



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

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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 framework by incorporating transaction costs directly into a Net Sharpe Ratio (NSR) objective function, enabling realistic dynamic portfolio rebalancing. Daily adjusted closing prices of NASDAQ-100 constituents from 2021 to 2025 are used, and the top 20 stocks selected via Sharpe Ratio (SR) ranking serve as the investment universe. HOA is applied under long-only constraints across five rebalancing periods with 252 trading days per period, using Equal Weight Portfolio (EWP) and the NASDAQ-100 index as benchmarks. Each experiment is repeated 25 independent runs to ensure robustness. The empirical results show that HOA achieves consistently strong risk-adjusted performance, with NSR values reaching up to 3.42 in 2021 and 2023 and 0.92 during adverse conditions in 2022. During the full investment horizon, HOA attains a final portfolio value of \$12,118.55 from an initial \$1,000, corresponding to a cumulative return of approximately 1,111.86%, with a SR of 3.1187 and NSR of 3.0878, while maintaining a maximum drawdown of 16.88% and total transaction cost of 0.6494%. Compared with PSO, ABC, GWO, FA, WOA, BA, and GA, HOA demonstrates superior stability, lower variance across runs, and competitive or better NSR performance under dynamic market conditions. Overall, although several competing methods achieve higher terminal wealth, they exhibit higher risk exposure and drawdown. The results highlight that integrating transaction costs within a metaheuristic-based optimization framework significantly improves the realism and robustness of portfolio allocation strategies, making the proposed approach suitable for practical large-scale financial decision-making.

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

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1. Introduction

Modern Portfolio Theory (MPT) becomes a fundamental framework in quantitative finance for balancing investment return and risk. By characterizing investors as expected utility maximizers who evaluate assets according to their contributions to portfolio-level return and variance, MPT has provided the theoretical foundation for portfolio optimization for several decades [1]. Along with the rapid advancement of financial technology, algorithmic investment strategies have become increasingly important for constructing personalized portfolios that align with investors'

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financial objectives and risk preferences [2]. Consequently, portfolio optimization remains one of the most important decision-making problems in quantitative finance, where investors seek to maximize expected returns while controlling risk exposure [3–5].

The original mean variance framework introduced by Markowitz mathematically seeks an optimal trade-off between expected return and portfolio risk under predefined investment constraints [6, 7]. However, most portfolio optimization models assume static portfolio allocations assumption that rarely hold in real financial environments. Financial markets are inherently dynamic, and portfolio weights continuously evolve due to price fluctuations, changing volatility patterns, liquidity variations, and transaction costs [8]. As a result, an initially optimal portfolio may gradually become suboptimal as market conditions change [9, 10]. Effective portfolio management therefore requires periodic portfolio rebalancing to maintain consistency with investors' objectives while accounting for market uncertainty and implementation costs [11–13].

Although portfolio rebalancing can improve risk-adjusted performance, excessive trading may significantly increase transaction costs, portfolio turnover, and market impact. Consequently, practical portfolio management requires simultaneous consideration of expected return, portfolio risk, and transaction costs. Incorporating these conflicting factors transforms portfolio rebalancing into a hard problem characterized by nonlinear, constrained, and nonconvex search spaces [14].

Metaheuristic algorithms (MAs) have emerged as powerful alternatives for solving any complex portfolio optimization problems because they do not rely on gradient information and are capable of exploring highly nonlinear and multimodal search spaces [15]. Their probabilistic exploration and exploitation mechanisms allow them to effectively avoid local optima while maintaining computational flexibility [16, 17]. Consequently, MAs have been widely applied across various optimization domains, including engineering, finance, logistics, and artificial intelligence [18, 19]. Among the different classes of metaheuristics, swarm intelligence has attracted attention due to its collective search, adaptability, and robustness [20]. Inspired by natural phenomena [21], swarm-based approaches have demonstrated promising performance in portfolio optimization.

Recently, the Hippopotamus Optimization Algorithm (HOA) has attracted research interest due to its balanced exploration and exploitation capabilities. HOA is a population-based bio-inspired optimization algorithm that models the social and defensive behaviors of hippopotamus herds [22, 23]. Through its exploration, predator-defense, and local exploitation mechanisms, HOA has demonstrated competitive performance in solving challenging optimization problems in various domains. Despite these promising characteristics, the application of HOA to transaction cost-aware portfolio optimization has not been explored, particularly in highly dynamic markets.

The NASDAQ-100 index represents one of the most influential stock market indices globally and consists primarily of large-cap non-financial companies from technology-driven and growth-oriented sectors [24, 25]. NASDAQ-100 constituents are characterized by high liquidity, substantial volatility, rapid price movements, and strong sensitivity to technological innovation and macroeconomic developments. These characteristics make the NASDAQ-100 an attractive environment for investigating adaptive and transaction-aware portfolio optimization strategies.

Although numerous studies have investigated portfolio allocation optimization using MAs, several important research gaps remain. First, many existing studies primarily focus on static portfolio allocation without considering portfolio rebalancing decisions. Second, transaction costs are frequently neglected rather than being directly incorporated into the optimization objective. As a consequence, the resulting portfolios may exhibit excessive turnover and become difficult to implement in practical trading environments. Third, relatively limited studies investigate portfolio optimization for NASDAQ-100 stocks using HOA. More importantly, the integration of transaction costs directly into a risk-adjusted portfolio optimization framework remains relatively underexplored, particularly when combined with newly population-based optimization techniques.

Motivated by these challenges, this study proposes a transaction cost-aware portfolio optimization framework for NASDAQ-100 stocks using the HOA. Unlike conventional portfolio optimization approaches that focus solely on return and risk characteristics, the proposed frame-

work explicitly incorporates transaction costs into the optimization objective through a net Sharpe ratio (SR) formulation. Specifically, the model seeks to maximize excess portfolio return after accounting for both the risk-free rate and rebalancing costs while controlling portfolio risk through covariance-based risk estimation. By including transaction costs directly into the objective function, the proposed framework discourages excessive portfolio turnover and promotes more practical portfolio allocations.

The main contributions of this study can be summarized as follows:

1. A transaction cost-aware portfolio optimization model is developed for NASDAQ-100 stocks by integrating expected return, risk, and rebalancing costs into a net SR objective function.
2. The HOA is adapted to solve the resulting portfolio optimization problem and determine optimal portfolio weights under long-only investment constraints.
3. Numerical experiments are performed to compare the HOA several state-of-the-art MAs. The comparative results provide empirical evidence of the superior optimization capability of HOA in maximizing SR, improving portfolio wealth growth, and reducing transaction-induced performance degradation in NASDAQ-100 portfolio management.

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

2. Methods

This study proposes a transaction cost-aware portfolio optimization framework for NASDAQ-100 stocks using the HOA. The methodology consists of three main subsection, namely data processing and asset selection, mathematical formulation of the portfolio optimization problem, and portfolio weight determination using HOA.

2.1. Data Processing and Asset Selection

Daily adjusted closing prices of NASDAQ-100 constituent stocks are collected from January 1, 2021 to December 31, 2025. This period is selected to capture both medium-term market dynamics and recent market conditions within the NASDAQ-100 index. To ensure consistency and eliminate survivorship-related inconsistencies, only stocks that remain continuously listed in the NASDAQ-100 index throughout the entire observation period are retained for further analysis. Consequently, the resulting dataset provides a more reliable basis for portfolio optimization and performance evaluation.

Based on the filtered dataset, 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.

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

where $P_i(\tau)$ denotes the adjusted closing price of the i -th asset on the τ -th trading day, and τ_{max} is the total number of trading observations [26]. The 252 corresponds to the average number of trading days in a year and is used to annualize both the expected return and volatility measures [27]. These statistical measures provide the fundamental information required to evaluate the risk-return characteristics of each asset before constructing the portfolio.

Using the annualized risk-free rate (R_f), the SR of the i -th asset can be calculated as [28]:

$$SR_i = \frac{\bar{R}_i - R_f}{\sigma_i}. \quad (2)$$

All eligible assets are ranked according to their SR values to identify stocks with superior risk-adjusted performance. Based on this ranking process, the twenty highest-ranked stocks are selected in this study as candidate assets for portfolio construction.

2.2. Portfolio Optimization Model

Suppose $\bar{\mathbf{R}}(t) = [\bar{R}_1(t), \bar{R}_2(t), \dots, \bar{R}_n(t)]^T$, $\Sigma(t) = [\sigma_{ij}(t)]$, and $\mathbf{w}(t) = [w_1(t), w_2(t), \dots, w_n(t)]^T$ 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.

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

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

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

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

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

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.

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

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

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

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

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

Accordingly, the portfolio optimization problem is formulated as follows.

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

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 $i = 1, 2, \dots, n$.

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.

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

where $k = 1, 2, \dots, N_{pop}$, 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. The normalization 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.

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

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 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:

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

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

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

2.4. Portfolio Performance Evaluation

To evaluate the effectiveness of the proposed HOA-based portfolio optimization framework, the obtained 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, respectively.

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:

$$V(\tau) = (1 + R_p(\tau))V(\tau - 1) \quad (14)$$

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:

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

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. The cumulative portfolio value at the t -th rebalancing period is then formulated as follows.

$$V(t) = V(t - 1) \prod_{\tau=1}^{\tau_{\max}} (1 + \mathbf{w}(t)^T \mathbf{R}(\tau)), \text{ where } t = 1, 2, \dots, t_{\max}. \quad (16)$$

Consequently, the final cumulative portfolio value after the T rebalancing periods can be calculated as follows.

$$V(t_{\max}) = V(0) \prod_{t=1}^{t_{\max}} \prod_{\tau=1}^{\tau_{\max}} (1 + \mathbf{w}(t)^T \mathbf{R}(\tau)). \quad (17)$$

This formulation reflects the evolution of portfolio wealth under time-varying asset allocations generated by the proposed HOA. To comprehensively assess portfolio performance, several evaluation metrics are considered, including final cumulative return, portfolio risk, SR, 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 and transaction cost considerations.

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. 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 and risk free rate were determined at $\lambda = 0.001$ and $R_f = 0.00015$ respectively.

To reduce stochastic variability, each optimization experiment was 25 multiple 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

3.1. Selected Stock Portfolio

To construct the candidate asset universe for portfolio optimization, all NASDAQ-100 constituent stocks were first evaluated using the SR criterion defined in Eq. (2). Stocks with higher SR indicate superior return per unit of risk and are therefore considered more attractive for portfolio allocation. Figure 1 illustrates the distribution of the selected stocks in this study.

Based on the SR ranking, AVGO achieved the highest SR value of 1.203, followed by NVDA and MU with SRs of 1.190 and 1.117, respectively. These assets exhibit relatively high annualized returns despite having comparatively higher volatility levels. In contrast, stocks such as ORLY and CSCO demonstrate lower return and risk characteristics, resulting in more moderate SR values. Several semiconductor and technology-related companies, including AVGO, NVDA, KLAC, and MU, dominate the upper-right region of the figure, reflecting the strong growth characteristics of technology-oriented NASDAQ-100 assets during the observation period.

Furthermore, the computed hypervolume value of $HV = 0.0835$, indicates the coverage quality of the obtained Pareto solution set relative to the reference point $(R_{\text{ref}}, \Sigma_{\text{ref}}) = (0.5846, 0.1937)$. A larger hypervolume value indicates a better trade-off between return maximization and risk minimization. The obtained result demonstrates that the selected candidate assets provide a diverse set of risk–return characteristics for HOA-based portfolio optimization and dynamic rebalancing analysis.

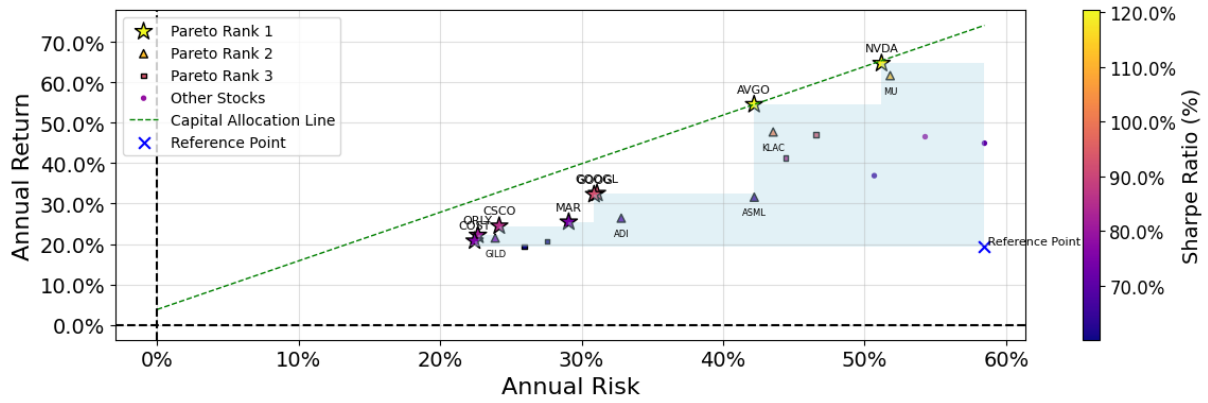


Fig. 1: Risk–return distribution of the selected NASDAQ-100 stocks based on SR ranking.

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 obtained 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 dynamically adjusted portfolio composition across different rebalancing periods according to evolving market characteristics. 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 framework, comparative experiments were conducted against several well-established 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 executed 25 independent times for every rebalancing period using the same experimental settings and objective function. The comparative performance statistics, including best, worst, mean, standard deviation (Std), and median of NSR value, are summarized in Table 2.

Table 2: Performance comparison between HOA and other metaheuristic algorithms across different rebalancing periods.

	Metric	HOA	PSO	ABC	GWO	FA	WOA	BA	GA
2021	Best	3.40×10^0	3.40×10^0	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	3.40×10^0	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	3.40×10^0	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}	1.78×10^{-16}	7.14×10^{-4}	4.27×10^{-2}	6.32×10^{-2}	7.84×10^{-2}	4.70×10^{-2}
	Median	3.40×10^0	3.40×10^0	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	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	3.46×10^{-1}	4.61×10^{-1}
	Worst	9.22×10^{-1}	9.15×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	9.12×10^{-1}	8.41×10^{-2}	5.04×10^{-1}	2.13×10^{-1}
	Mean	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-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}	2.22×10^{-17}	1.16×10^{-6}	2.38×10^{-3}	2.09×10^{-1}	4.90×10^{-2}	6.68×10^{-2}
	Median	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	9.22×10^{-1}	9.20×10^{-1}	8.11×10^{-1}	4.47×10^{-1}	3.30×10^{-1}
2023	Best	3.42×10^0	3.42×10^0	3.42×10^0	3.42×10^0	3.42×10^0	3.42×10^0	3.01×10^0	2.89×10^0
	Worst	3.42×10^0	3.35×10^0	3.42×10^0	3.42×10^0	3.41×10^0	3.12×10^0	2.77×10^0	2.71×10^0
	Mean	3.42×10^0	3.42×10^0	3.42×10^0	3.42×10^0	3.42×10^0	3.35×10^0	2.87×10^0	2.77×10^0
	Std	1.74×10^{-12}	2.09×10^{-2}	1.78×10^{-16}	3.31×10^{-4}	1.54×10^{-3}	7.26×10^{-2}	6.48×10^{-2}	5.00×10^{-2}
	Median	3.42×10^0	3.42×10^0	3.42×10^0	3.42×10^0	3.42×10^0	3.35×10^0	2.86×10^0	2.77×10^0
2024	Best	2.74×10^0	3.43×10^0	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	3.34×10^0	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	3.42×10^0	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}	3.20×10^{-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	3.43×10^0	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	2.61×10^0	2.60×10^0	2.61×10^0	2.61×10^0	2.61×10^0	2.61×10^0	2.05×10^0	1.94×10^0
	Worst	2.61×10^0	2.48×10^0	2.61×10^0	2.60×10^0	2.60×10^0	2.22×10^0	1.82×10^0	1.73×10^0
	Mean	2.61×10^0	2.59×10^0	2.61×10^0	2.61×10^0	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}	4.00×10^{-6}	6.51×10^{-4}	1.68×10^{-3}	9.66×10^{-2}	5.68×10^{-2}	4.62×10^{-2}
	Median	2.61×10^0	2.60×10^0	2.61×10^0	2.61×10^0	2.60×10^0	2.49×10^0	1.91×10^0	1.85×10^0

Based on Table 2, the proposed HOA consistently demonstrated highly competitive optimization performance across all rebalancing periods. In most investment periods, HOA achieved either the best or near-best objective values while simultaneously maintaining extremely small standard deviation values, indicating strong optimization stability and robustness. In particular, HOA obtained the best performance during the 2021, 2022, and 2025 investment periods, while producing competitive results comparable to ABC and GWO during the remaining periods. The obtained results indicate that the balanced exploration and exploitation mechanisms of HOA effectively guided the search process toward high-quality portfolio solutions under dynamic market conditions.

Compared with other MAs, several conventional metaheuristics such as BA and GA consistently produced inferior optimization results with larger objective values and lower solution quality. Meanwhile, population-based swarm algorithms such as PSO, GWO, and ABC demonstrated relatively competitive performance but generally exhibited larger variability across repeated executions. Furthermore, WOA occasionally experienced unstable optimization behavior, particularly during volatile market periods, as indicated by its relatively large standard deviation values. Overall, the comparative analysis demonstrates that the proposed HOA framework

provides strong optimization capability, high robustness, and stable convergence performance for transaction cost-aware portfolio optimization problems in NASDAQ-100 portfolio management.

Figure 2 further illustrates the convergence behavior of 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.

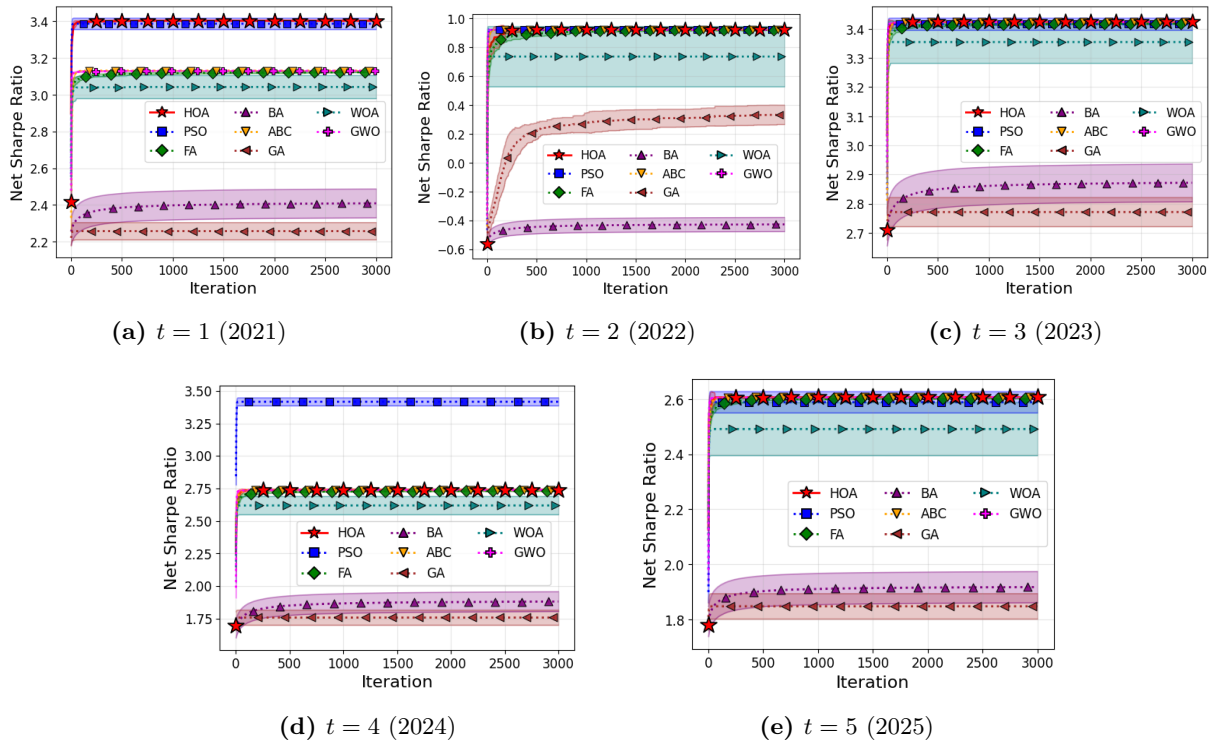


Fig. 2: Convergence comparison of fitness value between HOA and other metaheuristic algorithms.

3.4. Cumulative Portfolio Performance Analysis

Figure 3 presents the cumulative portfolio value evolution of the HOA and other benchmark algorithms throughout the entire investment horizon from January 2021 to December 2025 with initial investment of $V(0) = 1000$ USD. Meanwhile, Table 3 summarizes several important portfolio performance indicators, including portfolio value, annual return, risk, SR, NSR, maximum drawdown (MDD), and total transaction cost (TC). Overall, the obtained results demonstrate that all metaheuristic-based portfolio optimization methods outperformed both the EWP and the NASDAQ-100 benchmark in terms of cumulative portfolio growth and risk-adjusted performance.

As shown in Figure 3, the cumulative portfolio values generated by HOA, ABC, FA, GWO,

and PSO exhibited relatively stable and consistent upward trends across all rebalancing periods. In particular, HOA achieved highly competitive cumulative growth while maintaining smoother portfolio trajectories compared with several competing algorithms. Although WOA produced the highest cumulative portfolio value at the end of the investment horizon, its portfolio trajectory displayed noticeably larger fluctuations and higher volatility throughout the investment periods. This observation is consistent with the quantitative results in Table 3, where WOA obtained the highest annual return but also exhibited larger risk and maximum drawdown compared with HOA.

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

Algorithm	$V(t_{max})$	R_p	σ_p	SR	NSR	MDD	TC
ABC	12219.89	0.6584	0.2106	3.125369	3.094474	0.1689	0.006507
GWO	12227.45	0.6586	0.2107	3.124888	3.094033	0.1689	0.006501
FA	12407.77	0.6635	0.2123	3.124531	3.093428	0.1690	0.006603
HOA	12118.55	0.6556	0.2102	3.118687	3.087789	0.1688	0.006494
WOA	15248.91	0.7343	0.2369	3.098477	3.070948	0.1938	0.006522
PSO	12875.83	0.6760	0.2263	2.986569	2.958876	0.2157	0.006267
GA	7878.76	0.5176	0.2380	2.174144	2.152805	0.2260	0.005079
BA	6715.47	0.4694	0.2499	1.877953	1.855597	0.2609	0.005586
EWP	4031.84	0.3254	0.2684	1.211772	1.211772	0.3432	0.000000
NASDAQ	2049.90	0.1561	0.2295	0.679480	0.679480	0.3627	0.000000

Based on Table 3, the proposed HOA framework achieved a final portfolio value of \$12,118.55 with a total return of 1111.86% and an annual return of 65.56%. Furthermore, HOA obtained a SR of 3.118687 and a NSR of 3.087789, indicating strong risk-adjusted portfolio performance even after incorporating transaction costs. Compared with other algorithms, HOA demonstrated one of the best balances between return generation and portfolio risk control. In addition, HOA maintained a relatively small maximum drawdown of 16.88%. The obtained transaction cost value was also relatively small, indicating that the proposed framework successfully generated efficient portfolio reallocations without excessive trading activity.

In contrast, conventional MAs such as BA and GA generated considerably lower cumulative returns and inferior risk-adjusted performance. Although PSO and WOA achieved higher cumulative returns than HOA, both algorithms exhibited larger volatility and significantly higher maximum drawdown values. Meanwhile, EWP and NASDAQ-100 produced lower portfolio growth and SR values, highlighting the effectiveness of the proposed transaction cost-aware HOA framework for dynamic NASDAQ-100 portfolio optimization. Overall, the cumulative performance analysis confirms that HOA provides strong portfolio growth capability, stable convergence behavior, robust risk management, and competitive transaction cost efficiency under dynamic market environments.

4. Conclusion

This article proposes a transaction cost-aware portfolio optimization framework for NASDAQ-100 stocks using the HOA, where portfolio selection is formulated through a NSR that explicitly incorporates both risk and transaction costs. The empirical results demonstrate that HOA consistently delivers competitive and stable performance across all rebalancing periods from 2021 to 2025, outperforming or matching several well-established metaheuristic algorithms in terms of risk-adjusted returns, convergence stability, and robustness under varying market conditions. Although some competing methods achieve higher terminal portfolio values, they generally exhibit higher volatility and drawdown, whereas HOA maintains a more balanced trade-off between

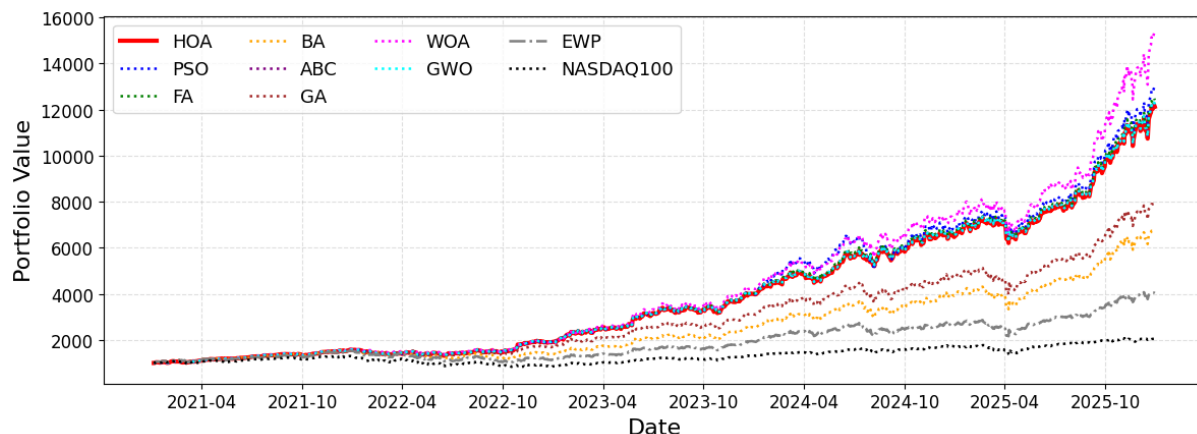


Fig. 3: Cumulative portfolio value between HOA and other metaheuristic algorithms from 2021 to 2025.

return, risk, and transaction cost efficiency. Overall, the findings confirm that HOA is an effective and robust optimization tool for dynamic portfolio allocation in realistic financial environments.

For future work, it is recommended that the current framework be extended toward multi-objective optimization to simultaneously capture return, risk, and transaction costs in a Pareto-based setting, while incorporating alternative risk measures such as CVaR or downside risk to better reflect tail behavior. In addition, adaptive transaction cost modeling that accounts for liquidity and market impact, as well as hybridization of HOA with local search or gradient-based refinement techniques, may further enhance solution quality and convergence efficiency. Finally, the proposed framework should be evaluated on broader asset classes, including cryptocurrencies and global multi-asset portfolios, to assess its generalizability and robustness across diverse market structures.

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.

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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 platform¹. 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 available from the corresponding author or the first author upon reasonable request. Requests for the research code and supplementary materials can be directed to: safrizal.braincore@gmail.com

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