CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 11 (2) (2026), Pages 1801–1818
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Adaptive Portfolio Rebalancing for NASDAQ-100 Stocks with Hippopotamus Optimization Algorithm under Transaction Costs

Safrizal Ardana Ardiyansa, Mohamad Muslikh*, and Syaiful Anam

Mathematics Department, Faculty of Science, Technology, and Mathematics, Brawijaya University Malang, East Java, Indonesia, 65145

Abstract

This study proposes a transaction cost-aware portfolio optimization framework for NASDAQ-100 stocks based on the Hippopotamus Optimization Algorithm (HOA). The mathematical model extends the classical mean-variance by incorporating transaction costs into a Net Sharpe Ratio (NSR) objective function. Daily adjusted closing prices of NASDAQ-100 constituent stocks from 2021 to 2025 are employed, where the twenty highest-ranked stocks according to the Sharpe Ratio (SR) are selected as the candidate investment universe. Each optimization experiment is independently repeated 25 times to evaluate robustness and solution stability. The results indicate that the proposed HOA consistently achieves competitive optimization performance with very small variability across repeated runs throughout the investment horizon. Although several competing algorithms attain comparable or slightly better objective values during particular rebalancing periods, HOA remains among the strongest-performing methods while exhibiting stable convergence behavior. Throughout the investment horizon, the proposed algorithm produces the highest average cumulative portfolio value of \$5,307.87 $\pm$ \$125.71 from an initial investment of \$1,000, corresponding to an average annual return of 40.03% $\pm$ 0.68%, together with the highest average SR and NSR of 1.5736 ± 0.0151, while maintaining competitive maximum drawdown and transaction cost. These findings demonstrate that incorporating transaction costs directly into the optimization objective enables HOA to achieve a favorable balance between portfolio growth, risk-adjusted performance, and trading efficiency under dynamic market conditions.

Keywords: Portfolio optimization; Hippopotamus Optimization Algorithm; transaction cost; Sharpe ratio; NASDAQ-100; metaheuristic algorithms.

1. Introduction

Modern Portfolio Theory (MPT) provides the fundamental framework for balancing expected return and investment risk through optimal asset allocation [1]. Although the classical mean variance model introduced by markowitz has been extensively adopted in quantitative finance, it generally assumes static portfolio allocations that remain unchanged over time [2, 3]. However, financial markets are highly dynamic, and changes in asset prices, volatility, and market conditions continuously alter portfolio compositions. Consequently, periodic portfolio rebalancing is required to maintain the desired risk and return while adapting to evolving market conditions [4–6].

*Corresponding author. E-mail: mslk@ub.ac.id

Received: May 15, 2026 Revised: June 26, 2026 Accepted: July 21, 2026
DOI: https://doi.org/10.18860/cauchy.v11i2.43876

An important challenge in portfolio rebalancing is the presence of transaction costs. Frequent adjustments may improve portfolio efficiency but simultaneously increase trading costs, portfolio turnover, and implementation risk. Ignoring these costs often leads to theoretically attractive yet practically inefficient investment strategies [7–9]. Therefore, practical portfolio optimization should simultaneously maximize return, control risk, and minimize transaction costs.

The incorporation of transaction costs substantially increases the complexity of the optimization problem, resulting in nonlinear, constrained, and nonconvex search spaces. Conventional optimization methods often struggle to efficiently solve such problems, motivating the adoption of metaheuristic algorithms (MAs), which have demonstrated strong capabilities in handling complex optimization problems without requiring gradient information [10–12]. Consequently, numerous MAs have been successfully applied to portfolio optimization and financial decision-making.

Despite these advances, several important research gaps still remain. First, many MA-based studies focus primarily on static portfolio allocation rather than dynamic portfolio rebalancing. Second, transaction costs are frequently ignored instead of being explicitly incorporated into the optimization objective. Such approaches may produce portfolios with excessive turnover that are difficult to implement in real trading environments. Third, although recently developed swarm intelligence algorithms have demonstrated competitive performance across various engineering and computational optimization problems [13–17], their application to transaction cost-aware portfolio optimization remains relatively limited. In particular, studies investigating newly developed swarm-based optimizers under realistic transaction cost considerations are still scarce.

Among recently proposed swarm-based optimizers, the Hippopotamus Optimization Algorithm (HOA) has attracted increasing attention because of its effective balance between global exploration and local exploitation through three search mechanisms [18, 19]. The original HOA study demonstrated its strong optimization capability and attained the top rank in 115 out of 161 benchmark functions, including unimodal, multimodal, and the CEC 2014 and CEC 2019 benchmark suites with problem dimensions of 10, 30, 50, and 100 [20]. Furthermore, previous studies have consistently shown that HOA outperforms numerous state-of-the-art MAs across diverse optimization problems. For example, HOA achieved superior performance over Binary Marine Predator Algorithm, Binary Grey Wolf Optimizer, Binary Salp Swarm Algorithm, Binary Particle Swarm Optimization, and Chaotic Binary Bat Algorithm, among other competitive methods, in feature selection and constrained optimization problems [21, 22]. These findings demonstrate the strong global search capability, effective convergence behavior, and robustness of HOA across complex optimization landscapes. However, despite these promising characteristics, its effectiveness for transaction cost-aware portfolio optimization has not yet been investigated.

The NASDAQ-100 index provides a particularly challenging benchmark for evaluating portfolio optimization algorithms because it consists primarily of highly liquid, technology-oriented, and growth-driven companies characterized by substantial price fluctuations and rapidly changing market conditions [23, 24]. These characteristics make transaction costs and portfolio turnover especially important considerations for maintaining long-term portfolio performance, thereby providing an appropriate testbed for evaluating transaction-aware optimization strategies.

Motivated by these gaps, this study proposes a transaction cost-aware portfolio optimization framework for NASDAQ-100 stocks using the HOA. Unlike conventional portfolio optimization approaches that primarily consider return and risk, the proposed framework explicitly incorporates transaction costs into a net Sharpe ratio (NSR) objective function. Consequently, the optimization simultaneously maximizes excess portfolio return after accounting for the risk-free rate and rebalancing costs while controlling portfolio risk through covariance-based risk estimation. By integrating transaction costs directly into the optimization objective, the proposed framework discourages excessive portfolio turnover and produces more practically implementable investment strategies. To the best of our knowledge, this is the first study to investigate the application of HOA for transaction cost-aware portfolio optimization using a NSR on NASDAQ-100 constituents.

The main contributions of this study are summarized as follows:

1. A transaction cost-aware portfolio optimization model is developed by integrating expected return, portfolio risk, and rebalancing costs into a NSR objective function.
2. The HOA is employed to solve the resulting constrained portfolio optimization problem and determine optimal portfolio weights under long-only investment constraints.
3. Extensive numerical experiments are conducted on NASDAQ-100 stocks by comparing the proposed HOA-based framework with several MAs. The comparative results demonstrate the effectiveness of HOA in maximizing the NSR value while reducing transaction-induced performance degradation and improving long-term portfolio performance.

The remainder of this article is organized as follows. Section 2 presents the transaction cost-aware portfolio optimization model, methodology, experimental setup, dataset, and evaluation metrics. Furthermore, Section 3 discusses the experimental results and comparative performance analysis. Finally, Section 4 concludes the paper and outlines directions for future research.

2. Methods

This article proposes a transaction cost-aware portfolio optimization framework for NASDAQ-100 stocks using the HOA. The methodology consists of five main subsections, namely data processing and asset selection, portfolio optimization model, portfolio weight determination using HOA, cumulative portfolio calculation, parameter configuration, and software.

2.1. Data Processing and Asset Selection

Daily adjusted closing prices of NASDAQ-100 constituent stocks were collected from January 1, 2021 to December 31, 2025. This period was selected to capture both medium-term market dynamics and recent market conditions within the NASDAQ-100 index. To ensure data consistency across all rebalancing periods, only stocks that remained continuously listed in the NASDAQ-100 index throughout the observation period were retained. This filtering criterion was adopted in this study to maintain a consistent investment universe during the comparative evaluation.

Rather than constructing the portfolio using information from the entire period, this study adopts a walk-forward evaluation that separates asset selection, parameter estimation, portfolio optimization, and performance evaluation. At each rebalancing period t, only historical observations available prior to the portfolio formation date are used.

First, the expected returns, volatilities, covariance matrix, and individual SR values of each stock are estimated from the current historical estimation window. Subsequently, all eligible NASDAQ-100 constituent stocks are ranked according to their estimated SR values, and the twenty stocks with the highest SR values are selected as the candidate assets for the current rebalancing period. Thus, the candidate asset universe is reconstructed at every rebalancing period using only information available up to that portfolio formation date rather than being fixed over the entire investment horizon.

The HOA then determines the optimal portfolio weights using these twenty selected assets. The resulting portfolio is held throughout the subsequent investment period, after which its performance is evaluated out-of-sample. The estimation window is then rolled forward, and the same sequence of asset selection, parameter estimation, portfolio optimization, and performance evaluation is repeated for the next rebalancing period. This workflow ensures that no future market information is used during portfolio construction, thereby reducing look-ahead bias.

Based on the historical observations within each estimation window, the daily return at the τ-th trading day, the annualized expected return, and the annualized variance of the i-th asset are respectively computed as follows:

$$R_i(\tau) = \frac{P_i(\tau) - P_i(\tau-1)}{P_i(\tau-1)}, \quad \bar{R}_i = \frac{252}{\tau_{\max}} \sum_{\tau=1}^{\tau_{\max}} R_i(\tau), \quad \sigma_i^2 = \frac{252}{\tau_{\max}-1} \sum_{\tau=1}^{\tau_{\max}} \left(R_i(\tau) - \bar{R}_i\right)^2, \quad (1)$$

where $P_i(\tau)$ denotes the adjusted closing price of the i-th asset on the τ-th trading day, and $\tau_{\max}$ denotes the number of trading observations within the corresponding estimation window [25]. The factor 252 corresponds to the average number of trading days in one financial year and is used to annualize both the expected return and volatility measures [26]. These statistics provide the information required to characterize the risk-return profile of each asset prior to portfolio optimization. Using the annualized risk-free rate (R_f), the SR of the i-th asset is computed as follows [27]:

$$SR_i = \frac{\bar{R}_i - R_f}{\sigma_i}. \tag{2}$$

At every rebalancing period, all eligible assets are ranked according to the SR values estimated from the corresponding historical estimation window. Since the optimization objective maximizes the NSR, assets with relatively low individual SR generally contribute less to improving the objective function because their expected excess returns are relatively small compared with their associated risk. Consequently, such assets are less likely to receive substantial portfolio weights unless they provide sufficiently strong diversification benefits through the covariance structure.

From the optimization perspective, the number of selected assets is directly equal to the dimensionality of the decision space solved by the HOA. Specifically, selecting n assets produces an n-dimensional continuous optimization problem, where each additional asset introduces one decision variable representing its portfolio weight. As the dimensionality increases, the feasible search space expands substantially, requiring more extensive exploration by the optimizer. This typically increases computational time, slows convergence, and may reduce optimization efficiency due to the greater complexity of searching high-dimensional continuous spaces.

Therefore, at each rebalancing period, the twenty highest-ranked stocks are selected as candidate assets for portfolio optimization. This dynamic asset selection strategy balances portfolio diversification and computational efficiency while allowing the candidate asset universe to adapt to changing market conditions over time. A candidate universe of twenty assets is sufficiently diverse to capture multiple sectors within the NASDAQ-100 while maintaining a moderate optimization dimensionality, enabling HOA to efficiently explore the search space and produce high-quality portfolio allocations.

2.2. Portfolio Optimization Model

Suppose $\bar{\boldsymbol{R}}(t) = [\bar{R}_1(t), \bar{R}_2(t), \ldots, \bar{R}_n(t)]^T$, $\Sigma(t) = [\sigma_{ij}(t)]$, and $\mathbf{w}(t) = [w_1(t), w_2(t), \ldots, w_n(t)]^T$ denote the expected returns of n assets, annualized covariance matrix of the selected assets, and portfolio weight vector at the t-th rebalancing period, respectively. Based on these definitions, the portfolio construction process is subject to the following long-only investment constraints.

$$\sum_{i=1}^{n} w_i(t) = 1, \text{ where } 0 \leq w_i(t) \leq 1, \; i = 1, 2, \ldots, n. \tag{3}$$

Based on these constraints, the portfolio return and risk respectively are defined as follows.

$$R_p(t) = \mathbf{w}(t)^T \bar{\boldsymbol{R}}(t), \quad \sigma_p^2(t) = \mathbf{w}(t)^T \Sigma(t) \mathbf{w}(t). \tag{4}$$

To account for portfolio rebalancing activities, transaction costs are incorporated directly into the optimization model. Let $\mathbf{w}(t-1) = [w_1(t-1), w_2(t-1), \ldots, w_n(t-1)]^T$ represent the portfolio allocation before rebalancing. The portfolio turnover at t-th rebalancing period is then computed as follows.

$$TO(t) = \sum_{i=1}^{n} |w_i(t) - w_i(t-1)|\,. \tag{5}$$

Assuming a proportional transaction cost rate λ, the transaction cost is expressed as $TC(t) = \lambda \cdot TO(t)$. Consequently, the net portfolio return after accounting for both the risk-free rate and transaction costs is defined as follows.

$$R_{net}(t) = R_p(t) - R_f - TC(t). \tag{6}$$

The portfolio performance is then evaluated using Net Sharpe Ratio (NSR) that defined as:

$$NSR(t) = R_{net}(t)/\sigma_p(t). \tag{7}$$

Substituting the Eqs. (4) and (6) into the Eq. (7) yields:

$$NSR(t) = \frac{\mathbf{w}(t)^T \bar{\boldsymbol{R}}(t) - R_f - \lambda \sum_{i=1}^{n} |w_i(t) - w_i(t-1)|}{\sqrt{\mathbf{w}(t)^T \Sigma(t) \mathbf{w}(t)}}. \tag{8}$$

Accordingly, the portfolio optimization problem is formulated as follows.

$$\max_{\mathbf{w}(t)} \frac{\mathbf{w}(t)^T \bar{\boldsymbol{R}}(t) - R_f - \lambda \sum_{i=1}^{n} |w_i(t) - w_i(t-1)|}{\sqrt{\mathbf{w}(t)^T \Sigma(t) \mathbf{w}(t)}} \text{ subject to } \sum_{i=1}^{n} w_i(t) = 1, \text{ where } 0 \leq w_i(t) \leq 1. \tag{9}$$

For the first investment period, an Equal Weight Portfolio (EWP) is adopted in this study as the initial allocation, therefore $w_i(0) = 1/n$ for $i = 1, 2, \ldots, n$.

2.3. Portfolio Weight Determination Using HOA

The resulting optimization problem in this study is solved using the proposed HOA. In this study, each hippopotamus represents a candidate portfolio allocation solution at the t-th rebalancing period. Specifically, the k-th agent is represented as follows.

$$\mathbf{H}_k(t) = [w_{k1}(t), w_{k2}(t), \ldots, w_{kn}(t)], \tag{10}$$

where $k = 1, 2, \ldots, N_{pop}$, N_{pop} denotes the population size, and n represents the number of selected assets. Accordingly, the dimension of each agent equals the number of portfolio assets. Since this article considers $n = 20$ selected NASDAQ-100 stocks, then each hippopotamus agent operates in a 20-dimensional space, where every dimension corresponds to the portfolio weight.

To ensure feasibility of the solutions, candidate portfolios are initialized randomly within the interval $[0, 1]$ and normalized to satisfy the constraint. Normalization stage is performed using Eq. (11). This normalization guarantees that the resulting portfolio weights satisfy the long-only investment constraints and maintain full capital allocation throughout the optimization process.

$$NORM\left(\mathbf{w}(t)\right) = \frac{\mathbf{w}(t)}{\sum_{i=1}^{n} w_i(t)}. \tag{11}$$

During the optimization process, HOA iteratively improves candidate portfolios through three phases, including exploration in the pond, defense movement against predators, and escape movement. These mechanisms enable the HOA to balance exploration and local exploitation in searching for the optimal portfolio allocation. Since the objective function was formulated as a maximization problem, it is transformed into a minimization problem for compatibility with the HOA framework through:

$$fit(\mathbf{w}(t)) = -NSR(t). \tag{12}$$

Accordingly, the optimization process aims to determine the optimal portfolio weight vector as:

$$\mathbf{w}^*(t) = \arg\max\left(NSR(t)\right), \tag{13}$$

2.4. Cumulative Portfolio Calculation

To evaluate the effectiveness of the proposed HOA, the portfolio performance is compared with several benchmark investment strategies, namely the EWP, the NASDAQ-100 index, and several single-stock portfolios with the highest SR. These benchmarks are selected to represent diversified passive allocation, overall market performance, and the best individual asset performance.

The NASDAQ-100 benchmark is represented using the cumulative return of the NASDAQ-100 index over the same investment horizon. In this study, two temporal indices are considered. Let τ denote the trading-day index and let t denote the portfolio rebalancing period. Accordingly, portfolio weights are updated only at each rebalancing period t, while portfolio wealth evolves continuously over trading days τ. For each strategy, portfolio wealth evolves according to

$$V(\tau) = (1 + R_p(\tau))\, V(\tau - 1). \tag{14}$$

Since the proposed framework applies dynamic portfolio rebalancing, the portfolio return at trading day τ is computed using the portfolio weights determined at rebalancing period t, namely

$$R_p(\tau) = \mathbf{w}(t)^T \mathbf{R}(\tau) = \sum_{i=1}^{n} w_i(t) R_i(\tau), \tag{15}$$

where $\mathbf{w}(t)$ denotes the portfolio weight vector at rebalancing period t, while $\mathbf{R}(\tau)$ represents the asset return vector at trading day τ.

Let $\tau_{\max}$ denote the number of trading days within each rebalancing period. Since portfolio rebalancing incurs proportional transaction costs, the portfolio value is updated at every rebalancing period after deducting the corresponding transaction cost. Consequently, the cumulative portfolio value at the t-th rebalancing period is computed as follows.

$$V(t) = V(t-1)\,(1 - TC(t)) \prod_{\tau=1}^{\tau_{\max}} \left(1 + \mathbf{w}(t)^T \mathbf{R}(\tau)\right), \qquad t = 1, 2, \ldots, t_{\max}. \tag{16}$$

Consequently, the final cumulative portfolio value after the entire investment horizon is calculated as follows.

$$V(t_{\max}) = V(0) \prod_{t=1}^{t_{\max}} \left[(1 - TC(t)) \prod_{\tau=1}^{\tau_{\max}} \left(1 + \mathbf{w}(t)^T \mathbf{R}(\tau)\right)\right]. \tag{17}$$

For all metaheuristic-based portfolio optimization methods, including HOA and the competing algorithms, the reported cumulative wealth incorporates transaction costs at every portfolio rebalancing according to the above formulation. In contrast, the EWP strategy and NASDAQ-100 benchmarks are treated as passive buy-and-hold strategies without periodic rebalancing; therefore, no transaction costs are applied to these benchmarks.

This formulation reflects the evolution of portfolio wealth under time-varying asset allocations generated by the proposed HOA. To assess portfolio performance, several evaluation metrics are considered in this study, including final cumulative return, portfolio risk, SR, NSR, maximum drawdown, transaction cost, and final portfolio wealth. These performance indicators enable comparative analysis between the proposed HOA-based portfolio optimization framework and the benchmark strategies under dynamic portfolio rebalancing conditions.

2.5. Parameter Configuration and Software

All computational experiments in this study were conducted using the Python programming language within the Google Colab environment. Google Colab was selected because it provides free cloud-based computational resources, supports the latest Python version, and can be accessed publicly without requiring dedicated local hardware installation. The experiments were executed using the standard CPU runtime configuration available in Google Colab.

To simplify the portfolio evaluation process, the number of trading days within each rebalancing horizon was fixed at $\tau_{\max} = 252$, which corresponds to the average number of trading days in one financial year [5]. Furthermore, the total number of rebalancing periods was set to $t_{\max} = 5$, representing the investment horizon from the beginning of 2021 until the end of 2025.

The proposed HOA optimization process was performed using several predefined control parameters. Let N_{pop} denote the population size and $Iter_{\max}$ denote the maximum number of optimization iterations. In this study, the parameter configuration was defined as $N_{pop} = 100$, and $Iter_{\max} = 3000$. The transaction cost rate was set to $\lambda = 0.001$ (0.1% of the traded amount) [28]. This λ value is consistent with assumptions commonly adopted in the finance literature for liquid equity markets, where transaction costs are typically modeled as a small fraction of the traded value, while still exerting measurable effects on portfolio performance and turnover [29]. The annual risk-free rate was obtained by annualizing the daily risk-free rate of 0.00015 over the maximum investment horizon, yielding $R_f = \tau_{\max} \times 0.00015 = 0.0378$ respectively.

To reduce stochastic variability, each optimization experiment was repeated 25 times, and the best-performing portfolio solution based on the objective function value was retained for further evaluation. The implemented framework utilized several standard Python scientific computing libraries, including NumPy, Pandas, Matplotlib, and yfinance for data acquisition and analysis.

3. Result and Discussion

This section presents the experimental results obtained using the proposed transaction cost-aware HOA framework and discusses its performance under dynamic portfolio rebalancing. The analysis begins with the selection of candidate assets based on their SR value, followed by the optimal portfolio allocations obtained by HOA across different rebalancing periods. Subsequently, the optimization performance of HOA is compared with several MAs through convergence behavior, optimization quality, and cumulative portfolio performance. Finally, a sensitivity analysis is conducted to evaluate the robustness of the proposed framework, and the limitations of the study are discussed.

3.1. Selected Stock Portfolio

To construct the candidate asset universe for portfolio optimization, all eligible NASDAQ-100 constituent stocks were ranked according to the SR criterion defined in Eq. (2) at each rebalancing period using the corresponding historical estimation window. The twenty highest-ranked stocks were subsequently selected for portfolio optimization during the following investment period. Stocks with higher SR indicate superior return per unit of risk and are therefore considered more attractive for portfolio allocation. Figure 1 shows the risk–return distribution of the selected stocks for the 2025 rebalancing period as a representative example.

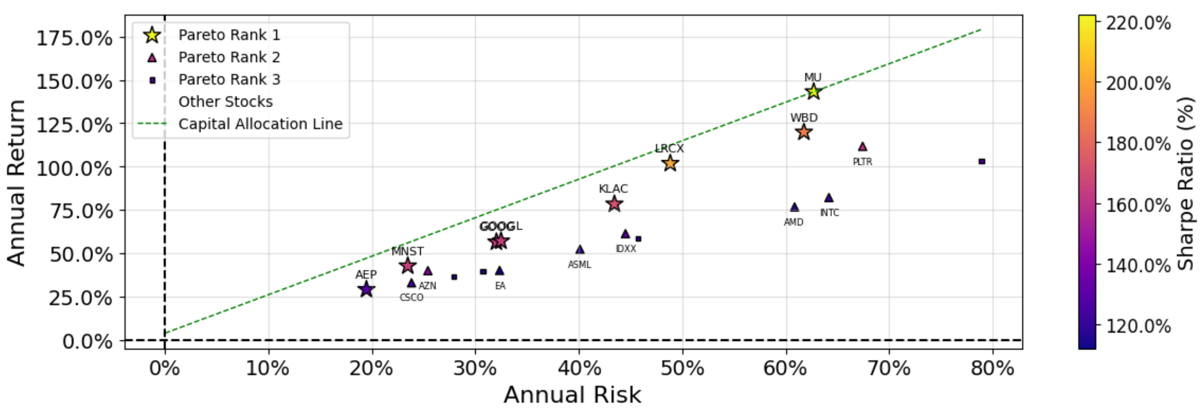


Fig. 1: Risk–return distribution of the selected NASDAQ-100 stocks based on SR ranking for the 2025 rebalancing period.

Based on the SR ranking, MU achieved the highest SR value of 2.223, followed by LRCX and WBD with SR values of 2.007 and 1.880, respectively. These stocks combine relatively high annualized returns with favorable risk-adjusted performance despite exhibiting moderate to high levels of volatility. KLAC and MNST also ranked among the highest-performing assets, with SR values exceeding 1.65, indicating strong return generation relative to their associated risks.

As illustrated in Figure 1, several semiconductor-related companies, including MU, LRCX, and KLAC, are concentrated in the upper-right region of the risk–return plane, reflecting the strong growth characteristics of the semiconductor industry during the corresponding historical estimation period. In contrast, other selected stocks, such as AEP, CSCO, and AZN, exhibit lower risk and return levels, resulting in comparatively lower SR values while still contributing potential diversification benefits within the candidate asset universe.

3.2. HOA-Based Portfolio Optimization Results

This subsection presents the portfolio optimization results obtained using the proposed HOA under the transaction cost-aware NSR and transaction cost. For each rebalancing period, HOA determines the optimal portfolio allocation by maximizing the NSR subject to expected return and risk in the corresponding period. The results demonstrate the ability of HOA to dynamically adapt portfolio compositions according to changing market conditions across different investment periods.

Table 1: HOA-based optimal portfolio allocation (%) for each rebalancing period.

Period	*NSR*	AAPL	ORLY	AMD	AMAT	GOOG	CRWD	ADI	PCAR	CSCO	MRVL	AVGO
2021	3.401297	24.84	19.04	17.13	15.31	13.99	8.57	1.13	–	–	–	–
2022	0.922234	31.83	56.16	–	–	–	–	–	12.01	–	–	–
2023	3.424034	–	–	–	–	26.61	21.27	–	22.05	14.97	7.33	5.88
2024	2.739217	21.09	17.42	–	4.28	22.50	19.46	–	–	–	–	13.20
2025	2.607385	33.11	22.51	13.58	–	–	–	–	–	–	–	–

Table 1 presents the optimal portfolio allocations obtained using the proposed HOA for each rebalancing period from 2021 to 2025. The obtained results demonstrate that HOA successfully generated adaptive portfolio compositions under different market conditions while maximizing the transaction cost-aware NSR objective function. In the first and third investment periods, the proposed framework achieved the highest NSR values of 3.401297 and 3.424034, respectively, indicating strong risk-adjusted portfolio performance during periods characterized by favorable recovery and growth in technology-oriented NASDAQ-100 stocks. In contrast, the second period produced the lowest NSR of 0.922234, reflecting the adverse market conditions during 2022, including inflationary pressure, increasing interest rates, and heightened market volatility.

Furthermore, the resulting allocations reveal that HOA adjusted portfolio composition across different rebalancing periods. Technology and semiconductor-related companies such as AAPL, GOOG, CRWD, AMD, AVGO, and AMAT frequently appeared in the optimal portfolios, reflecting their strong contribution to portfolio performance within the NASDAQ-100 market environment. Moreover, the optimization results indicate that HOA was capable of balancing portfolio diversification and concentration depending on market conditions. During volatile market periods, the obtained portfolio tended to become more concentrated in relatively stable-performing assets such as ORLY and AAPL, whereas more favorable market conditions resulted in broader portfolio diversification across multiple sectors. Overall, these findings demonstrate that the proposed HOA framework effectively adapts portfolio allocation strategies while maintaining strong risk-adjusted performance under dynamic portfolio rebalancing conditions.

3.3. Comparison with Other Metaheuristic Algorithms

To evaluate the effectiveness and robustness of the proposed HOA, comparative experiments were conducted against several MAs, namely Particle Swarm Optimization (PSO), Artificial

Bee Colony (ABC), Grey Wolf Optimizer (GWO), Firefly Algorithm (FA), Whale Optimization Algorithm (WOA), Bat Algorithm (BA), and Genetic Algorithm (GA). Each algorithm was independently executed 25 times for every rebalancing period using identical experimental settings and the same objective function. The comparative performance statistics, including the best, worst, mean, standard deviation (Std), and median NSR values, are summarized in Table 2.

Table 2: Performance comparison between HOA and other metaheuristic algorithms.

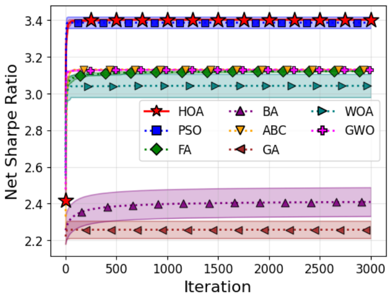
	Metric	HOA	PSO	ABC	GWO	FA	WOA	BA	GA
2021	Best	$\mathbf{3.40 \times 10^{0}}$	$\mathbf{3.40 \times 10^{0}}$	3.13×10^{0}	3.13×10^{0}	3.13×10^{0}	3.13×10^{0}	2.60×10^{0}	2.38×10^{0}
	Worst	$\mathbf{3.40 \times 10^{0}}$	3.29×10^{0}	3.13×10^{0}	3.13×10^{0}	3.01×10^{0}	2.92×10^{0}	2.31×10^{0}	2.19×10^{0}
	Mean	$\mathbf{3.40 \times 10^{0}}$	3.39×10^{0}	3.13×10^{0}	3.13×10^{0}	3.09×10^{0}	3.04×10^{0}	2.41×10^{0}	2.26×10^{0}
	Std	1.56×10^{-12}	3.07×10^{-2}	$\mathbf{1.78 \times 10^{-16}}$	7.14×10^{-4}	4.27×10^{-2}	6.32×10^{-2}	7.84×10^{-2}	4.70×10^{-2}
	Median	$\mathbf{3.40 \times 10^{0}}$	$\mathbf{3.40 \times 10^{0}}$	3.13×10^{0}	3.13×10^{0}	3.11×10^{0}	3.05×10^{0}	2.40×10^{0}	2.25×10^{0}
2022	Best	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	3.46×10^{-1}	4.61×10^{-1}
	Worst	$\mathbf{9.22 \times 10^{-1}}$	9.15×10^{-1}	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	9.12×10^{-1}	8.41×10^{-2}	5.04×10^{-1}	2.13×10^{-1}
	Mean	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	9.20×10^{-1}	7.36×10^{-1}	4.28×10^{-1}	3.33×10^{-1}
	Std	2.37×10^{-16}	1.95×10^{-3}	$\mathbf{2.22 \times 10^{-17}}$	1.16×10^{-6}	2.38×10^{-3}	2.09×10^{-1}	4.90×10^{-2}	6.68×10^{-2}
	Median	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	$\mathbf{9.22 \times 10^{-1}}$	9.20×10^{-1}	8.11×10^{-1}	4.47×10^{-1}	3.30×10^{-1}
2023	Best	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	3.01×10^{0}	2.89×10^{0}
	Worst	$\mathbf{3.42 \times 10^{0}}$	3.35×10^{0}	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	3.41×10^{0}	3.12×10^{0}	2.77×10^{0}	2.71×10^{0}
	Mean	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	3.35×10^{0}	2.87×10^{0}	2.77×10^{0}
	Std	1.74×10^{-12}	2.09×10^{-2}	$\mathbf{1.78 \times 10^{-16}}$	3.31×10^{-4}	1.54×10^{-3}	7.26×10^{-2}	6.48×10^{-2}	5.00×10^{-2}
	Median	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	$\mathbf{3.42 \times 10^{0}}$	3.35×10^{0}	2.86×10^{0}	2.77×10^{0}
2024	Best	2.74×10^{0}	$\mathbf{3.43 \times 10^{0}}$	2.74×10^{0}	2.74×10^{0}	2.74×10^{0}	2.73×10^{0}	2.02×10^{0}	1.93×10^{0}
	Worst	2.74×10^{0}	$\mathbf{3.34 \times 10^{0}}$	2.74×10^{0}	2.74×10^{0}	2.73×10^{0}	2.46×10^{0}	1.74×10^{0}	1.67×10^{0}
	Mean	2.74×10^{0}	$\mathbf{3.42 \times 10^{0}}$	2.74×10^{0}	2.74×10^{0}	2.73×10^{0}	2.62×10^{0}	1.88×10^{0}	1.76×10^{0}
	Std	4.22×10^{-10}	3.04×10^{-2}	$\mathbf{3.20 \times 10^{-16}}$	1.54×10^{-4}	2.80×10^{-3}	7.03×10^{-2}	7.63×10^{-2}	5.78×10^{-2}
	Median	2.74×10^{0}	$\mathbf{3.43 \times 10^{0}}$	2.74×10^{0}	2.74×10^{0}	2.73×10^{0}	2.63×10^{0}	1.91×10^{0}	1.76×10^{0}
2025	Best	$\mathbf{2.61 \times 10^{0}}$	2.60×10^{0}	$\mathbf{2.61 \times 10^{0}}$	$\mathbf{2.61 \times 10^{0}}$	$\mathbf{2.61 \times 10^{0}}$	$\mathbf{2.61 \times 10^{0}}$	2.05×10^{0}	1.94×10^{0}
	Worst	$\mathbf{2.61 \times 10^{0}}$	2.48×10^{0}	$\mathbf{2.61 \times 10^{0}}$	2.60×10^{0}	2.60×10^{0}	2.22×10^{0}	1.82×10^{0}	1.73×10^{0}
	Mean	$\mathbf{2.61 \times 10^{0}}$	2.59×10^{0}	$\mathbf{2.61 \times 10^{0}}$	$\mathbf{2.61 \times 10^{0}}$	2.60×10^{0}	2.49×10^{0}	1.92×10^{0}	1.85×10^{0}
	Std	3.80×10^{-5}	3.88×10^{-2}	$\mathbf{4.00 \times 10^{-6}}$	6.51×10^{-4}	1.68×10^{-3}	9.66×10^{-2}	5.68×10^{-2}	4.62×10^{-2}
	Median	$\mathbf{2.61 \times 10^{0}}$	2.60×10^{0}	$\mathbf{2.61 \times 10^{0}}$	$\mathbf{2.61 \times 10^{0}}$	2.60×10^{0}	2.49×10^{0}	1.91×10^{0}	1.85×10^{0}

Table 2 summarizes the optimization performance of HOA and the competing MAs over five rebalancing periods. The shown results indicate that the proposed HOA achieved competitive NSR values across all investment periods. In 2021, HOA obtained the highest mean NSR while exhibiting negligible variation across repeated runs. During the 2022, 2023, and 2025 investment periods, HOA produced objective values comparable to those obtained by PSO, ABC, GWO, and FA. In contrast, PSO achieved higher objective values during the 2024 rebalancing period, indicating that HOA was not the best-performing algorithm under every market condition.

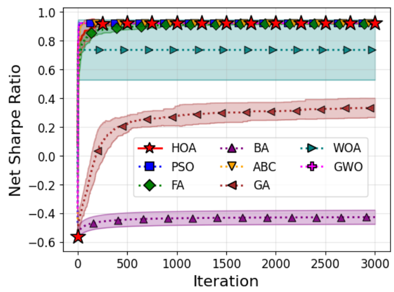
Another notable observation is the low variability of the solutions obtained by HOA across repeated executions. The standard deviation values were close to zero in all investment periods, indicating that the algorithm repeatedly converged to nearly identical solutions despite its stochastic search mechanism. This behavior suggests that HOA provides stable optimization performance and reliable convergence for the considered portfolio optimization problem.

BA and GA generally produced lower NSR values than the remaining algorithms, indicating relatively weaker optimization performance for the considered portfolio optimization problem. PSO, ABC, GWO, FA, and WOA also generated competitive solutions, although their relative performance varied across different rebalancing periods. For example, PSO produced the highest objective values during the 2024 investment period, whereas ABC and GWO frequently achieved objective values comparable to those of HOA in several other periods.

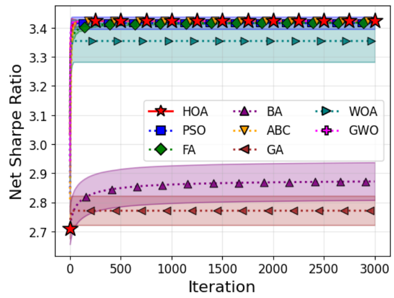
Overall, the results suggest that no single algorithm consistently dominated all rebalancing periods. Instead, the HOA demonstrated competitive optimization performance while providing stable and repeatable solutions across different market conditions. These findings indicate that



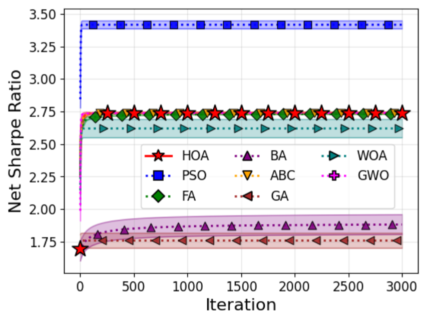
(a) $t = 1$ (2021)



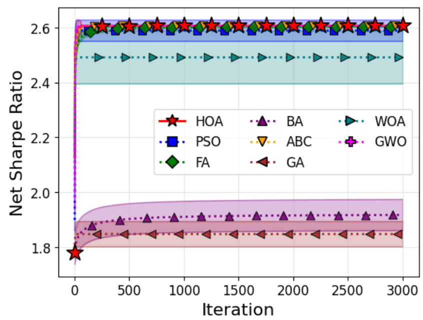
(b) $t = 2$ (2022)



(c) $t = 3$ (2023)



(d) $t = 4$ (2024)



(e) $t = 5$ (2025)

Fig. 2: Convergence comparison of fitness value between HOA and other metaheuristic algorithms.

HOA constitutes a robust alternative for transaction cost-aware portfolio optimization rather than a universally superior optimization algorithm.

Figure 2 further illustrates the convergence behavior of the proposed HOA and the competing MAs during the optimization process for each rebalancing period. As shown in Figures 2(a)–(e), HOA consistently converged rapidly toward high-quality solutions within the early optimization iterations and maintained stable convergence trajectories throughout the remaining search process. In several investment periods, HOA achieved convergence performance comparable to or better than PSO, ABC, and GWO, while exhibiting substantially smaller fluctuations compared with WOA, BA, and GA. The convergence curves also demonstrate that HOA maintained an effective balance between global exploration and local exploitation, enabling the algorithm to avoid premature convergence while preserving optimization stability.

Moreover, the convergence trajectories reveal that the optimization difficulty varied across different market periods. During highly volatile market conditions such as the 2022 investment period, most algorithms experienced slower convergence and larger performance variability. Nevertheless, HOA maintained stable convergence behavior and continued to obtain highly competitive NSR values. In contrast, BA and GA frequently converged toward lower-quality solutions, while WOA occasionally exhibited unstable convergence patterns with larger oscillations. These findings further confirm the effectiveness and robustness of the proposed HOA framework for dynamic and transaction cost-aware portfolio optimization in NASDAQ-100 portfolio management.

3.4. Cumulative Portfolio Performance Analysis

Figure 3 presents the cumulative portfolio value evolution of HOA and the benchmark algorithms over the entire investment horizon from January 2021 to December 2025, assuming an initial investment of $V(0) = 1000$ USD. Since MAs are stochastic, the cumulative performance evaluation was conducted over 25 independent optimization runs for each algorithm. The plotted cumulative wealth trajectories correspond to the mean portfolio wealth across these runs, while Table 3 reports the corresponding mean performance metrics together with their standard deviations, including the final portfolio value, annual return, portfolio risk, SR, NSR, maximum drawdown

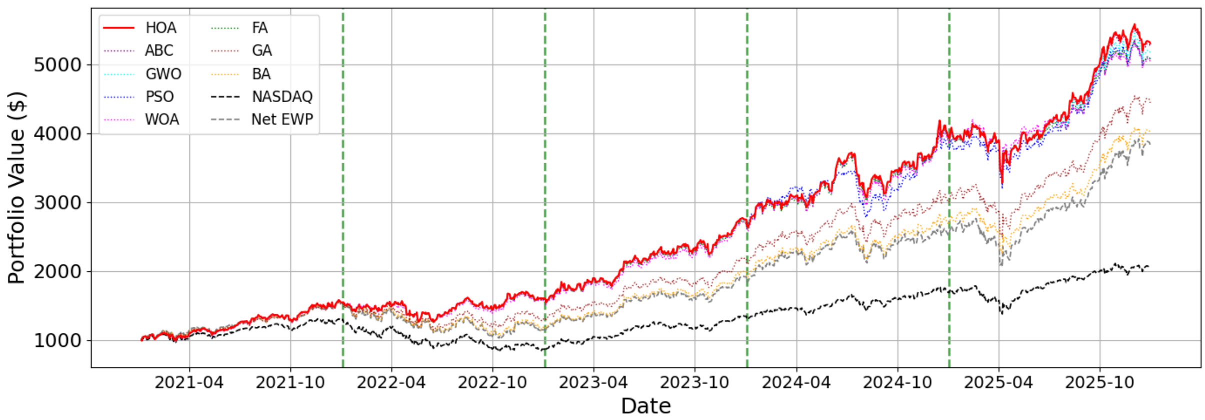


Fig. 3: Cumulative portfolio value between HOA and other metaheuristic algorithms from 2021 to 2025.

(MDD), and total transaction cost (TC). For all metaheuristic-based portfolio optimization methods, cumulative wealth was computed after deducting proportional transaction costs at every portfolio rebalancing period according to the formulation presented in Section 2. In contrast, the EWP and NASDAQ-100 benchmarks were treated as passive buy-and-hold strategies and therefore incurred no transaction costs.

As illustrated in Figure 3, the cumulative portfolio values produced by HOA, ABC, GWO, FA, and PSO algorithms followed similar growth trajectories throughout the investment horizon. The vertical dashed green lines in Figure 3 indicate the portfolio rebalancing dates, at which the portfolio weights were updated and proportional transaction costs were deducted according to the proposed transaction cost model. Consequently, small changes in the portfolio value trajectories around these rebalancing points reflect both the updated asset allocations and the impact of transaction costs incurred during portfolio adjustment. Despite these periodic rebalancing costs, the HOA portfolio remained among the leading strategies throughout all investment periods and finished with the highest cumulative portfolio value. By comparison, WOA exhibited noticeably larger fluctuations despite achieving competitive returns during some periods, while BA and GA consistently produced lower portfolio growth.

Table 3 further shows that the proposed HOA achieved the highest average final portfolio value of \$5307.87 ± \$125.71, corresponding to an annual return of 40.03% ± 0.68%. HOA also achieved the highest SR of 1.5736 ± 0.0151 and the highest NSR of 1.5736 ± 0.0151, indicating the strongest average risk-adjusted performance among the evaluated algorithms. These results suggest that the cumulative wealth improvement achieved by HOA was accompanied by favorable risk-adjusted returns rather than solely by taking greater investment risk.

Table 3: Overall cumulative portfolio performance metrics across the entire investment horizon.

Algorithm	$V(t_{max})$	R_p	σ_p	SR	NSR	MDD	TC
HOA	5307.87 ±0125.71	40.03 ±0.68	23.04 ±0.22	1.5736 ±0.0151	1.5736 ±0.0151	21.70 ±0.73	0.6494 ±0.00
ABC	5268.22 ±0031.38	39.83 ±0.17	23.08 ±0.06	1.5616 ±0.0029	1.5616 ±0.0029	21.49 ±0.28	0.6507 ±0.00
GWO	5172.55 ±0231.14	39.29 ±1.27	22.95 ±0.40	1.5470 ±0.0293	1.5470 ±0.0293	21.40 ±1.01	0.6509 ±0.00
FA	5074.17 ±0254.15	38.75 ±1.39	22.83 ±0.53	1.5317 ±0.0349	1.5317 ±0.0349	21.09 ±1.31	0.6510 ±0.01
PSO	5078.74 ±0242.88	38.78 ±1.35	23.10 ±0.49	1.5150 ±0.0475	1.5150 ±0.0475	21.93 ±1.02	0.6495 ±0.02
WOA	5048.68 ±1101.30	38.08 ±6.75	25.13 ±2.47	1.3842 ±0.3107	1.3842 ±0.3107	25.26 ±8.57	0.7831 ±0.05
GA	4446.75 ±0546.11	34.94 ±3.33	25.10 ±0.98	1.2453 ±0.1570	1.2453 ±0.1570	26.64 ±3.05	0.4812 ±0.02
BA	3997.07 ±0335.97	32.14 ±2.23	26.02 ±0.83	1.0910 ±0.0943	1.0910 ±0.0943	32.46 ±2.83	0.4064 ±0.04
Net EWP	3825.72 ±0000.00	30.95 ±0.00	26.71 ±0.00	1.0171 ±0.0000	1.0171 ±0.0000	34.96 ±0.00	0.0000 ±0.00
NASDAQ	2046.59 ±0000.00	15.48 ±0.00	22.68 ±0.00	0.5159 ±0.0000	0.5159 ±0.0000	35.12 ±0.00	0.0000 ±0.00

Nevertheless, the remaining performance metrics indicate that different algorithms exhibit different strengths. For example, GWO achieved the smallest average portfolio volatility, whereas

FA produced the lowest average maximum drawdown. Likewise, BA incurred the lowest transaction cost, although this was accompanied by substantially lower cumulative wealth and weaker risk-adjusted performance. Therefore, no single algorithm dominated every evaluation metric simultaneously. Overall, the experimental results indicate that the proposed HOA provides one of the most favorable overall trade-offs among cumulative return, risk-adjusted performance, portfolio risk, drawdown, and transaction cost. Rather than claiming uniform superiority across every evaluation criterion, the results demonstrate that HOA is a robust and competitive optimization method that consistently achieves high-quality portfolio allocations while maintaining stable performance throughout the investment horizon.

3.5. Sensitivity Analysis

A sensitivity analysis was conducted to evaluate the influence of the population size on the convergence behavior and solution quality of HOA. The population size (N_{pop}) was varied from 50 to 100 in increments of five, while the maximum number of iterations was fixed at 3000. Each configuration was independently executed 25 times to account for the stochastic nature of the algorithm. The convergence behavior was examined both visually through the distribution of fitness values in Figure 4 and quantitatively using the average NSR values together with their standard deviations at representative optimization stages in Table 4.

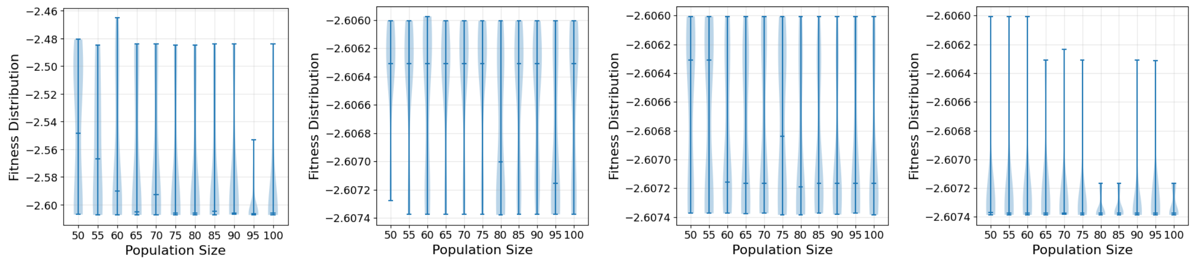


Fig. 4: Fitness values distribution obtained by HOA at iteration 25, 125, 500, and 1750.

Figure 4 illustrates the distribution of fitness values obtained at iterations 25, 125, 500, and 1750. During the early search stage, the violin plots exhibit relatively wide distributions, indicating that the optimization process is still dominated by exploration and remains sensitive to the random initialization of candidate solutions. Larger population sizes generally produce slightly narrower distributions because the increased number of search agents improves the diversity of candidate solutions and enhances the exploration capability of the algorithm. As the optimization progresses, however, the distributions rapidly contract and become increasingly similar across all tested population sizes, indicating that the influence of the initial population size gradually diminishes as the search shifts from exploration to exploitation.

Table 4: NSR values obtained by HOA under different population sizes and maximum iterations.

$Iter_{\max}$	$N_{\text{pop}} = 50$	$N_{\text{pop}} = 60$	$N_{\text{pop}} = 70$	$N_{\text{pop}} = 80$	$N_{\text{pop}} = 90$	$N_{\text{pop}} = 100$
10	2.503593 ±0.053809	2.529302 ±0.072391	2.499153 ±0.057712	2.523795 ±0.074822	2.524622 ±0.062147	2.530200 ±0.065970
20	2.539048 ±0.053013	2.558831 ±0.055601	2.548867 ±0.055853	2.567694 ±0.052106	2.569429 ±0.049211	2.568994 ±0.047359
50	2.584460 ±0.038002	2.589832 ±0.038901	2.588334 ±0.041553	2.599586 ±0.026116	2.596152 ±0.029880	2.600855 ±0.018870
100	2.606106 ±0.001194	2.601614 ±0.024358	2.606360 ±0.000430	2.606768 ±0.000547	2.606539 ±0.000483	2.606534 ±0.000541
250	2.606437 ±0.000484	2.606593 ±0.000539	2.606534 ±0.000531	2.606880 ±0.000537	2.606695 ±0.000511	2.606753 ±0.000554
500	2.606608 ±0.000561	2.606824 ±0.000535	2.606827 ±0.000592	2.606953 ±0.000522	2.607008 ±0.000450	2.606963 ±0.000504
1000	2.606950 ±0.000541	2.607081 ±0.000427	2.607167 ±0.000410	2.607269 ±0.000291	2.607216 ±0.000294	2.607171 ±0.000314
1500	2.607203 ±0.000341	2.607184 ±0.000331	2.607177 ±0.000408	2.607333 ±0.000085	2.607294 ±0.000217	2.607297 ±0.000096
2000	2.607315 ±0.000087	2.607255 ±0.000275	2.607332 ±0.000076	2.607340 ±0.000078	2.607309 ±0.000218	2.607314 ±0.000094
3000	2.607333 ±0.000070	2.607323 ±0.000088	2.607352 ±0.000061	2.607359 ±0.000056	2.607364 ±0.000054	2.607356 ±0.000060

The numerical results reported in Table 4 further support these observations. During the initial iterations ($Iter_{\max} = 10, 25,$ and 50), noticeable differences exist among the tested population sizes, with relatively large standard deviations ranging approximately from 1.89×10^{-2} to 7.48×10^{-2}, reflecting substantial stochastic variation during global exploration. Nevertheless, after approximately 100 iterations, the mean NSR values obtained under different population sizes become increasingly similar, while the standard deviations decrease by more than two orders of magnitude. At the final iteration ($Iter_{\max} = 3000$), all investigated configurations converge to nearly identical mean NSR values (approximately 2.6073), with very small standard deviations on the order of 10^{-5} to 10^{-4}. This behavior indicates that HOA consistently converges toward the same high-quality solution regardless of the number of search agents.

Although increasing the population size slightly accelerates convergence during the intermediate optimization stages, the improvement in the final solution quality is marginal. For example, the difference between the smallest and largest average final NSR values across all evaluated population sizes is less than 4×10^{-5}, which is negligible compared with the variability observed during the early search process. Therefore, employing excessively large populations provides limited practical benefit while inevitably increasing computational cost due to the larger number of objective function evaluations required at each iteration.

Overall, both Figure 4 and Table 4 demonstrate that HOA exhibits low sensitivity to the population size within the investigated range. The algorithm achieves stable convergence, consistently produces high-quality solutions, and maintains very low variability across independent runs. Based on these findings, a population size of $N_{\text{pop}} = 100$ was adopted in the remaining experiments because it provides the most consistent convergence behavior while preserving the best average solution quality.

3.6. Statistical Significance Analysis

Although the descriptive results indicate that HOA generally provides competitive portfolio optimization performance, statistical hypothesis testing is required to determine whether the observed differences among algorithms are statistically significant. Since the performance metrics were obtained from repeated independent optimization runs and normality cannot be assumed, the non-parametric Friedman test was employed to compare the eight MAs across all evaluation metrics. The Friedman test evaluates the null hypothesis that all algorithms achieve equivalent performance distributions under repeated experiments.

Table 5: Friedman test results for cumulative portfolio performance metrics.

Metric	Statistic	p-value	Decision
$V(t_{\max})$	83.1333	3.16×10^{-15}	Reject H_0
R_p	83.7467	2.37×10^{-15}	Reject H_0
σ_p	106.8533	4.12×10^{-20}	Reject H_0
SR	119.1467	1.15×10^{-22}	Reject H_0
NSR	119.1467	1.15×10^{-22}	Reject H_0
MDD	105.3867	8.30×10^{-20}	Reject H_0
TC	143.1067	1.14×10^{-27}	Reject H_0

Table 5 summarizes the Friedman test results for the cumulative portfolio performance metrics. For every evaluated metric, the obtained p-values are substantially smaller than the significance level of $\alpha = 0.05$. Therefore, the null hypothesis (H_0) is rejected for all performance measures, indicating that statistically significant performance differences exist among the evaluated MAs.

Since the Friedman test only indicates that significant performance differences exist among the evaluated algorithms without identifying which algorithms differ, a post-hoc Wilcoxon signed-rank test was subsequently performed in this study. The Wilcoxon test compared the performance of the proposed HOA against each competing metaheuristic over the 25 independent optimization runs. The significance level was set to $\alpha = 0.05$.

Table 6: Pairwise Wilcoxon signed-rank test p-values comparing HOA with competing MAs.

Metric	ABC	GWO	FA	PSO	WOA	BA	GA
$V(t_{\max})$	↑ (0.004034)	↑ (0.017087)	↑ (0.000577)	↑ (0.000144)	– (0.405965)	↑ (0.000000)	↑ (0.000000)
R_p	↑ (0.004034)	↑ (0.017087)	↑ (0.000577)	↑ (0.000165)	– (0.375496)	↑ (0.000000)	↑ (0.000000)
σ_p	– (0.262456)	– (0.802144)	– (0.959902)	– (0.149806)	↓ (0.000006)	↓ (0.000000)	↓ (0.000000)
SR	↑ (0.000027)	↑ (0.000009)	↑ (0.000051)	↑ (0.000004)	↑ (0.003685)	↑ (0.000000)	↑ (0.000000)
NSR	↑ (0.000027)	↑ (0.000009)	↑ (0.000051)	↑ (0.000004)	↑ (0.003685)	↑ (0.000000)	↑ (0.000000)
MDD	– (0.879467)	– (0.873948)	– (0.968687)	– (0.169394)	↓ (0.004034)	↓ (0.000000)	↓ (0.000000)
TC	↓ (0.000000)	↓ (0.000000)	– (0.063324)	– (0.634505)	↓ (0.000000)	– (1.000000)	– (1.000000)

↑: HOA is significantly higher than the competing algorithm ($p < 0.05$).

↓: HOA is significantly lower than the competing algorithm ($p < 0.05$).

–: No statistically significant difference ($p \geq 0.05$).

The obtained results indicate that HOA significantly outperformed most competing algorithms with respect to the final portfolio value ($V(t_{\max})$) and annual return (R_p). Specifically, HOA achieved significantly higher cumulative portfolio values than ABC, BA, FA, GA, GWO, and PSO ($p < 0.05$), whereas no statistically significant difference was observed between HOA and WOA. Similar conclusions were obtained for the annual return metric.

For the risk-adjusted performance measures, HOA demonstrated even stronger statistical superiority. The proposed algorithm achieved significantly higher SR and NSR values than all competing algorithms, including WOA ($p < 0.05$ for all pairwise comparisons). These results provide statistical evidence that the superior risk-adjusted performance observed in the descriptive analysis is consistently maintained across repeated optimization runs.

Regarding portfolio risk and maximum drawdown, HOA produced significantly lower portfolio volatility if compared than BA, GA, and WOA algorithms, while the differences relative to ABC, FA, GWO, and PSO algorithms were not statistically significant. Similarly, HOA achieved significantly smaller maximum drawdowns than BA, GA, and WOA algorithms, whereas the remaining pairwise comparisons did not reach statistical significance.

For transaction costs, HOA generated significantly lower trading costs than ABC, GWO, and WOA algorithms, while exhibiting statistically comparable transaction costs to BA, FA, GA, and PSO algorithms. These findings suggest that the improved portfolio performance obtained by HOA was not achieved by substantially increasing portfolio turnover.

Overall, the Wilcoxon signed-rank analysis corroborates the descriptive and Friedman test results. Although HOA does not significantly outperform every competing algorithm for every individual metric, it consistently achieves statistically superior performance for the most important portfolio evaluation criteria, particularly cumulative portfolio value, annual return, SR, and NSR, thereby confirming the robustness and effectiveness of the proposed transaction cost-aware portfolio optimization framework.

3.7. Limitations of the Study

Several limitations should be acknowledged when interpreting the findings of this study. First, the candidate asset universe was restricted to the twenty highest-ranked stocks based on the SR, while only companies that remained continuously listed in the NASDAQ-100 throughout the observation period were retained. This strategy reduces the search space and focuses the optimization on assets with superior historical risk-adjusted performance.

However, it may introduce both look-ahead bias in the asset selection stage and survivorship bias by excluding firms that exited the index during the study period. Consequently, the reported results should primarily be interpreted as an evaluation of the optimization capability of the proposed HOA framework under a fixed candidate universe rather than as the performance of a fully implementable real-time investment strategy.

Second, transaction costs were modeled using a constant proportional transaction cost rate for all assets and rebalancing periods. Although this assumption is commonly adopted in portfolio optimization studies, actual trading costs depend on factors such as market liquidity, bid–ask spreads, slippage, and market impact. Incorporating adaptive or liquidity-aware transaction cost models would further improve the realism and practical applicability of the proposed framework.

4. Conclusion

This article proposed a transaction cost-aware portfolio optimization framework for NASDAQ-100 stocks using the HOA, where portfolio allocation was formulated by maximizing the NSR while explicitly incorporating transaction costs into the optimization objective. Experimental results over the 2021–2025 investment horizon demonstrated that the proposed framework is capable of generating high-quality portfolio allocations under dynamic market conditions. Across the five rebalancing periods, HOA achieved competitive optimization performance and exhibited small variability across repeated runs, indicating strong robustness and reliable convergence behavior.

The comparative analysis further showed that different MAs exhibited different strengths depending on the evaluation criterion. While some competing algorithms attained comparable or occasionally better objective values in particular rebalancing periods, HOA remained among the strongest-performing methods throughout the experiments. Over the entire investment horizon, the proposed framework generated the highest cumulative portfolio value while maintaining competitive risk-adjusted performance, moderate transaction costs, and controlled portfolio drawdown. These findings suggest that the principal advantage of HOA lies in providing a favorable balance between portfolio growth, optimization stability, and trading efficiency, rather than uniformly outperforming every competing algorithm under every performance metric.

For future studies, the proposed framework can be extended to multi-objective portfolio optimization by simultaneously optimizing return, risk, transaction costs, and additional financial objectives within a Pareto-based framework. Alternative downside risk metric, such as Conditional Value-at-Risk (CVaR) or semi-variance, may also be incorporated to better capture tail-risk behavior. Furthermore, more realistic transaction cost models that account for market liquidity, bid–ask spreads, slippage, and market impact could improve practical applicability. Finally, evaluating the proposed framework on broader asset universes, including international equity markets, cryptocurrencies, and multi-asset portfolios, would provide further evidence regarding its generalizability and robustness under diverse market environments.

CRediT Authorship Contribution Statement

Safrizal Ardana Ardiyansa Conceptualization, Data Curation, Methodology, Software, Visualization, Writing–Original Draft. **Mohamad Muslikh** Supervision, Project Administration, Funding Acquisition, Writing–Review & Editing. **Syaiful Anam** Supervision, Writing–Review & Editing.

Declaration of Generative AI and AI-assisted technologies

Generative AI and AI-assisted technologies were used during the preparation of this manuscript. In particular, ChatGPT (OpenAI, GPT-5.5 version) was utilized to assist with grammar checking, language refinement, sentence restructuring, and general writing assistance to improve the clarity and readability of the manuscript. The authors have carefully reviewed, verified, and edited all AI-assisted outputs and take full responsibility for the final content of this manuscript, including its accuracy, originality, and scientific integrity.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests, personal relationships, affiliations, or conflicts of interest that could have appeared to influence the work reported in this article. Furthermore, the authors confirm that no external organization or sponsor had any role in the design of this article, data collection, analysis, interpretation of results, manuscript preparation, or decision to submit this work for publication.

Funding and Acknowledgments

This research did not receive external funding. The authors express their sincere gratitude to all individuals and institutions who provided support, guidance, and research facilities during the completion of this study.

Data and Code Availability

The financial dataset used in this article were obtained from Yahoo Finance, particularly from the NASDAQ-100 stock market, which is publicly accessible through the Yahoo Finance platform[1]. The historical stock price data used in the experiments can be accessed and downloaded directly from the corresponding Yahoo Finance pages for each asset included in the NASDAQ-100 index.

The source code, implementation details, and additional computational materials supporting the findings of this study are publicly available through the following Kaggle repository[2]. The repository contains the implementation of the HOA-based portfolio optimization framework, data preprocessing, portfolio evaluation scripts, and the configuration settings used in this study. Additional information may be requested from the first author at safrizal.braincore@gmail.com.

References

[1] G. Tsomidis. "Portfolio Construction Under Behavioral Distortions and Narrow Framing: A Machine Learning Approach". In: *Mathematics* 14 (2026), p. 607. DOI: 10.3390/math14040607.

[2] F. Şerban and B.-P. Vrnceanu. "Mean–Variance–Entropy Framework for Cryptocurrency Portfolio Optimization". In: *Mathematics* 13 (2025), p. 1693. DOI: 10.3390/math13101693.

[3] W. B. Lee and A. G. Constantinides. "Practical Applications of Quantum Computing in Finance: Mathematical Foundations and Deployment Challenges". In: *Encyclopedia* 6 (2026), p. 95. DOI: 10.3390/encyclopedia6050095.

[4] T. S. Dai, B. J. Chen, Y. J. Sun, et al. "Constructing Optimal Portfolio Rebalancing Strategies with a Two-Stage Multiresolution-Grid Model". In: *Computational Economics* 64 (2024), pp. 3117–3142. DOI: 10.1007/s10614-024-10555-y.

[5] A. Bányai, T. Tatay, G. Thalmeiner, and L. Pataki. "Consumer Expenditure-Based Portfolio Optimization". In: *International Journal of Financial Studies* 13 (2025), p. 99. DOI: 10.3390/ijfs13020099.

[6] L. Bonga-Bonga. "Navigating Extreme Market Fluctuations: Asset Allocation Strategies in Developed vs. Emerging Economies". In: *Econometrics* 14 (2026), p. 16. DOI: 10.3390/econometrics14010016.

[7] J. G. Astaíza-Gómez. "Uncertainty, Risk, and Opaque Stock Markets". In: *International Journal of Financial Studies* 13 (2025), p. 35. DOI: 10.3390/ijfs13010035.

[8] C. Huang and Z. Jing. "Reinforcement Learning for Single-Stock Portfolio Optimization in Equity Markets". In: *International Journal of Computational Intelligence Systems* 19 (2026), p. 37. DOI: 10.1007/s44196-025-01105-x.

[1] https://finance.yahoo.com/quote/%5ENDX/

[2] https://www.kaggle.com/code/safrizalardanaa/adaptive-portfolio-rebalancing-for-nasdaq-100

[9] J. Yu and K.-C. Chang. “Smart Tangency Portfolio: Deep Reinforcement Learning for Dynamic Rebalancing and Risk–Return Trade-Off”. In: *International Journal of Financial Studies* 13 (2025), p. 227. DOI: 10.3390/ijfs13040227.

[10] V. Tomar, M. Bansal, and P. Singh. “Metaheuristic Algorithms for Optimization: A Brief Review”. In: *Engineering Proceedings* 59 (2023), p. 238. DOI: 10.3390/engproc2023059238.

[11] M. Faizan and M. A. Mohammad. “Metaheuristic Algorithms for Feature Selection (2014–2024)”. In: *International Journal of Applied Metaheuristic Computing* 16 (2026), pp. 1–23. DOI: 10.4018/IJAMC.397402.

[12] D. Lee, S. Noh, J. Kim, and S. Lee. “Efficient Hyperparameter Optimization Using Metaheuristics for Machine Learning in Truss Steel Structure Cross-Section Prediction”. In: *Buildings* 15 (2025), p. 2791. DOI: 10.3390/buildings15152791.

[13] S. Anam, S. A. Ardiyansa, Z. Fitriah, and M. Muslikh. “Optimizing Heart Risk Attack Diagnosis by Hybridizing XGBoost and Chaotic Binary Bat Algorithm”. In: *Applied Computational Intelligence and Soft Computing* 2026 (2026), p. 2588501. DOI: 10.1155/acis/2588501.

[14] H. A. Fajri, S. A. Ardiyansa, S. Anam, N. C. Maharani, and E. Julianto. “Improving Support Vector Machine Performance with Binary Gaussian Improved Whale Optimization Algorithm: A Case Study on Diabetes Data”. In: *BAREKENG: Jurnal Ilmu Matematika dan Terapan* 19 (2025), pp. 2531–2542. DOI: 10.30598/barekengvol19iss4pp2531-2542.

[15] L. P. D. Jayanti, S. Anam, S. A. Ardiyansa, and N. C. Maharani. “Health Insurance Claim Classification Using Support Vector Machine with Velocity Pausing Particle Swarm Optimization”. In: *CAUCHY: Jurnal Matematika Murni dan Aplikasi* 10 (2025), pp. 698–710. DOI: 10.18860/cauchy.v10i2.31914.

[16] M. S. Uzer. “New Hybrid Approaches Based on Swarm-Based Metaheuristic Algorithms and Applications to Optimization Problems”. In: *Applied Sciences* 15 (2025), p. 1355. DOI: 10.3390/app15031355.

[17] T. Ivanovski, M. Brkić Bakarić, and M. Matetić. “Recent Advances in Metaheuristic Algorithms”. In: *Algorithms* 19 (2026), p. 19. DOI: 10.3390/a19010019.

[18] V. N. Thatha, M. G. Karthik, V. G. Gaddam, et al. “Histopathological Image Based Breast Cancer Diagnosis Using Deep Learning and Bio Inspired Optimization”. In: *Scientific Reports* 15 (2025), p. 19034. DOI: 10.1038/s41598-025-04136-8.

[19] N. Mars, L. Houcine, M. Chaabani, and A. Zaafouri. “Hippopotamus Algorithm for Optimal Sizing of Hybrid Renewable Energy System”. In: *Results in Engineering* 29 (2026), p. 109772. DOI: 10.1016/j.rineng.2026.109772.

[20] M. H. Amiri, N. M. Hashjin, M. Montazeri, S. Mirjalili, and N. Khodadadi. “Hippopotamus Optimization Algorithm: A Novel Nature-Inspired Optimization Algorithm”. In: *Scientific Reports* 14 (2024), p. 5032. DOI: 10.1038/s41598-024-54910-3.

[21] N. M. Hashjin, M. H. Amiri, A. Beheshti, and M. K. Najafabadi. “Q2HO-MFTV: A Binary Hippopotamus Optimization Algorithm for Feature Selection with a Brief Review of Binary Optimization”. In: *Knowledge-Based Systems* 327 (2025), p. 114119. DOI: 10.1016/j.knosys.2025.114119.

[22] S. A. Ardiyansa, M. Muslikh, and A. R. Alghofari. “Binary Hippopotamus Algorithm with Random Forest for Optimizing Feature Selection Problem”. In: *Numerical Algebra, Control and Optimization* 15 (2025), pp. 1176–1191. DOI: 10.3934/naco.2025009.

[23] E. Suleymanov, M. Gubadli, and U. Yagubov. “Test of Volatile Behaviors with the Asymmetric Stochastic Volatility Model: An Implementation on Nasdaq-100”. In: *Risks* 12 (2024), p. 76. DOI: 10.3390/risks12050076.

[24] S. Maheshwari and D. R. Naik. “Efficiency in Operations of NASDAQ-Listed Technology Companies from 2011 to 2023”. In: *Journal of Risk and Financial Management* 17 (2024), p. 205. DOI: 10.3390/jrfm17050205.

[25] L. L. Ortiz-Cerezo, A. A. Carsteanu, and J. B. Clempner. “Sharpe-Ratio Portfolio in Controllable Markov Chains: Analytic and Algorithmic Approach for Second-Order Cone Programming”. In: *Mathematics* 10 (2022), p. 3221. DOI: 10.3390/math10183221.

[26] M. Zatwarnicki and K. Zatwarnicki. “Timing Usage of Technical Analysis in the Cryptocurrency Market”. In: *Applied Sciences* 15 (2025), p. 12802. DOI: 10.3390/app152312802.

[27] Y. Lin and B. Liu. “A Framework for Enhancing Stock Investment Performance by Predicting Important Trading Points with Return-Adaptive Piecewise Linear Representation and Batch Attention Multi-Scale Convolutional Recurrent Neural Network”. In: *Entropy* 25 (2023), p. 1500. DOI: 10.3390/e25111500.

[28] F. Şerban and S. Dedu. “Robust Portfolio Optimization in Crypto Markets Using Second-Order Tsallis Entropy and Liquidity-Aware Diversification”. In: *Risks* 13 (2025), p. 180. DOI: 10.3390/risks13090180.

[29] S. Isaenko. “Transaction Costs, Frequent Trading, and Stock Prices”. In: *Journal of Financial Markets* 64 (2023), p. 100775. DOI: 10.1016/j.finmar.2022.100775.