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Lightweight Optimization of Investment Portfolios: An Empirical Study Based on the SPEA2 Multi-Objective Evolutionary Algorithm

Hamid Moharami[1], **Malihe Danesh**[1,*]

[1] Department of Science and Technology of Mazandaran, Behshahr, Iran; hamid.moharami@mazust.ac.ir; m.danesh@mazust.ac.ir.

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Abstract

Portfolio optimization is a classical yet computationally complex problem in computational finance, particularly when multiple conflicting objectives, such as maximizing return and controlling investment risk, are considered simultaneously. Many existing evolutionary and interactive optimization approaches can generate high-quality portfolio solutions; however, their long runtime and high computational cost limit their practical use in resource-constrained or time-sensitive decision-making environments. This paper presents a lightweight portfolio optimization framework that reduces computational complexity by deliberately limiting the search space through the selection of a small but representative set of assets. The proposed framework employs the Strength Pareto Evolutionary Algorithm 2 (SPEA2) as the main optimization engine, owing to its Pareto-based selection mechanism and external archive structure, which support effective convergence while maintaining lower computational overhead. Experiments were conducted on a dataset consisting of 14 selected stocks over a monthly investment horizon. The performance of SPEA2 was compared with the widely used Non-dominated Sorting Genetic Algorithm II (NSGA-II) under identical experimental settings. The results show that SPEA2 achieved a final portfolio value of $1,847,560.42, compared with $1,775,711.48 for NSGA-II. In addition, SPEA2 completed the optimization process in 8,041 seconds, whereas NSGA-II required 160,809.30 seconds, making SPEA2 approximately 20 times faster. The combined time-return efficiency also favored SPEA2, with a profit of $105.46 per second compared with $4.82 for NSGA-II. These findings indicate that SPEA2, when combined with controlled dimensionality reduction, can provide a practical and efficient approach for portfolio optimization under computational and time constraints.

Keywords: Portfolio optimization, Multi-objective evolutionary algorithms, Strength Pareto Evolutionary Algorithm 2, Non-dominated Sorting Genetic Algorithm II.

1 | Introduction

Portfolio optimization has been recognized as a fundamental problem in financial economics since the introduction of the classical Markowitz mean–variance model [1]. This model provided an analytical

Corresponding Author: m.danesh@mazust.ac.ir

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framework for balancing expected return and risk and became the foundation for a large body of subsequent research. However, the increasing complexity of financial markets, the growth of data dimensions, and the emergence of various practical constraints have gradually reduced the effectiveness of classical analytical methods in dealing with nonlinear constraints, conflicting objectives, and uncertainty.

In response to these limitations, multi-objective optimization has emerged as a suitable approach for financial problems, and several theoretical frameworks have been developed in this area [2]. Among these approaches, multi-objective evolutionary algorithms have gained a prominent position in solving portfolio optimization problems due to their flexibility and ability to search effectively in large decision spaces. The Non-dominated Sorting Genetic Algorithm II (NSGA-II), one of the most widely used methods, has been employed in many studies due to its fast convergence and elitism mechanism [3]. Alongside NSGA-II, the Strength Pareto Evolutionary Algorithm 2 (SPEA2), which relies on Pareto strength and an external archive, has been proposed as an efficient alternative [4].

In recent years, some studies have focused on interactive evolutionary frameworks based on decision-makers' preferences to improve the quality of optimal portfolios. One such approach is the EvoFolio framework, which has reported promising results in terms of solution quality [5]. Nevertheless, the high computational cost and long runtime of these methods create challenges for their practical application in real-world scenarios with limited resources.

Despite these advances, many existing studies have primarily focused on solution quality, while computational efficiency and runtime have received less systematic attention. The objective of this paper is to present and evaluate a computationally efficient approach for investment portfolio optimization that significantly reduces runtime while preserving solution quality. To this end, this study focuses on the use of the SPEA2 multi-objective evolutionary algorithm and examines its performance within a specific empirical framework using a limited but representative set of assets, with particular emphasis on computational efficiency.

2 | Literature Review

Early research on portfolio optimization was largely based on the Markowitz mean–variance model, which introduced a formal analytical framework for balancing expected return and investment risk [1]. Although this model remains a cornerstone of modern portfolio theory, its practical application is limited by several factors, including restrictive assumptions, sensitivity to parameter estimation, and difficulty in handling nonlinear constraints and complex market conditions. These limitations have encouraged the use of interactive, evolutionary, and multi-objective optimization approaches for financial decision-making problems [2].

Within this line of research, multi-objective evolutionary algorithms have been widely applied to portfolio optimization because of their flexibility and ability to explore large and complex decision spaces. Algorithms such as NSGA-II and SPEA2 have been used to approximate Pareto-based solution sets, allowing decision-makers to examine different trade-offs between return and risk under conflicting objectives [3], [4]. More recent evolutionary portfolio optimization frameworks, such as EvoFolio, have further demonstrated the potential of multi-objective evolutionary algorithms for generating diversified and competitive portfolio solutions [5]. In addition, broader studies on evolutionary multi-objective optimization and multicriteria optimization provide the theoretical foundation for applying these methods to complex financial problems [6], [7].

Much of the existing literature has focused on improving the quality of the obtained Pareto front, convergence behavior, and diversity among non-dominated solutions. Accordingly, performance evaluation has often relied on indicators such as hypervolume, crowding distance, and other criteria designed to assess the structure and quality of the solution set [8]. While these criteria are important for evaluating optimization performance, they do not fully capture the computational practicality of an algorithm, especially in applications where runtime and resource consumption are critical.

In portfolio optimization and related financial applications, multi-objective evolutionary algorithms have been extensively studied because they can handle conflicting objectives, complex constraints, and large search spaces more effectively than many classical analytical approaches [9]. At the same time, the integration of machine learning and deep learning models into portfolio optimization has created new opportunities for improving return prediction, risk estimation, and adaptive asset allocation [10]. However, these advanced approaches often introduce additional model complexity, parameter tuning requirements, and computational overhead.

Recent studies have continued this trend by applying more advanced optimization and learning-based frameworks to portfolio management. For example, NSGA-III and parallel NSGA-III have been used to address multi-objective and multi-period portfolio optimization problems under more realistic investment constraints [11], [12]. Other studies have proposed deep reinforcement learning, supervised learning with attention mechanisms, and machine learning-based asset allocation frameworks to improve portfolio performance and support adaptive decision-making under changing market conditions [13–15]. Although these approaches can improve solution quality and flexibility, their increased methodological complexity may also lead to longer execution times and higher resource requirements, which can limit their practical use in real-world investment environments where timely decisions are required.

Overall, the literature indicates that considerable progress has been made in improving the quality, diversity, and adaptability of optimized portfolios. However, computational efficiency and runtime have received comparatively less attention as independent and practically important evaluation criteria. Recent runtime analysis studies on evolutionary multi-objective algorithms further highlight that algorithmic design choices can significantly influence computational effort and scalability [16]. This gap is particularly relevant for portfolio management applications that operate under time or resource constraints. Therefore, further research is needed on lightweight optimization frameworks that can reduce computational overhead while maintaining an acceptable balance between solution quality, runtime efficiency, and implementation feasibility.

3 | Research Methodology

Fig. 1 illustrates the overall framework proposed in this study. The process begins with the selection of 14 liquid and market-important stocks in order to reduce the dimensionality of the portfolio optimization problem. After organizing the historical price data, monthly asset returns are calculated and prepared as comparable inputs for both algorithms. The portfolio optimization problem is then formulated as a multi-objective problem based on the mean–variance framework, with the simultaneous objectives of maximizing expected return and minimizing portfolio risk under standard allocation constraints.

Under identical experimental settings, including an initial capital of $1,000,000, a population size of 250, 50 generations, and a monthly investment horizon, the SPEA2 algorithm is implemented as the main proposed method, while NSGA-II is used as a benchmark method. Finally, the optimized portfolios are evaluated and compared using financial performance indicators and computational efficiency measures, including final portfolio value, net profit, return percentage, runtime, speed ratio, and time-return efficiency. This framework provides a structured basis for assessing the effectiveness and practicality of the proposed lightweight optimization approach.

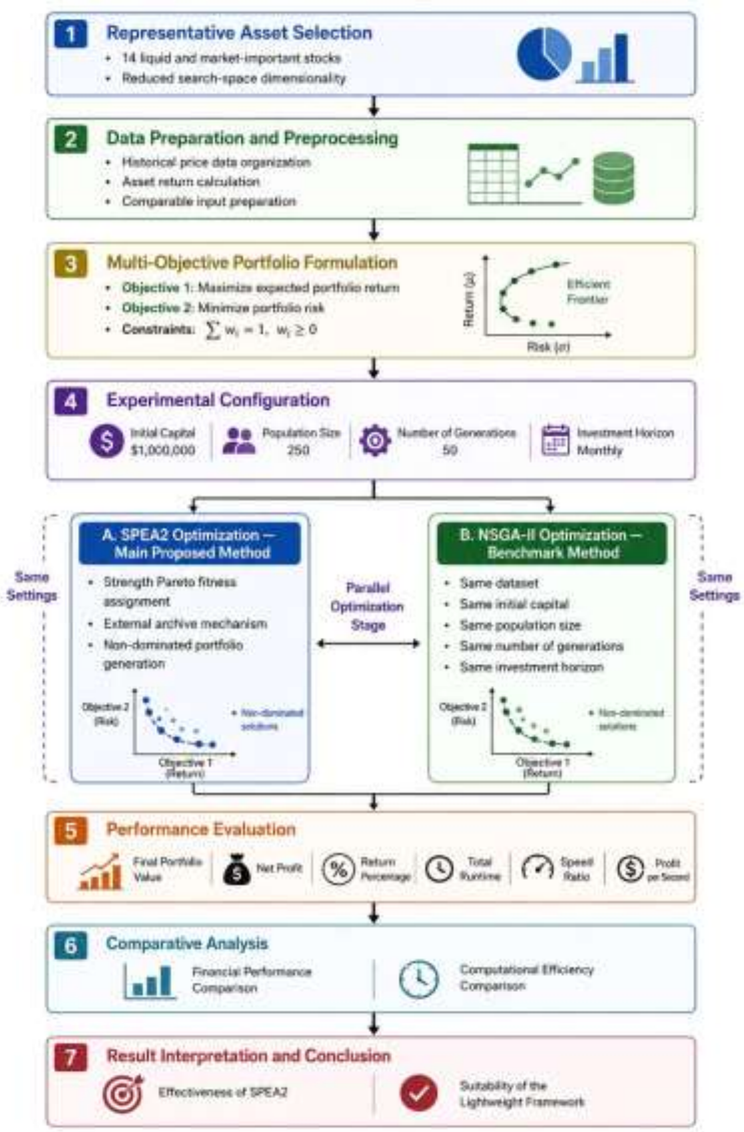

Fig. 1. Overall framework of the proposed method.

3.1 | Portfolio Optimization Problem

In this study, the portfolio optimization problem is formulated as a multi-objective optimization problem based on the classical Markowitz mean–variance framework [1]. The main objective is to identify portfolio allocations that provide a desirable trade-off between expected return and investment risk. In this setting, return maximization and risk minimization are treated as conflicting objectives, meaning that improving one objective may lead to a deterioration in the other. Therefore, a multi-objective evolutionary approach is appropriate for exploring alternative portfolio solutions and identifying non-dominated allocations.

3.2 | Dimensionality Reduction

Unlike many previous studies that employ large asset universes to increase portfolio diversity, this study focuses on a selected set of 14 stocks with high liquidity and market importance. This selection is consistent with the lightweight optimization perspective adopted in this research. By reducing the number of candidate assets, the dimensionality of the search space is directly decreased, which can lower the computational burden of the evolutionary optimization process.

The deliberate use of a limited but representative asset set is intended to improve computational efficiency without completely sacrificing the practical relevance of the portfolio construction process. From this perspective, dimensionality reduction is not treated merely as a data simplification step, but as a core component of the proposed lightweight optimization framework. This approach is particularly relevant in investment environments where computational resources are limited or where portfolio decisions need to be generated within a shorter time.

In this study, the SPEA2 is used as the main portfolio optimization method. The NSGA-II is also implemented as a reference method to evaluate the relative performance and computational efficiency of SPEA2 under identical experimental conditions.

3.3 | Data Description and Preprocessing

The experimental dataset consists of 14 selected stocks chosen based on liquidity and market importance. The use of a limited but representative set of assets supports the main objective of this study, which is to examine whether a lightweight evolutionary optimization framework can reduce computational cost while maintaining competitive portfolio performance.

The investment horizon was defined monthly. Monthly observations were used to evaluate the behavior of the optimized portfolios over time and to compare the performance of SPEA2 and NSGA-II under the same temporal conditions. Before running the optimization process, the available price data were organized in a structured format so that each asset was consistently represented across all investment periods. This preprocessing step ensured that both algorithms received the same input data and that the comparison was not affected by inconsistencies in the dataset.

The initial capital was fixed at $1,000,000 for both algorithms. Portfolio values and gains were calculated using the allocation weights generated by each algorithm and the corresponding asset returns over the monthly horizon. Since the purpose of this study is to evaluate computational efficiency within a lightweight optimization setting, the preprocessing stage focused on preparing a clean, comparable input structure rather than expanding the asset universe or incorporating additional market assumptions.

This procedure provided a consistent basis for evaluating financial outputs, runtime, and combined time-return efficiency. As a result, the observed differences between SPEA2 and NSGA-II can be interpreted as differences arising from their optimization behavior rather than from variations in input data or experimental setup.

3.4 | Objective Functions and Constraints

Each candidate portfolio is represented by a vector of asset allocation weights. Each weight indicates the proportion of the initial capital assigned to a specific asset. For a portfolio consisting of n assets, the weight vector is defined as *Eq. (1)*:

$$w = (w_1, w_2, \ldots, w_n,), \tag{1}$$

where w_i denotes the investment weight assigned to asset i, and n represents the total number of selected assets. In this study, n =14.

The first objective is to maximize the expected portfolio return. The expected return of a portfolio is calculated as the weighted sum of the expected returns of its constituent assets:

$$R_P = \sum W_i r_i, \tag{2}$$

where R_p represents the expected portfolio return, w_i is the weight assigned to asset i, and r_i denotes the expected return of asset i. As shown in *Eq. (1)*, the expected return of the portfolio is obtained as the weighted average of the expected returns of the constituent assets. The second objective is to minimize investment risk. In the classical mean–variance framework, portfolio risk is commonly represented by the variance or standard deviation of portfolio returns. Accordingly, the portfolio variance is expressed as *Eq. (3)*:

$$\sigma_p^2 = w^T \sum w, \quad (3)$$

where σ_p^2 denotes the portfolio variance, w is the vector of asset weights, and Σ represents the covariance matrix of asset returns.

Therefore, the portfolio optimization problem in this study is treated as a multi-objective problem with two conflicting objectives: Maximizing expected return and minimizing portfolio risk. These objectives reflect the fundamental trade-off in investment decision-making, where portfolios with higher expected returns may also involve higher levels of risk.

The optimization process is subject to standard portfolio allocation constraints. Specifically, the portfolio weights are required to satisfy $\sum_{i=1}^{n} w_i = 1$, ensuring that the entire initial capital is allocated among the selected assets. Furthermore, all portfolio weights must be non-negative $(w_i \geq 0, i - 1,2,...,n)$, indicating that short selling is not allowed in the experimental setting. Consequently, each generated portfolio represents a feasible long-only investment allocation among the selected assets.

These objective functions and constraints define the feasible search space explored by SPEA2 and NSGA-II. Since the same mathematical formulation and constraints are applied to both algorithms, the experimental comparison focuses on their optimization behavior, financial outputs, and computational efficiency under identical portfolio construction conditions.

3.5 | Algorithm Configuration

To ensure a fair comparison between the SPEA2-based framework and the reference NSGA-II algorithm, both algorithms were implemented under identical experimental settings. The same dataset, investment horizon, number of assets, initial capital, population size, and number of evolutionary generations were used for both methods. This configuration made it possible to compare the algorithms based on their optimization behavior rather than differences in experimental design.

The population size was set to 250 individuals, and each algorithm was executed for 50 evolutionary generations. Each individual in the population represented a candidate portfolio, where the decision variables corresponded to the allocation weights assigned to the selected assets. Since the dataset consisted of 14 stocks, each candidate solution included 14 portfolio weights subject to the allocation constraints defined in the previous section.

The initial capital was set at $1,000,000, and the investment horizon was evaluated monthly. SPEA2 was selected as the main optimization algorithm because of its strength in Pareto fitness assignment and external archive mechanism. These features allow SPEA2 to preserve high-quality non-dominated solutions while maintaining diversity among candidate portfolios. NSGA-II was used as the benchmark algorithm because it is one of the most widely adopted multi-objective evolutionary algorithms in portfolio optimization and provides a suitable basis for comparative evaluation.

In both algorithms, the evolutionary process was designed to search for portfolio allocations that provide a suitable balance between return and risk. At the end of the optimization process, the obtained portfolios were evaluated using financial performance indicators and computational efficiency measures. The same evaluation criteria were applied to both algorithms to ensure consistency in the comparison.

4 | Experimental Results and Analysis

In this section, the performance of the SPEA2 multi-objective evolutionary algorithm, as the main proposed method, is examined. Its results are compared with those of the reference NSGA-II algorithm in terms of computational efficiency and financial outputs. Both algorithms were executed under identical settings, including a population size of 250,50 evolutionary generations, a monthly investment horizon, and a set of 14 assets, in order to provide a fair comparison [3], [4].

4.1 | Evaluation Criteria

The performance of the optimization algorithms was evaluated using both financial and computational criteria. This dual evaluation was necessary because the main objective of this study was not only to identify portfolios with favorable financial outcomes, but also to examine whether such outcomes could be achieved with lower computational cost.

The first financial criterion was final portfolio value. This measure indicates the total value of the optimized portfolio at the end of the investment horizon and provides a direct assessment of the financial outcome generated by each algorithm. A higher final portfolio value indicates that the algorithm produced a more profitable allocation under the experimental conditions of this study.

The second financial criterion was net profit, calculated as the difference between final portfolio value and initial capital. Since the initial capital was fixed at $1,000,000 for both algorithms, net profit provided a clear basis for comparing the monetary gains obtained by SPEA2 and NSGA-II.

The third criterion was return percentage, which expresses net profit relative to initial capital. This measure was used to normalize financial gain and make the results easier to interpret. It also provides a percentage-based view of the portfolio growth achieved by each optimization method.

In addition to financial performance, computational efficiency was evaluated using total runtime. Runtime measures the total execution time required by each algorithm to complete the optimization process under identical experimental settings. This criterion is particularly important in practical investment environments, where timely decision-making can be as important as solution quality.

The speed ratio was also used to compare the relative computational performance of SPEA2 and NSGA-II. This measure indicates how many times faster one algorithm is than the other and provides a straightforward interpretation of the runtime difference between the two methods.

Finally, a combined time-return efficiency criterion was used to evaluate the financial output obtained per unit of computational time. As defined by *Eq. (4)*, time-return efficiency is calculated as the ratio of net profit to total runtime and is expressed in dollars per second:

$$\text{Time} - \text{return} - \text{efficiency} = \text{Net Pr o fit}/\text{TotalRuntime}. \quad (4)$$

This criterion provides an integrated view of the trade-off between portfolio profitability and computational cost. Therefore, an algorithm with higher time-return efficiency can be considered more suitable for resource-constrained or time-sensitive portfolio optimization scenarios.

By these criteria together, the evaluation framework captures both the financial quality of the optimized portfolios and the computational practicality of the algorithms. The proposed framework is consistent with the study's main objective: to assess whether SPEA2 can provide a lightweight yet effective alternative for multi-objective portfolio optimization.

4.2 | Financial Performance Evaluation

To evaluate the financial outputs of SPEA2, its results are reported alongside those of the reference NSGA-II algorithm. Based on the recorded outputs, the final portfolio value for NSGA-II was $1,775,711.48, while that for SPEA2 was $1,847,560.42. In addition, the net portfolio gain was $775,711.48 for NSGA-II and $847,560.42 for SPEA2. The results are summarized in *Table 1*.

Table 1. Comparison of the financial performance of optimized portfolios.

Algorithm	Initial Capital ($)	Final Portfolio Value ($)	Net Profit ($)	Return (%)
NSGA-II	1,000,000	1,775,711.48	775,711.48	77.57
SPEA2	1,000,000	1,847,560.42	847,560.42	84.76

To examine the dynamic behavior of the portfolios over time, the trend of portfolio value generated by each algorithm was also analyzed. As shown in *Fig. 2*, the NSGA-II algorithm produced a relatively stable trend with more limited fluctuations. In contrast, as shown in *Fig. 3*, the portfolio obtained by SPEA2 experienced greater fluctuations and reached higher portfolio values in some periods. This difference in fluctuation patterns indicates the more dynamic behavior of the SPEA2-based portfolio compared with NSGA-II and provides a more complete view of the temporal performance of the two algorithms.

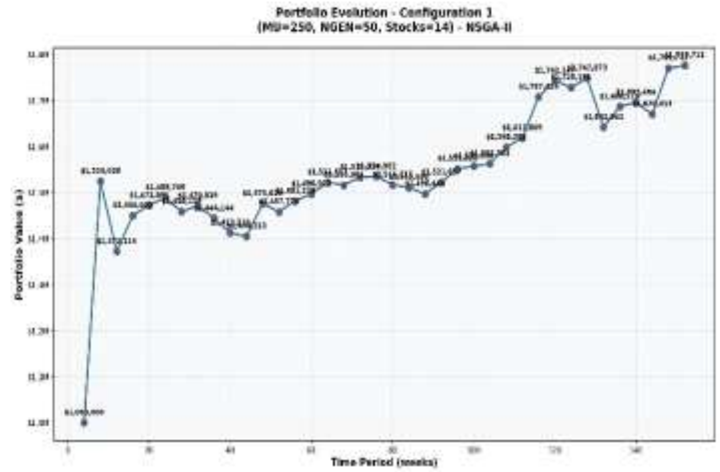

Fig. 2. Trend of the optimized portfolio value using the NSGA-II algorithm.

The temporal trends of portfolio values show that both algorithms maintained an overall upward trend during the study period despite short-term fluctuations. The absence of severe and persistent declines in the portfolio value paths indicates the relative stability of the obtained results within the experimental framework of this study and provides a reliable temporal basis for interpreting the final outcomes.

These results show that, based on the data used in this study, the faster algorithm, SPEA2, did not produce weaker outputs merely because of its reduced runtime. On the contrary, according to the reported criteria, it achieved a higher final value.

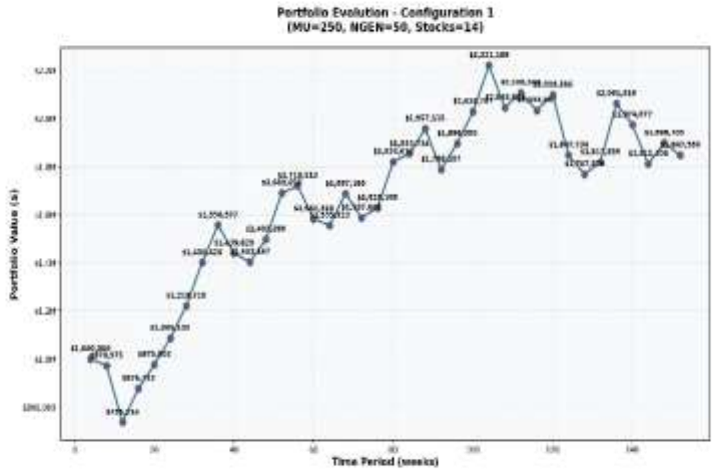

Fig. 3. Trend of the optimized portfolio value using the SPEA2 algorithm.

4.3 | Computational Efficiency

Based on the experimental results, a significant difference was observed in the runtime of the two algorithms (*Table 2*). The total runtime of NSGA-II was 44 hours, 40 minutes, and 09 seconds, equal to 160,809.30 seconds. In contrast, the total runtime of SPEA2 was 2 hours, 14 minutes, and 01 second, equal to 8,041 seconds. Therefore, SPEA2 was approximately 20 times faster than NSGA-II in this experiment.

Table 2. Comparison of the runtime of multi-objective evolutionary algorithms.

Algorithm	Total Runtime	Total Runtime	Speed Ratio
NSGA-II	44:40:09	160,809.30	×1
SPEA2	02:14:01	8,041.00	≈20×faster

From an analytical perspective, this difference can be related to the different evaluation and selection mechanisms used in the two algorithms. In NSGA-II, multi-level non-dominated sorting and crowding distance calculation in each generation account for a considerable part of the computational cost. In contrast, SPEA2 relies on the Pareto strength concept and an external archive to manage convergence and diversity simultaneously, which can reduce computational overhead in many problems. The empirical runtime difference observed in this study is consistent with these structural differences.

4.4 | Combined Time-Return Efficiency Evaluation

To provide a clearer view of practical performance, a combined efficiency criterion was calculated and reported: profit per second of computational runtime. As defined by *Eq. (5)*, this criterion was obtained by dividing the final net profit by the total computational runtime.

$$\text{Efficiency} = \text{Net Pr o fit/Runtime}. \tag{5}$$

The calculated efficiency values for both algorithms are presented in *Table 3*.

Table 3. Comparison of the combined time-return efficiency of the algorithms.

Algorithm	Net Profit ($)	Runtime (Seconds)	Efficiency ($/Sec)
NSGA-II	775,711.48	160,809.30	4.82
SPEA2	847,560.42	8,041.00	105.46

As shown in *Table 3*, the difference between the two algorithms is not limited to runtime alone. A considerable gap is also observed in terms of output relative to computational time. Such an index is particularly important when the objective is to move closer to practical use in environments with limited resources or the need for fast decision-making.

The results of the combined time-return efficiency criterion indicate that the performance difference between the algorithms is not merely related to execution time, but is also meaningful in terms of return relative to computational cost. This issue becomes especially important when compared with more complex approaches discussed in the literature. Although such approaches may improve solution quality in some cases, their high computational cost and long runtime restrict their practical applicability. Within this framework, the results of this section show that SPEA2, under the experimental settings of this study, was able to establish a suitable balance between financial output and computational time.

5 | Conclusion

This paper investigated portfolio optimization with a focus on computational efficiency by applying the SPEA2 multi-objective evolutionary algorithm to a reduced set of representative assets. Its performance was compared with NSGA-II under the same experimental conditions.

The results showed that SPEA2 required significantly less computational time while achieving higher financial performance in terms of final portfolio value, net profit, return percentage, and time-return efficiency. In addition, the portfolio value analysis indicated that both algorithms followed an overall upward trend, although SPEA2 reached higher values during several periods.

These findings suggest that SPEA2 provides an effective balance between solution quality and computational cost, making it a suitable choice for portfolio optimization in time-sensitive or resource-constrained environments. Future research can extend this work by considering larger asset sets, different investment horizons, additional risk measures, and comparisons with other multi-objective optimization algorithms.

Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

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Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

Conflict of Interest

The author declares that they have no conflicts of interest.

Consent for Publication

The author confirms consent for the publication of this work.

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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