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EMPIRICAL STUDY OF MULTI-OBJECTIVE RISK PORTFOLIO OPTIMIZATION BASED ON NSGA-II

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EMPIRICAL STUDY OF MULTI-OBJECTIVE RISK PORTFOLIO OPTIMIZATION BASED ON NSGA-II

ABSTRACT

The purpose of the article. The application of multi-objective optimization in portfolio management has gained significant attention in asset management. This study aims to uncover the potential advantages of dynamic portfolio optimization using a multi-objective genetic algorithm to address the challenges of ever-changing market conditions.

Methodology. By incorporating multi-objective optimization, this paper comprehensively examines three key portfolio objectives: minimizing two risk types and maximizing returns. The approach involves constructing portfolios, initializing the population using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and employing crossover and mutation steps to achieve Pareto optimality. Additionally, this study compares the performance of two risk minimization strategies through traditional portfolio backtesting.

Results of the research. The results indicate that the multi-objective risk genetic algorithm not only effectively explores the portfolio space but also handles conflicting optimization objectives, thereby enhancing the comprehensiveness and flexibility of investment decisions. However, its performance depended on the chosen risk measurement methods, and the backtesting returns were unstable.

Keywords: portfolio optimization, risk measure, multi-objective, NSGA-II, empirical study.

JEL Class: C52, C61, G11.

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INTRODUCTION

Portfolio optimization remains a critical task, requiring the effective allocation of asset weights to manage investments efficiently. Traditional portfolio optimization methods typically focus on a single objective, such as maximizing returns or minimizing risk (standard deviation). However, real-world investment scenarios often involve multiple conflicting objectives, rendering the complexity of multi-objective optimization beyond the capabilities of conventional single-objective approaches (Chiam et al., 2008).

The introduction of genetic algorithms (GA) has enabled addressing these complex issues. Nonetheless, research on applying non-dominated sorting genetic algorithm II (NSGA-II) to optimize under real market data and complex constraints still needs to be completed. Therefore, this paper aims to use NSGA-II for three-objective optimization and to compare these results with traditional minimum-risk optimization methods through backtesting using real data.

Based on this, the paper is organized as follows: Section 1 is the literature review, which provides a detailed discussion of the application of NSGA-II in portfolio optimization. Section 2 provides a concise overview of NSGA-II and details the multi-objective optimization process undertaken. Additionally, the risk measurement methods utilized in this study are described in detail. Furthermore, Section 3 presents and compares the optimization results obtained using real-world data. Finally, the work and findings are summarized in the conclusion.

1. LITERATURE REVIEW

The application of multi-objective genetic algorithms in portfolio optimization falls into three areas. First, improvements to the genetic algorithm itself, including modifications or the use of non-traditional parameters. Second, the hybridization of multiple algorithms for optimization. Lastly, empirical comparisons of optimization results were obtained using different algorithms. It is important to note that these three types of applications are not mutually exclusive and are often combined (Ertenlice and Kalayci, 2018).

For instance, Liu et al. (2017) integrated the affinity propagation algorithm to generate a set of portfolio candidates. They employed a genetic algorithm to optimize the Sharpe ratio-based objective function, achieving an optimal portfolio strategy with higher returns and lower risk. Lou (2023) introduced more refined selection strategies, dynamic mutation parameters, and initialization optimizations to the NSGA-II algorithm and used Monte Carlo Markov Chain (MCMC) to perform ten-year portfolio forecasts, resulting in enhanced outcomes. Similarly, Chen et al. (2018) utilized group balance and Sharpe ratio to identify

Pareto-optimal solutions. The screening of similar stocks within a group can also be carried out using the mixed K-value clustering method, which can mix multiple algorithms.

Pal et al. (2021) applied clustering and a variable-length NSGA-II for dynamic adjustments, with results indicating a higher return rate than the benchmark index. To address potential issues of nonlinearity and discontinuity in quadratic programming, Deb et al. (2011) coupled NSGA-II with clustering and local search procedures, improving the accuracy of the proposed method.

Comparing different algorithms' performance, applicability, and empirical effectiveness is also critical. Kaucic et al. (2019) observed that negatively skewed assets are prematurely excluded in cases of skewed and fat-tailed returns. Their results across five datasets indicate that the enhanced NSGA-II outperformed other methods. Similarly, Anagnostopoulos and Mamanis (2011) compared five evolutionary algorithms and tested the effectiveness of steady-state evolution in mean-variance optimization with cardinality constraints, finding that NSGA-II demonstrated strong performance and was well-suited for large-scale problems.

However, Mishra et al. (2009) found that multi-objective particle swarm optimization (MOPSO) outperformed NSGA-II, and indicator based evolutionary algorithm (IBEA) was shown to be closer to the actual Pareto front compared to NSGA-II (Bhagavatula et al., 2014). These findings suggest two possibilities: either NSGA-II may lag behind newer algorithms (Liagkouras and Metaxiotis, 2018), or the empirical results produced by NSGA-II may be unstable (Fortin and Parizeau, 2013).

Evaluating NSGA-II under realistic data and constraints is essential, as strategies and objectives greatly influence outcomes. Yang (2006) noted that in multi-objective models, uncertainty reduces risk tolerance and stabilizes portfolio weights, creating a preventive effect. Macedo et al. (2017) found that using technical indicators with trading strategies impacts the efficient frontier, optimizing asset allocation and enhancing robustness against transaction costs and market shifts. Meanwhile, broader constraints, such as cardinality and budget limits, should be addressed while highlighting transaction costs and estimation errors as critical challenges in portfolio optimization and rebalancing (Meghwani and Thakur, 2017).

2. METHODOLOGY

The methodology section introduces the risk measurement methods and portfolio optimization techniques. Finally, this research presents the NSGA-II algorithm, outlining its process and key concepts. This section discusses the standard deviation as a measure of risk, which measures the dispersion of data points relative to the mean (Markowitz, 1952). The formula is as follows:

$$\sigma_{ij} = cov(R_i, R_j), \tag{1}$$

$$\sigma_p = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}}, \tag{2}$$

where:
the portfolio consists of n assets;
σ_{ij} is the covariance of the return R_i and R_j;
σ_p is the standard deviation of the portfolio;
w_i is the weight of each asset i;
w_j is the weight of each asset j.

Next, Conditional Value at Risk (CVaR) is the average potential loss exceeding the Value at Risk (VaR) at a given significance level, providing a more comprehensive measure of extreme risk. The formula is shown in Equation (4):

$$VaR_\alpha = inf\{x \in \mathbb{R}: P(L \geq x) \leq \alpha\}, \tag{3}$$

$$CVaR_\alpha = \frac{1}{\alpha} \int_{VaR_\alpha}^{\infty} L\, f(L) dL\,, \tag{4}$$

where:
inf means the lower bound;
Let L be the random variable representing portfolio loss;
α denote the significance level, 5% in this paper;
the function $f(L)$ represents the probability density function of the loss L.

According to the two risk measurement methods mentioned above, this study can construct a three-objective portfolio based on the two risk measure methods, as illustrated in Equation (5):

$$\begin{aligned} Objective\text{:} \quad & Max \quad \mu_p = \sum_{i=1}^{n} w_i \mu_i\,, \\ & Min \quad \sigma_p, \\ & Min \quad CVaR_\alpha, \\ Subject\ to\text{:} \quad & \sum_{i=1}^{n} w_i = 1\,, \\ & w_i \geq 0, \qquad i = 1, 2, \ldots, n, \end{aligned} \tag{5}$$

where:
μ_p is the expected return of the portfolio;
μ_i is the expected return of a single asset.

The formula is analogous to traditional portfolio optimization methods. In subsequent comparisons, this study will construct portfolios with a single risk to obtain the results of backtested cumulative returns. Next, this section will introduce the NSGA-II. Figure 1 provides its pseudocode to illustrate the overall process.

Algorithm 3 NSGA-II algorithm

procedure NSGA-II($\mathcal{N}', g, f_k(\mathbf{x}_k)$) ▷ $\mathcal{N}'$ members evolved g generations to solve $f_k(\mathbf{x})$
  Initialize Population $\mathbb{P}'$
  Generate random population - size $\mathcal{N}'$
  Evaluate Objective Values
  Assign Rank (level) Based on Pareto dominance - *sort*
  Generate Child Population
    Binary Tournament Selection
    Recombination and Mutation
  for $i = 1$ to g **do**
    for each Parent and Child in Population **do**
      Assign Rank (level) based on Pareto - *sort*
      Generate sets of nondominated vectors along PF_{known}
      Loop (inside) by adding solutions to next generation starting from the *first* front until $\mathcal{N}'$ individuals found determine crowding distance between points on each front
    end for
    Select points (elitist) on the lower front (with lower rank) and are outside a crowding distance
    Create next generation
      Binary Tournament Selection
      Recombination and Mutation
  end for
end procedure

Figure 1. NSGA-II pseudo code diagram

Source: Coello et al. (2007: 93).

Figure 1 illustrates the pseudocode of the NSGA-II, an algorithm designed to optimize multiple objectives through several key steps. Initially, the algorithm generates an initial population and evaluates the objective function values for each individual. Next, it ranks the individuals using non-dominated sorting and calculates the crowding distance. The algorithm then employs binary tournament selection to choose parents for crossover and mutation operations. Subsequently, the parent and offspring populations are merged, followed by non-dominated sorting, to select the best individuals for the next generation based on Pareto ranking and crowding distance. This process is repeated until a specified number of generations is reached, resulting in a set of near-optimal non-dominated solutions.

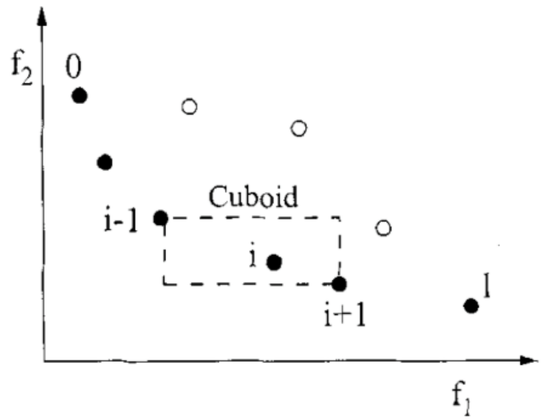

Figure 2. Illustration of crowding distance calculation

Source: Deb et al. (2002: 185).

Figure 2 illustrates how crowding distance helps maintain solution diversity. From a geometric perspective, the figure demonstrates how the algorithm calculates crowding distance based on differences in objective values within a two-dimensional objective space. Using two objective functions as an example, the black and white dots in the figure represent two non-dominated fronts. For a given solution i, the crowding distance is estimated by calculating the differences in objectives between this solution and its nearest neighbors $i-1$ and $i+1$ within the same non-dominated front. This distance metric reflects the density of solutions around i. It aids the algorithm in distributing selected solutions evenly along the Pareto front, thereby avoiding convergence to a narrow region and preserving solution diversity.

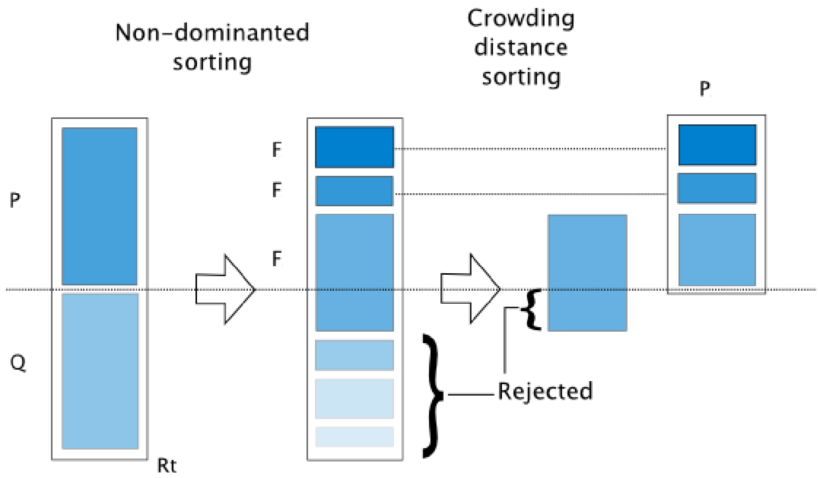

Figure 3. Illustration of elite sorting strategy

Source: Deb et al. (2002: 186).

Figure 3 illustrates the selection process in the NSGA-II algorithm, highlighting the critical roles of elitism and crowding distance in the optimization process. The initial population is merged with the offspring population Q_0, resulting in a combined population of size $2N$. The algorithm first applies fast, non-dominated sorting to this combined population, dividing it into multiple fronts and calculating the crowding distance for each individual. Priority is given to selecting individuals from the first front, representing optimal Pareto solutions.

If the required number of individuals still needs to be chosen, the algorithm selects from subsequent fronts. To ensure diversity in the solution space, individuals within the same front are chosen based on their crowding distance, providing a wide distribution across the objective space. This selection strategy enables NSGA-II to explore the solution space effectively while identifying solutions close to the global optimum.

After constructing a portfolio, evaluating the risk-return profile of the investment strategy using several key performance metrics is essential (Zhou et al., 2022). Among these, the Sharpe ratio, Sortino ratio, Maximum Drawdown (MDD), and Calmar ratio are widely recognized for their effectiveness in capturing different performance dimensions. Their respective calculation methods are detailed in Equations (6–9).

MDD is a measure of the largest peak-to-trough decline in portfolio value during a given period, reflecting the worst-case loss an investor could face (Almahdi and Yang, 2017). It is defined as:

$$MDD = max\left|\frac{V_t - V_{peak}}{V_{peak}}\right|, \tag{6}$$

where:
V_t is the portfolio value at time t;
V_{peak} is the highest portfolio value observed up to t.

A lower MDD indicates better capital preservation. For simplicity, the risk-free rate is considered as the minimum expected return. The formulas for the performance ratios share a similar structure:

$$Sharpe = \frac{R_p - R_f}{\sigma_p}, \tag{7}$$

$$Calmar = \frac{R_p - R_f}{MDD}, \tag{8}$$

$$Sortino = \frac{R_p - R_f}{\sigma_p^-}, \tag{9}$$

where:
R_p is the portfolio return;
R_f is the risk-free rate;
$R_p - R_f$ is the excess return;
σ_p is the portfolio standard deviation;
σ_p^- is the portfolio semi-deviation.

The Sharpe ratio, Calmar ratio, and Sortino ratio are essential indicators for evaluating the risk-adjusted performance of a portfolio. The Sharpe ratio assesses a portfolio's efficiency by comparing its excess return to total risk, offering a comprehensive view of risk-adjusted returns. The Calmar ratio focuses on the relationship between excess return and MDD, emphasizing the portfolio's ability to generate returns while minimizing the risk of significant capital loss. Meanwhile, the Sortino ratio refines the Sharpe ratio by isolating downside risk-returns falling below a specified target – providing a more targeted evaluation of risk relative to adverse outcomes.

3. EMPIRICAL RESULTS

To simplify the complexity of the application and enhance practical feasibility, this research performs the optimization using the NSGA-II framework implemented in the Pymoo library (Blank and Deb, 2020). The optimization utilizes daily data of Dow Jones Industrial Average (DJIA) constituent stocks from January 1, 2018 to December 31, 2023. To maintain ease of use, this study used the default optimization parameters provided by Pymoo, except for setting the population size to 200 and the number of generations to 600. The risk-free rate is set to 2%.

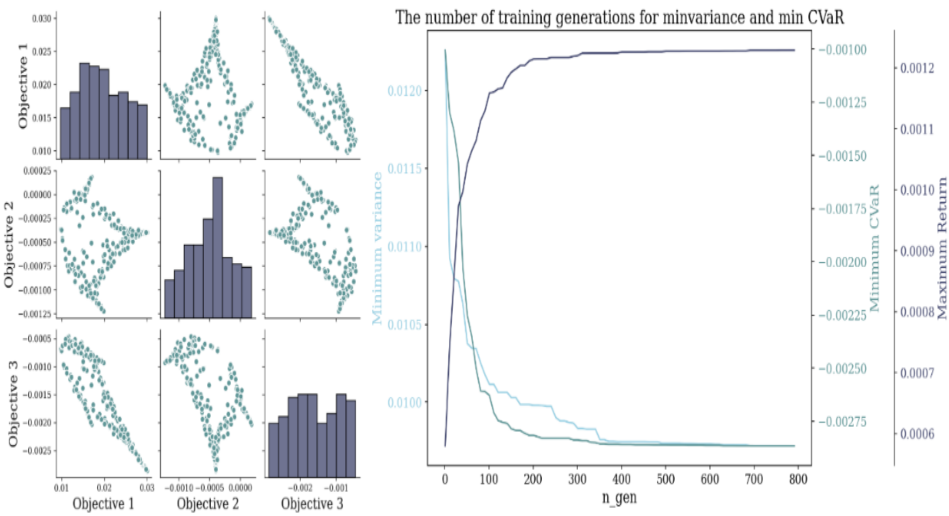

Figure 4. NSGA-II and Monte Carlo portfolio optimization results

Source: derived from calculations.

Subplot 1 displays scatter plots of Pareto optimal solutions obtained from NSGA-II for various objectives in Figure 4. The diagonal histograms represent the density distributions of each objective's values. The observed dispersion reflects the complexity of real data, which prevents perfect optimization and results in the selection of relatively superior points.

Subplot 2 illustrates the stabilization of minimum variance and minimum CVaR after about 600 iterations, indicating convergence. This stabilization provides a solid foundation for comparing NSGA-II with traditional methods, ensuring the results are well-validated for assessing its relative performance.

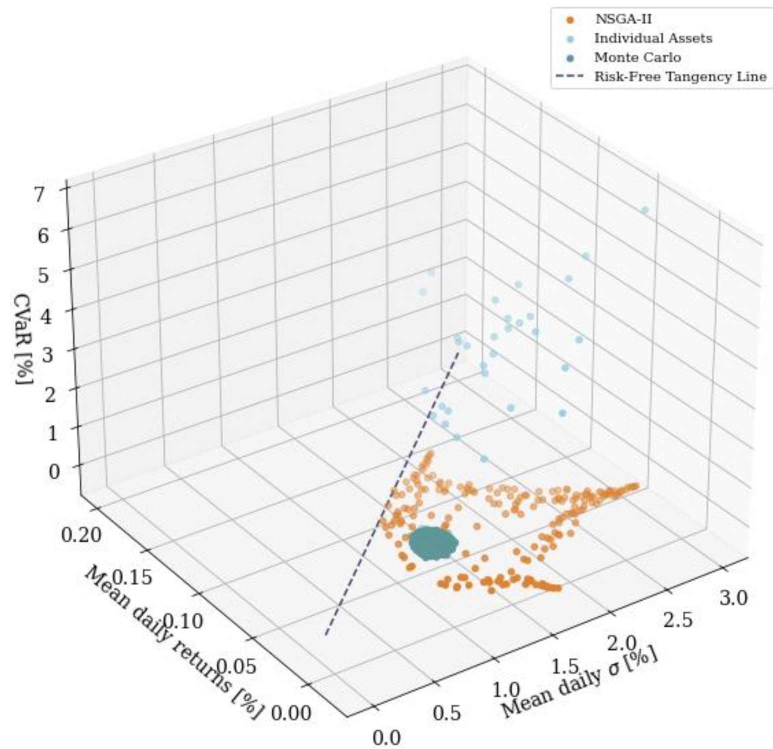

Figure 5. NSGA-II and Monte Carlo portfolio optimization results

Source: derived from calculations.

As shown in Figure 5, the Pareto optimal solution set obtained from NSGA-II demonstrates significantly greater expansiveness than the 100,000 Monte Carlo simulations. This indicates that NSGA-II explores a broader solution space to identify higher-quality, non-dominated solutions and more effectively balances multiple conflicting objectives while handling complex constraints. Consequently, NSGA-II offers a more comprehensive and precise approach to portfolio optimization. Next, the portfolio optimization backtest results are shown in Figure 6.

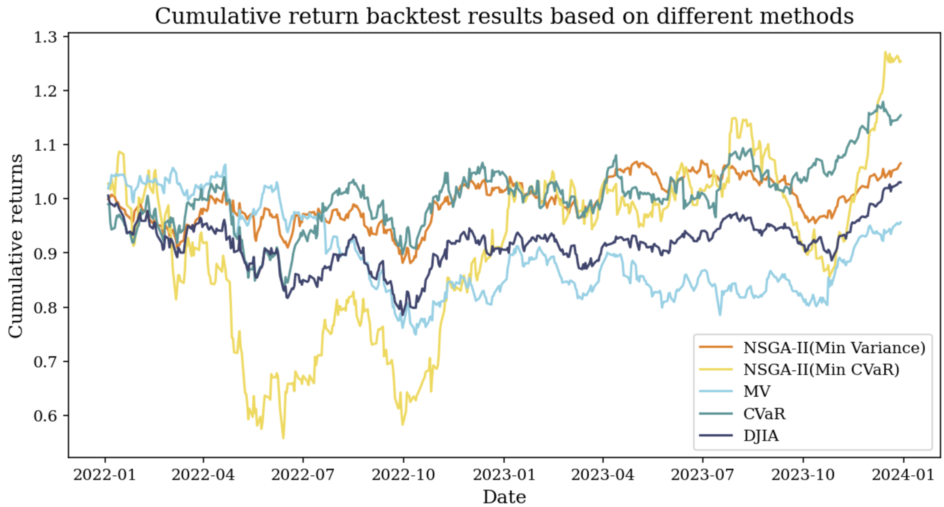

Figure 6. Cumulative return backtest results based on different methods

Source: derived from calculations.

As shown in Figure 6, the constructed portfolios remained relatively stable throughout the backtesting period. The NSGA-II portfolios consistently outperformed the index, particularly those optimized for minimum variance and traditional minimum CVaR. However, the NSGA-II portfolio optimized for minimum CVaR experienced relatively large fluctuations and underwent three significant drawdowns. On the other hand, the classical minimum variance portfolio failed to surpass the index for consecutive 14 months, maintaining negative returns. This indicates that portfolios constructed using traditional methods may have limited ability to sustain returns, and achieving optimal results may require selecting the optimization method based on the chosen risk measure. The performance of each portfolio can be seen in Table 1.

Table 1. Performance table for evaluating different portfolios

Portfolio	Cum	Mean	Sharpe	Calmar	Sortino	MDD
MV	0.956	-0.004	-0.125	-0.081	-0.206	0.295
CVaR	1.212	0.126	0.439	0.376	0.694	0.283
NSGA-II(MV)	1.061	0.038	0.141	0.141	0.244	0.130
NSGA-II(CVaR)	1.254	0.187	0.438	0.343	0.707	0.487
DJIA	1.030	0.028	0.050	0.037	0.083	0.219

Note: Cum represents the cumulative return, Mean refers to the average daily annualized return, and MDD denotes the maximum drawdown.

Source: derived from calculations.

Table 1 presents the key performance metrics for several portfolios. Except for the MV portfolio, the optimized portfolios outperform the benchmark index across most indicators. However, the two CVaR-based portfolios exhibit greater MDD, indicating significant capital losses during specific periods. Notably, the Sortino ratio, which accounts for downside risk, is the highest among all portfolios, underscoring their robust risk-adjusted performance. Despite the higher drawdown, the superior performance of the NSGA-II (CVaR) portfolio across other metrics makes it the most attractive option overall.

In contrast, the classical MV portfolio demonstrates a maximum drawdown of 0.295, indicating insufficient risk management. Its other performance significantly needs to catch up to the other optimized portfolios, with returns failing to justify the level of risk undertaken. Therefore, the MV portfolio is not a favorable choice, particularly in high-risk contexts, where its inadequate returns highlight its inefficiency. These findings suggest that while the NSGA-II (CVaR) portfolio exhibits specific vulnerabilities in capital preservation, its overall performance renders it the most compelling option for portfolio selection.

DISCUSSION

This study provides a significant value by integrating the NSGA-II algorithm into portfolio optimization, showcasing its potential to balance conflicting objectives such as risk and return. By comparing traditional minimum CVaR optimization with multi-objective approaches, the research highlights how advanced algorithms can improve portfolio performance and expand the scope of risk management strategies. However, the study has notable limitations, including its reliance on historical data and the assumption of market stationarity, which may not fully capture future market dynamics.

The instability of the NSGA-II portfolio optimized for minimum CVaR during the backtesting process might stem from the algorithm's reliance on historical data and its tendency to prioritize short-term performance trade-offs. NSGA-II's stochastic nature, while beneficial for exploring diverse solutions, may introduce noise, leading to suboptimal selections under certain market conditions.

By contrast, traditional minimum CVaR optimization directly minimizes extreme losses, offering more consistent risk management, albeit at the expense of flexibility. This raises the question of whether NSGA-II's exploratory capabilities can be adjusted or augmented–such as integrating robust optimization techniques–to mitigate instability while maintaining its innovative strengths.

Future research could delve into the underlying algorithmic mechanisms driving these differences, particularly under varying market conditions. Additionally, it would be valuable to incorporate considerations such as transaction costs or liquidity constraints, or to explore alternative optimization objectives to enhance portfolio performance.

CONCLUSIONS

This paper used NSGA-II for multi-objective optimization with different risk measures and compared the results with traditional backtesting methods. The findings indicate that the Pareto solutions obtained through NSGA-II have a relative advantage over those from Monte Carlo methods. However, the cumulative returns from backtesting depend on the chosen risk measures. This suggests that multi-objective optimization is feasible in empirical tests, but further evaluation metrics for the portfolio must be considered.

Additionally, this study observed that the results of multi-objective algorithms may vary with parameter adjustments, indicating potential instability in cumulative returns during empirical testing. Another concern is how long the optimized portfolio can maintain relatively stable returns, implying that the holding period of the portfolio requires careful consideration.

The findings of this study provide valuable insights for empirical portfolio optimization and highlight several issues that need attention. Although multi-objective optimization and NSGA-II have been extensively studied, further empirical evidence may be necessary to ensure their consistent ability to maintain low-risk levels and generate returns in real-world scenarios.

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DISCLOSURE STATEMENT

The authors report no conflicts of interest.

BIBLIOGRAPHY

Almahdi, S. and Yang, S. Y. (2017). *An adaptive portfolio trading system: A risk-return portfolio optimization using recurrent reinforcement learning with expected maximum drawdown.* Expert Systems with Applications, 87, pp. 267–279. https://doi.org/10.1016/j.eswa.2017.06.023.

Anagnostopoulos, K. P. and Mamanis, G. (2011). *The mean–variance cardinality constrained portfolio optimization problem: An experimental evaluation of five multiobjective evolutionary algorithms*. Expert Systems with Applications, 38(11). https://doi.org/10.1016/j.eswa.2011.04.233.

Bhagavatula, S. S., Sanjeevi, S. G., Kumar, D. and Yadav, C. K. (2014). *Multi-objective indicator based evolutionary algorithm for portfolio optimization*. IEEE International Advance Computing Conference (IACC), https://doi.org/10.1109/IAdCC.2014.6779499.

Blank, J. and Deb, K. (2020). *Pymoo: Multi-Objective Optimization in Python*. IEEE Access, 8, pp. 89497–89509. IEEE Access. https://doi.org/10.1109/ACCESS.2020.2990567.

Chen, C.-H., Chiang, B.-Y. and Hong, T.-P. (2018). *An Approach for Optimizing Group Stock Portfolio Using Multi-Objective Genetic Algorithm*. 5th International Conference on Behavioral, Economic, and Socio-Cultural Computing (BESC), pp. 213–215. https://doi.org/10.1109/BESC.2018.8697275.

Chiam, S. C., Tan, K. C. and Al Mamum, A. (2008). *Evolutionary multi-objective portfolio optimization in practical context*. International Journal of Automation and Computing, 5(1), pp. 67–80. https://doi.org/10.1007/s11633-008-0067-2.

Coello, C. A. C., Lamont, G. B. and Veldhuizen, D. A. V. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems*. Genetic and Evolutionary Computation Series. Springer US. https://doi.org/10.1007/978-0-387-36797-2.

Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T. (2002). *A fast and elitist multiobjective genetic algorithm: NSGA-II*. IEEE Transactions on Evolutionary Computation, 6(2), pp. 182–197. https://doi.org/10.1109/4235.996017.

Deb, K., Steuer, R. E., Tewari, R. and Tewari, R. (2011). *Bi-objective Portfolio Optimization Using a Customized Hybrid NSGA-II Procedure*. Evolutionary Multi-Criterion Optimization, pp. 358–373. https://doi.org/10.1007/978-3-642-19893-9_25.

Ertenlice, O. and Kalayci, C. B. (2018). *A survey of swarm intelligence for portfolio optimization: Algorithms and applications*. Swarm and Evolutionary Computation, 39, pp. 36–52. https://doi.org/10.1016/j.swevo.2018.01.009.

Fortin, F-A. and Parizeau, M. (2013). *Revisiting the NSGA-II crowding-distance computation*. Proceedings of the 15th Annual Conference on Genetic and Evolutionary Computation, pp. 623–630. https://doi.org/10.1145/2463372.2463456.

Kaucic, M., Moradi, M. and Mirzazadeh, M. (2019). *Portfolio optimization by improved NSGA-II and SPEA 2 based on different risk measures. Financial Innovation, 5(1),* https://doi.org/10.1186/s40854-019-0140-6.

Liagkouras, K. and Metaxiotis, K. (2018). *Handling the complexities of the multi-constrained portfolio optimization problem with the support of a novel MOEA*. Journal of the Operational Research Society, 69(10), pp. 1609–1627. https://doi.org/10.1057/s41274-017-0209-4.

Liu, C., Gan, W. and Chen, Y. (2017). *Research on Portfolio Optimization Based on Affinity Propagation and Genetic Algorithm*. 14th Web Information Systems and Applications Conference (WISA), pp. 122–126. https://doi.org/10.1109/WISA.2017.9.

Lou, K. (2023). *Optimizing Portfolios with Modified NSGA-II Solutions*. 2023 IEEE 3rd International Conference on Data Science and Computer Application (ICDSCA), pp. 375–380. https://doi.org/10.1109/ICDSCA59871.2023.10393316.

Macedo, L. L., Godinho, P. and Alves, M. J. (2017). *Mean-semivariance portfolio optimization with multiobjective evolutionary algorithms and technical analysis rules*. Expert Systems with Applications, 79, pp. 33–43. https://doi.org/10.1016/j.eswa.2017.02.033.

Markowitz, H. (1952). *Portfolio Selection*. The Journal of Finance, 7(1), pp. 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x.

Meghwani, S. S. and Thakur, M. (2017). *Multi-criteria algorithms for portfolio optimization under practical constraints*. Swarm and Evolutionary Computation, 37, pp. 104–125. https://doi.org/10.1016/j.swevo.2017.06.005.

Mishra, S. K., Panda, G. and Meher, S. (2009). *Multi-objective particle swarm optimization approach to portfolio optimization*. World Congress on Nature & Biologically Inspired Computing (NaBIC), pp. 1612–1615. https://doi.org/10.1109/NABIC.2009.5393659.

Pal, R., Chaudhuri, T. D. and Mukhopadhyay, S. (2021). *Portfolio formation and optimization with continuous realignment: A suggested method for choosing the best portfolio of stocks using variable length NSGA-II*. Expert Systems with Applications, 186. https://doi.org/10.1016/j.eswa.2021.115732.

Yang, X. (2006). *Improving Portfolio Efficiency: A Genetic Algorithm Approach*. Computational Economics, 28(1), pp. 1–14. https://doi.org/10.1007/s10614-006-9021-y.

Zhou, Y., Chen, W. and Lin, D. (2022). *Design of Optimum Portfolio Scheme Based on Improved NSGA-II Algorithm*. Computational Intelligence and Neuroscience, https://doi.org/10.1155/2022/7419500.

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