$ is the price of stock i at time t,

$P_{i,t-1}$ is the price of stock i at time $t-1$

C. Portfolio Optimization Models

To construct the portfolios, we implement three portfolio construction models, namely, the Equal-Weight (EW) model, the Mean-Variance (MV) model, and the Black-Litterman (BL) model. These portfolios are all constructed for the preselected stocks using their expected returns and covariance matrix, and their performance will be evaluated by back-testing using real data.

1) Equal-Weight (EW) portfolio

The EW portfolio model serves as a baseline comparison against optimized portfolios. It is a simple approach where all *N* assets in the portfolio are assigned equal weights, ensuring full investment and diversification without estimation of expected returns or covariances. The weight for each asset is calculated as:

$$w_i = \frac{1}{N} \quad (2)$$

where:

w_i is the weight of asset i

N is the number of stocks

Previous research has stated that the EW portfolio can perform competitively with optimized models, especially during conditions of uncertainty where predictions are difficult [17].

2) Mean-Variance (MV) Portfolio

The MV model, introduced by Markowitz [1], attempts to optimize a portfolio by maximizing the portfolio's risk-adjusted return or the Sharpe Ratio. In this study, we use the ANN-predicted returns as the expected return and the covariance matrix as risk estimation. To trace the efficient frontier, we formulated the MV optimization as a quadratic programming formula as follows:

$$\min\ w^T \Sigma\, w \quad (3)$$

Subject to:

$$w^T \mu \geq r_t,$$

$$\sum_{i=1}^{N} w_i = 1$$

$$0 \leq w_i \leq 0.10, \qquad i = 1, \ldots, N$$

where:

w is the vector of portfolio weights,

Σ is the covariance matrix of actual returns,

μ is the vector of ANN-predicted expected returns,

r_t is the target return level

A maximum weight constraint of 10% per stock is placed because preliminary experiments conducted without a maximum allocation constraint led to portfolios with unrealistically high returns (over 100%), driven by a single stock receiving the majority allocation due to its high predicted return. To prevent this concentration risk, improve diversification, and provide realistic investment practices, a maximum allocation constraint was applied. During high-volatility periods such as COVID-19, this constraint enforced broader diversification, limiting the impact of extreme individual stock movements on overall portfolio performance.

By systematically varying r_t within the predicted return range, the efficient frontier is generated, and for each feasible portfolio, the Sharpe ratio is computed as:

$$S = \frac{w^T \mu}{\sqrt{w^T \Sigma w}} \quad (4)$$

The portfolio achieving the highest Sharpe ratio on the efficient frontier is selected as the tangency portfolio for back testing. This portfolio represents the optimal trade-off between return and risk for our MV model.

3) Black-Litterman (BL) Model

The BL model, introduced by Black and Litterman [3] extends the MV model by incorporating investor views with equilibrium market returns to generate adjusted expected returns. We follow a practical guidance from Idzorek [4] for constructing the inputs required and generating the portfolio.

a) Posterior expected return (μ_{BL}) for BL:

$$\mu_{BL} = [(\tau\Sigma)^{-1} + P^T \Omega^{-1} P]^{-1} [(\tau\Sigma)^{-1} \pi + P^T \Omega^{-1} q] \quad (5)$$

where:

Σ is the covariance matrix of actual returns,

$\tau = 0.05$ is the scalar reflecting prior uncertainty,

π is the implied equilibrium return vector,

P is the pick matrix,

Ω is the confidence matrix for the views,

q is the view vector.

b) Implied Equilibrium returns (π)

The implied equilibrium was calculated using:

$$\pi = \lambda \Sigma w_m \quad (6)$$

where:

λ is the risk aversion coefficient set to 3.0 [4],

w_m was set as equal weights across assets due to unavailable MAI market capitalization data.

c) View Matrix (P) and View Vector (q)

Three relative views were constructed from ANN predictions using the two highest and two lowest ranked stocks: (1) top-ranked outperforms lowest-ranked, (2) second-ranked outperforms second-lowest-ranked, (3) top-ranked outperforms second-lowest-ranked. P assigns +1 to the outperformer and -1 to the underperformer, while q contains the predicted return differences from the ANN model.

d) Confidence Matrix (Ω)

$$\Omega = \begin{bmatrix} Var(view_1) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & Var(view_k) \end{bmatrix} \quad (7)$$

where:

$$Var(view_k) = [\tau\, P\, \Sigma\, P^T]_{kk}$$

This ensures each view's confidence reflects the underlying asset volatility and view structure appropriately.

e) Portfolio Optimization

The computed posterior expected returns μ_{BL} (5) were then used within the MV optimization framework under identical constraints to identify the portfolio for back testing:

Full investment ($\sum_{i=1}^{N} w_i = 1$),

Long-only, no short selling assets($w_i \geq 0$),

Maximum allocation per stock ($w_i \leq 0.10$)

D. Backtesting and Evaluation Metrics

1) Backtesting on 2019 data

Portfolios were first constructed for the year 2019 using prices predicted by the ANN model, which was trained on historical data before 2019. Using these predicted returns and the covariance matrix, the EW, MV, and BL portfolios were constructed and evaluated using the actual daily prices during 2019. This sample testing allowed a comparative analysis of the three models under the same prediction environment.

2) Out-of-sample evaluation (2020-2024)

To further assess the robustness and stability of the 2019 constructed portfolios under changing market conditions, the same optimized portfolios from 2019 were held without rebalancing and evaluated using actual daily price data from January 2020 to December 2024, including the impact of market regime changes (COVID-19 volatility), on the ANN-enhanced portfolio strategies.

3) Updated Portfolio Construction with 2019–2023 Data

To assess the potential benefits of rebalancing, the same pipeline was repeated using updated predictions generated from the ANN model retrained 2019 to 2023 data. New EW, MV, and BL portfolios were constructed using these updated predications and evaluated on actual 2024 daily prices to determine whether incorporating updated predictive information during market volatility could enhance portfolio performance.

For each phase and portfolio construction method, performance was evaluated using daily return, cumulative return, annualized volatility, annualized return, and Sharpe ratio. Volatility was annualized using 252 trading days, and the Sharpe ratio was calculated under the assumption of a zero risk-free rate.

IV. Results

A. Portfolio Weights Across Regimes

1) 2019 Tangency Porfolio Weights

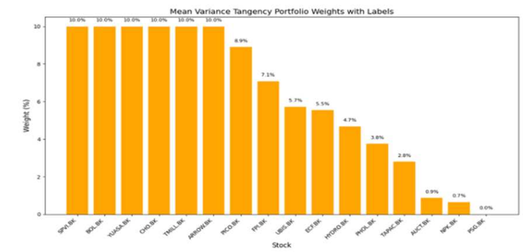

Fig. 1. 2019 MV Tangency Portfolio Weights with Labels

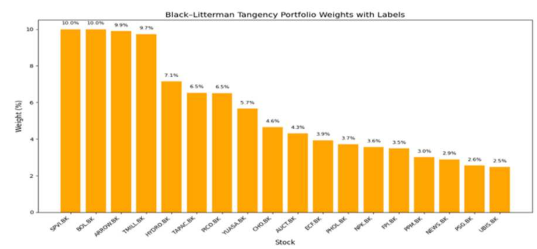

Fig. 2. 2019 BL Tangency Portfolio Weights with Labels

2) 2024 Tangency Portfolio Weights

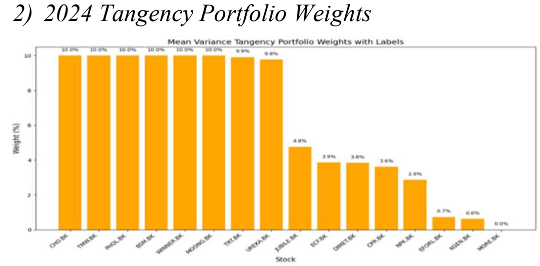

Fig. 3. 2024 MV Tangency Portfolio Weights with Labels

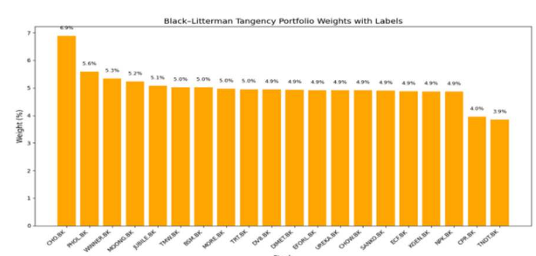

Fig. 4. 2024 BL Tangency Portfolio Weights with Labels

Figures 2-4 represent the portfolio weights obtained under the MV and BL frameworks for the years 2019 and 2024, respectively. These figures show which stocks have been selected in each portfolio and what weights they have been assigned. One noticeable factor is that BL model provided more diversification of stocks which incorporates both investor views and market equilibrium, often resulting in more balanced portfolio allocations across multiple assets.

Notably, four stocks: CHO.BK, PHOL.BK, ECF.BK, and NPK.BK consistently appeared in both the 2019 and 2024 optimized portfolios, suggesting the ANN model consistently ranked them highly across both training periods, likely due to their relatively stable price patterns and favorable predicted return differentials within the MAI stocks.

B. Portfolio Performance on 2019

The portfolios constructed using predicted 2019 returns were evaluated on actual 2019 daily prices to assess and compare initial performance.

TABLE I. PORTFOLIO PERFORMANCE METRICS ON 2019

Portfolio	Annual Return (%)	Volatility (%)	Sharpe Ratio
EW	1.41%	21.98%	0.00
MV	17.03%	12.93%	1.32
BL	38.04%	17.89%	2.13

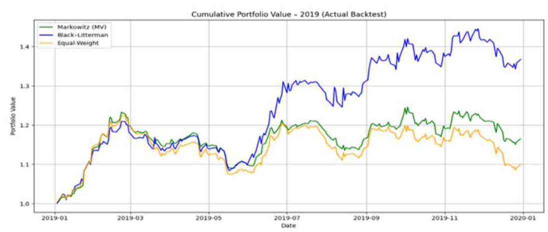

Fig. 5. Cumulative portfolio value in 2019 using actual backtesting data.

Table I presents the performance metrics where the BL portfolio achieved the highest Return of 38.04% and a Sharpe ratio of 2.13 among the three methods, indicating effective risk-adjusted performance. Fig. 1 displays the cumulative portfolio value throughout the year 2019, showing the BL portfolio outperforming, followed by the MV portfolio and finally the EW portfolio.

C. Portfolio Performance on 2020-2024

The 2019-constructed portfolios were held without rebalancing and evaluated on actual daily prices from January 2020 to December 2024 to assess their stability and performance under changing market conditions, including the COVID-19 period.

TABLE II. 2019 PORTFOLIO PERFORMANCE METRICS ON 2020-2024

Portfolio	Annual Return (%)	Volatility (%)	Sharpe Ratio
EW	84.67%	32.11%	2.64
MV	0.85%	19.21%	0.04
BL	38.80%	22.46%	1.73

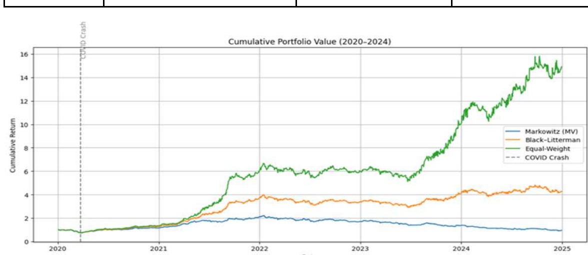

Fig. 6. Cumulative portfolio value using actual data from 2020-2024.

Table II presents that the EW portfolio from 2019 showed the highest cumulative return over the five years, outperforming MV and BL by a significant margin, demonstrating that basic diversification without optimization could show strong performance in volatile market period.

Further stock-level attribution analysis reveals that this performance was primarily driven by three outlier stocks during the COVID-19 recovery period: PSG.BK (880% total return), KGEN.BK (186%), and PHOL.BK (152%), all benefiting from low base prices and explosive rebounds typical of small-cap emerging market stocks post-COVID. However, 10 of the remaining 17 stocks posted negative returns over the same period, suggesting that EW's high aggregate return reflects outlier-driven performance rather than broad portfolio strength which is a known limitation of equal-weighting in small-cap markets where a single high-growth stock can disproportionately inflate returns. Meanwhile, MV and BL were penalised by relying on pre-COVID ANN predictions that became outdated during the crisis, overweighting stocks that underperformed while underweighting these high-growth outliers.

D. Updated Portfolio Performance on 2024

To test how these strategies, adapt to changing market conditions, we retrained the models in 2019-2023 data and rebalanced the portfolios before testing them on real 2024 market data. This approach reflects a realistic practice of updating portfolios under new market regimes and allows us to see if the MV, BL, and EW models can maintain strong risk-return performance during a volatile year.

TABLE III. PORTFOLIO PERFORMANCE METRICS ON 2024

Portfolio	Annual Return (%)	Volatility (%)	Sharpe Ratio
EW	-21.16%	21.05%	-0.07
MV	-2.92%	19.69%	-0.15
BL	-1.96%	22.47%	-0.09

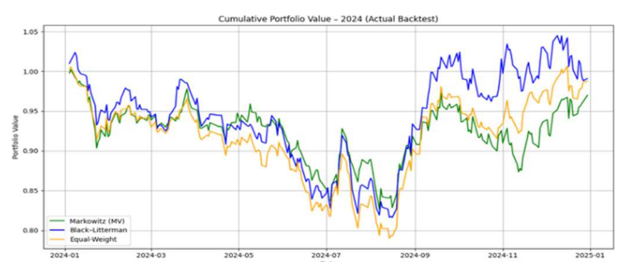

Fig. 7. Cumulative portfolio value in 2024 using actual backtest data.

TABLE III shows that all portfolios faced negative returns in a volatile regime, but the BL strategy outperformed the others, limiting losses to -1.96% compared to -2.92% for MV and -21.16% for EW. Although none achieved a positive Sharpe ratio, BL maintained a better risk-return profile under market stress, similar to its relative outperformance in the previous back testing of 2019. The negative performance across all portfolios in 2024 likely reflects broader market weakness in the MAI index during that period, which affected most small-cap stocks regardless of the optimization strategy applied. Additionally, the retrained ANN was trained on data that included the COVID recovery period, which may not have been representative of 2024 market conditions, potentially reducing the effectiveness of the updated portfolios. This suggests that while all optimization models struggle during market downturns, the BL approach may provide slightly more resilience.

V. Discussion, Limitation and Future Work

During the initial portfolio formulation using 2019 data, the BL model significantly outperformed both MV and EW portfolios in terms of better returns and diversification. However, when back testing these same portfolios further using 2020-2024 data, the EW portfolio outperformed significantly, largely driven by a small number of high-growth outlier stocks following the COVID-19 period as discussed in section IV. Meanwhile, MV and BL model showed poorer result as ANN predictions became outdated during the crisis.

In 2024, the reconstructed portfolios showed a slight advantage for BL, but performance was not consistently better than the 2019 optimized portfolios. This suggests that portfolio updates do not always improve outcomes, underscoring the importance of rebalancing timing and frequency. We hypothesize three reasons for this: (1) the 2019-2023 training period included extreme COVID-era market movements that may have biased the ANN toward patterns that did not persist into 2024; (2) the high volatility during this training period may have made it harder to accurately estimate relationships between stocks, leading to suboptimal portfolio weights; and (3) the MAI market shifted into a broader downturn in 2024 that neither the ANN nor the optimization models could anticipate from historical data alone. Overall, although machine learning and optimization frameworks are promising, simple strategies like EW may be more reliable in uncertain market conditions.

This study has several limitations. The back testing assumes a frictionless market with no transaction costs or slippage, which in a volatile emerging market like the MAI could meaningfully reduce returns, particularly for strategies requiring frequent rebalancing. Additionally, BL investor views were derived solely from ANN predictions with uniformly set confidence levels, limiting the incorporation of genuine qualitative or fundamental market insights.

Future work could improve ANN predictions through finer stock-level hyperparameter tuning and exploration of other machine learning models. Richer Black-Litterman investor views should be explored by incorporating analyst consensus estimates or macroeconomic indicators, alongside per-view confidence calibration following Idzorek [4] rather than uniform confidence levels. Additionally, a sensitivity analysis on the 10% maximum weight constraint would clarify how this parameter influences portfolio concentration and risk-adjusted performance across different market regimes in the MAI and similar emerging markets.

VI. Conclusion

This paper examined whether a machine learning predictive model, such as ANN, incorporated with portfolio optimization models, could improve portfolio performance for MAI stocks under different market conditions. The findings suggest that the Black-Litterman model generally offers better risk-adjusted returns and diversification compared to the Mean-Variance model, while during periods of volatility like 2020-2024, an Equal-Weight model can out-perform them driven largely by a small number of high-growth outlier stocks. These findings highlight the limitations of solely relying on model-based optimization during real market conditions and the importance of strategizing when and how to apply a more advanced portfolio optimization and utilize investor views for emerging markets such as MAI. With this, future improvements on prediction accuracy by machine learning or model refinement through better insights on investors' views can further support the effectiveness of this approach.

Acknowledgment

This study was supported by Sirindhorn International Institute of Technology, Thammasat University.

References

[1] H. M. Markowitz, "Portfolio Selection," *J. Finance*, vol. 7, no. 1, pp. 77-91, Mar. 1952, doi: 10.2307/2975974.

[2] E. J. Elton and M. J. Gruber, "Modern portfolio theory, 1950 to date," *J. Bank. Finance*, vol. 21, nos. 11–12, pp. 1743–1759, Dec. 1997, doi: 10.1016/S0378-4266(97)00048-4.

[3] F. Black and R. Litterman, "Global Portfolio Optimization," *Financ. Anal. J.*, vol. 48, no. 5, pp. 28–43, Sep./Oct. 1992, doi: 10.2469/faj.v48.n5.28.

[4] T. M. Idzorek, "A step-by-step guide to the Black-Litterman model: Incorporating user-specified confidence levels," Zephyr Associates, Inc., Tech. Rep., Jul. 20, 2004. [Online]. Available: https://people.duke.edu/~charvey/Teaching/BA453_2006/Idzorek_onBL.pdf (accessed Jan. 27, 2026).

[5] G. Bekaert and C. R. Harvey, "Time-Varying World Market Integration," *J. Finance*, vol. 50, no. 2, pp. 403–444, Jun. 1995, doi: 10.1111/j.1540-6261.1995.tb04790.x.

[6] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003, doi: 10.1016/S0925-2312(01)00702-0.

[7] T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," *Eur. J. Oper. Res.*, vol. 270, no. 2, pp. 654–669, Oct. 2018, doi: 10.1016/j.ejor.2017.11.054.

[8] M. López de Prado, *Advances in Financial Machine Learning*. Hoboken, NJ, USA: John Wiley & Sons, 2018.

[9] M. A. Truyols-Pont, A. Bilbao-Terol, and M. Arenas-Parra, "Machine learning for sustainable portfolio optimization applied to a water market," *Mathematics*, vol. 12, no. 24, Art. no. 3975, Dec. 2024, doi: 10.3390/math12243975.

[10] World Bank, "The World Bank in Thailand," World Bank. Accessed: Jul. 02, 2025. [Online]. Available: https://www.worldbank.org/en/country/thailand/overview.

[11] A. Meucci, "The Black-Litterman approach: Original model and extensions," *SSRN Electron. J.*, 2008, doi: 10.2139/ssrn.1117574.

[12] A. Chaweewanchon and R. Chaysiri, "Markowitz Mean-Variance Portfolio Optimization with Predictive Stock Selection Using Machine Learning," *Int. J. Financ. Stud.*, vol. 10, no. 3, Art. no. 64, Aug. 2022, doi: 10.3390/ijfs10030064.

[13] M. N. Khan, S. G. M. Fifield, and D. M. Power, "The impact of the COVID 19 pandemic on stock market volatility: Evidence from a selection of developed and emerging stock markets," *SN Bus. Econ.*, vol. 4, no. 6, Art. no. 63, May 2024, doi: 10.1007/s43546-024-00659-w.

[14] A. Ang and G. Bekaert, "International asset allocation with regime shifts," *Rev. Financ. Stud.*, vol. 15, no. 4, pp. 1137–1187, Fall 2002, doi: 10.1093/rfs/15.4.1137.

[15] The Stock Exchange of Thailand, "Home - The Stock Exchange of Thailand." Accessed: Jul. 07, 2025. [Online]. Available: https://www.set.or.th/en/home.

[16] D. Enke and S. Thawornwong, "The use of data mining and neural networks for forecasting stock market returns," *Expert Syst. Appl.*, vol. 29, no. 4, pp. 927–940, Nov. 2005, doi: 10.1016/j.eswa.2005.06.024.

[17] V. DeMiguel, L. Garlappi, and R. Uppal, "Optimal versus naive diversification: How inefficient is the 1/ N portfolio strategy?," *Rev. Financ. Stud.*, vol. 22, no. 5, pp. 1915–1953, May 2009, doi: 10.1093/rfs/hhm075.