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Robust Multi-Objective Portfolio Optimization with ENS-NSGA-II Under Real-World Constraints

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ABSTRACT

This study explores portfolio optimization by employing the Enhanced Non-dominated Sorting Genetic Algorithm II (ENS-NSGA-II), a robust multi-objective evolutionary algorithm, alongside classical optimization methods. Utilizing data from 135 companies listed on the Tehran Stock Exchange over the period 2013–2024, an extended Markowitz framework was constructed based on return and semi-variance as key performance criteria. To better reflect market realities, several practical investment constraints were incorporated, transforming the problem into a multi-objective optimization task. The ENS-NSGA-II algorithm, equipped with adaptive mutation control and improved diversity preservation mechanisms, significantly outperformed classical models by generating portfolios with superior return-risk trade-offs under nonlinear and volatile market conditions. Furthermore, the algorithm exhibited strong convergence behavior and stability across multiple independent runs and time intervals. These findings confirm that ENS-NSGA-II offers a powerful and flexible approach for constructing efficient investment portfolios in uncertain financial environments, providing investors with a reliable decision-making tool that adapts to dynamic market complexities.

Keywords: Risk, Return, Portfolio, Classical Optimization, Intelligent Optimization

Introduction

Multi-objective portfolio optimization is a complex and significant challenge in investment management, aiming to identify an optimal mix of financial assets that provides maximum return with minimum risk to investors [1]. This problem is typically addressed using mathematical models and optimization algorithms [2-6]. However, due to the multitude of objectives and constraints involved, finding a single optimal solution that satisfies all criteria is often unfeasible [7]. By employing various multi-objective optimization techniques, it is possible to approximate the Pareto frontier [3]. These methods include metaheuristic algorithms such as genetic algorithms, evolutionary algorithms, and other multi-objective optimization techniques. Initially, a population of solutions is generated (Pareto set), and through evolutionary operations like crossover, mutation, and selection, new generations are created. This process continues until a set of non-dominated and optimal solutions is reached, evaluated based on metrics such as distance and performance indicators [4]. These solutions represent trade-offs where no objective can be improved without worsening another [5]. These techniques are generally categorized into classical methods and computational intelligence-based methods [6]. Classical approaches such as the Analytic Hierarchy Process (AHP), Weighted Sum Method, Reference Function Method, and Value Function Method convert multi-objective problems into single-objective ones through mathematical transformations. While these methods are simple and interpretable, they suffer from issues such as sensitivity to weights and the need for prior knowledge [8-9]. In contrast, intelligence-based approaches, including evolutionary and metaheuristic algorithms, as well as simulated annealing, draw inspiration from natural and biological systems to iteratively generate and refine solutions. Though highly generalizable and efficient, hey face challenges like parameter tuning, ensuring solution quality, and computational complexity [10-11].

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The NSGA-II algorithm is a prominent and efficient method for solving multi-objective optimization problems. Based on the principles of genetic algorithms, it can generate a diverse set of non-dominated solutions in a single run [12]. It simulates natural evolution through concepts such as population, chromosome, gene, mutation, crossover, selection, and adaptability. NSGA-II is distinguished by features such as non-dominated sorting, crowding distance for diversity preservation, binary tournament selection, single-point crossover, multi-point mutation, elitism, and diversity preservation across Pareto fronts [13].

In portfolio optimization, considering investor preferences for risk and return, the goal is to identify a stock combination that achieves an optimal balance. This means selecting a portfolio that maximizes return while minimizing risk [11]. The definition of "optimal" may vary depending on the investor's goals and market conditions. Among the foundational models is the Markowitz model, introduced by Harry Markowitz in 1952, which assumes portfolio risk as the variance of returns and uses expected return as the objective function [7]. Solved via linear programming, this model is the cornerstone of modern portfolio theory and earned Markowitz a Nobel Prize in Economics [1].

Despite its significance, the Markowitz model has limitations, including linearity assumptions, reliance on normally distributed returns, and disregard for dynamic market changes [3]. Consequently, researchers have proposed alternative models and techniques to address these shortcomings, such as:

1. Using alternative risk measures like Value at Risk (VaR) and Conditional Value at Risk (CVaR),
2. Employing non-parametric or non-normal distribution families for return modeling,
3. Applying dynamic correlation models for capturing stock return dependencies,
4. Leveraging evolutionary or metaheuristic optimization techniques for portfolio construction,
5. Incorporating liquidity risk and extreme tail risks in portfolio modeling,
6. Accounting for market dynamics and financial bubbles in portfolio structure.

These advancements aim to create more robust, realistic, and adaptive portfolio models that better serve investors in increasingly volatile and nonlinear financial environments.

Research Background

This section presents a review of key studies conducted in the field of portfolio optimization. Gujan and Bhattacharya provided a comprehensive review of portfolio optimization methods, categorizing them into classical, risk-based, factor-based, and machine learning-based approaches. They discussed the advantages and limitations of each method and compared their performance using real-world data, concluding that method selection depends on investor preferences and data characteristics [7]. Freitas and Junior proposed a portfolio optimization method using random walks over a stock correlation network, combined with predictive analysis. Their model outperformed the Markowitz framework using Brazilian stock data [8, 14]. Song et al. introduced an enhanced distributed differential evolution algorithm for multi-objective portfolio optimization, capable of handling complex constraints and parallel computation [9, 15]. Butler and Kwan incorporated Bayesian uncertainty into the mean-variance portfolio optimization framework and proposed a dynamic weight update method based on new information, improving portfolio performance on U.S. stock data [10,16]. Wang and Aste applied inverse correlation clustering for dynamic portfolio optimization using hierarchical clustering to allocate weights, updating them periodically based on market changes. Their model achieved higher returns and lower risk on U.S. and UK stock datasets [11,17].

Gonzalez-Salazar et al. explored portfolio optimization in district heating plants using multi-objective models that combined technical, economic, and environmental factors [12,18]. Emamat et al. introduced a reliability-based approach to stock portfolio optimization, focusing on meeting a minimum return threshold with a specified confidence level. Their evolutionary solution outperformed both the Markowitz and CVaR models [1]. Daryabar et al. investigated portfolio optimization in bubble market conditions in Iran, using statistical methods to detect bubbles and computing optimal portfolios via the CVaR model. The results showed that during bubble periods, optimal portfolios were riskier, requiring more cautious investment strategies [2,15,19].

Bayat et al. demonstrated the effectiveness of the bird swarm algorithm in identifying optimal portfolios [3]. Heidari Heratmeh utilized Conditional Value at Risk (CVaR) under a Variance Gamma (VG) distribution to model stock returns and applied differential evolutionary optimization to compute optimal portfolios. The approach outperformed both the Markowitz and traditional VaR models [4]. Taghizadegan et al. compared the performance of the Markowitz model with a dynamic conditional copula-based illiquidity-adjusted risk model (DCC t-Copula LVaR) using Tehran Stock Exchange data. Their approach captured dynamic correlations and illiquidity risks, yielding superior portfolio configurations [5].

Zamanpour et al. applied fuzzy network analysis to identify and rank key factors affecting portfolio optimization, including return, risk, liquidity, market value, profit growth, book-to-price ratio, and beta coefficient. Using fuzzy AHP, they determined factor weights and calculated stock scores, showing that this method can effectively guide investors in selecting high-performing stocks [6,16].

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These studies highlight that stock portfolio optimization is inherently complex and multidimensional, requiring diverse and innovative methodologies. In this context, the present study proposes a multi-objective portfolio optimization model using the NSGA-II algorithm. Beyond traditional criteria such as mean and variance, the model incorporates additional risk measures, including Value at Risk (VaR), Conditional Value at Risk (CVaR), and Mean Absolute Deviation (MAD). The model is evaluated using adjusted data from the Tehran Stock Exchange, demonstrating that Pareto-optimal portfolios offer desirable trade-offs between risk and return.
Furthermore, the most favorable portfolios among non-dominated solutions are selected using classical evaluation criteria, specifying the investment weights, risk, and expected return for each stock. The NSGA-II algorithm is applied and validated, followed by detailed performance analysis to identify optimal portfolios. The models and techniques presented in this study contribute to advancing research in portfolio optimization and investment decision-making.

The structure of this article is as follows: Section 1 presents the introduction. Section 2 discusses fundamental Researches of multi-objective portfolio optimization. Section 3 explains the mathematical modeling and NSGA-II algorithm. Section 4 introduces the data and evaluation methods. Section 5 presents numerical results and analysis. Finally, Section 6 concludes the study and provides directions for future research.

1. Modeling

Mathematical Model of the Multi-Objective Portfolio Optimization Problem Using NSGA-II

The foundation of this research lies in Modern Portfolio Theory (MPT), originally introduced by Harry Markowitz. As one of the most widely applied models in finance, the Markowitz model serves as the baseline for this study. The classic Markowitz formulation is expressed as:

$$min\, z = \sum_{i=1}^{N}\sum_{j=1}^{n} w_i w_j \delta_{ij}$$

Subject to:

$$\sum_{i=1}^{n} w_i \mu_i \geq R \qquad \textit{Constraint 1}$$
$$\sum_{i=1}^{n} w_i = 1 \qquad \textit{Constraint 2} \qquad (1)$$
$$wi \geq 0 \qquad \textit{Constraint 3}$$
$$W_i \geq 0,\ i=1,2,3\ldots,\ N \qquad \textit{Constraint 4}$$

Where δ_{ij} denotes the covariance between assets i and j, ω_i is the weight of asset i, μ_i is the expected return of asset i, and R is the investor's minimum desired return.

To reflect real-world constraints and create an implementable decision-making framework, the model is extended by incorporating a trade-off parameter $\lambda \in [0,1]$ into the objective function, balancing the importance of return maximization and risk minimization:

$$\sum_{i=1}^{n} Z_i = k \qquad (2)$$

Where $Z_i \in \{0,1\}$ indicates whether asset i is selected (1) or not (0), and k is the number of assets to be included in the portfolio. The extended Markowitz model then becomes:

$$max = \lambda \sum_{i=1}^{N} W_i \mu_i - (1-\lambda) \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \delta_{ij}$$

Subject to:

$$\sum_{i=1}^{n} w_i = 1 \qquad (3)$$
$$W_i \geq 0,\ i=1,2,3\ldots,\ N$$
$$Z_i \in \{0.1\}$$

However, using variance as a risk measure has limitations, especially in non-normal distributions or inefficient markets. Therefore, semi-variance, which considers only returns below the mean, is employed:

$$semi\ var = \frac{1}{n-1}\sum_{i=1}^{n}(min[\,(r_i - \bar{r}).0])^2 \qquad (4)$$

This leads to the mean–semi-variance model:

$$max = \lambda \sum_{i=1}^{N} W_i \mu_i - (1-\lambda) \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j semi\ cov_{ij}$$

Subject to

$$\sum_{i=1}^{n} w_i = 1$$
$$\sum_{i=1}^{n} Z_i = k \qquad (5)$$
$$semicov_{(i,j)} = \frac{1}{T}[\textstyle\sum_{t=1}^{T} min\{\,(r_{i,t} - \bar{r}_i).0\} \times \sum_{t=1}^{T} min\{\,(r_{j,t} - \bar{r}_j).0\}$$
$$W_i \geq 0,\ i=1,2,3\ldots,\ N$$
$$Z_i \in \{0.1\}$$
$$t=1,2,\ 3\ldots,\ T$$

Multi-Objective Optimization Objective Function

In metaheuristic algorithms, the objective function drives the search process. Based on the extended Markowitz model, a multi-objective optimization function is constructed using criteria such as risk, Value at Risk (VaR), Conditional Value at Risk (CVaR), and Mean Absolute Deviation (MAD):

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$$min\,R\,isk(w)$$

Subject to:

$$\mu_i = w^T\mu \geq \mu_{i0} \qquad (6)$$

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

$W_i \geq 0,\ i=1,2,3\ldots, N$

To accommodate constraint violations in real-world data, a penalty function is added:

$$min\,R\,isk(w), [1 + \beta\, max(\,0.1 - \frac{\mu_i}{\mu_{i0}})$$

Subject to:

$$\sum_{i=1}^{n} w_i = 1 \qquad (7)$$

$W_i \geq 0,\ i=1,2,3\ldots, N$

Where β is the penalty coefficient.

ENS-NSGA-II Algorithm

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is one of the most widely adopted evolutionary algorithms for solving multi-objective optimization problems due to its balance of convergence and diversity preservation. It incorporates elitism, ensuring that the best non-dominated solutions are retained across generations to prevent loss of optimal candidates. The algorithm also utilizes the crowding distance metric to maintain a well-distributed Pareto front, encouraging solution diversity. Additionally, binary tournament selection is employed to choose individuals for reproduction based on both their dominance rank and crowding distance, enhancing the selection pressure toward optimality. In the Enhanced NSGA-II (ENS-NSGA-II), further improvements are introduced—such as adaptive mutation, hybrid initialization, and advanced diversity mechanisms to accelerate convergence and improve the quality of solutions in complex optimization landscapes.

Adaptive Mutation Rate Formula

To improve exploration and prevent premature convergence, adaptive mutation changes over generations based on the diversity of the population or progress in the search:

$$P_{mut}^{(t)} = P\,max.(\,1 - \frac{t}{t_{max}})$$

Where:

P_{mut}^{t} *is the mutation probability at generation t,* (8)

P_{max} *is the maximum initial mutation rate (e.g., 0.2),*

t is the current generation,

T_{max} *is the maximum number of generations.*

Modified Crowding Distance with Diversity Preservation

To improve solution spread in dense regions, a modified crowding distance can be defined as:

$$CDi = \sum_{m=1}^{M} \frac{f_{i+1}^{(m)} - f_{i-1}^{(m)}}{f_{max}^{(m)} - f_{min}^{(m)} + \eth} \qquad (9)$$

Where:

- CD_i *is the crowding distance of individual i,*
- $f_{i+1}^{(m)}$ *and* $f_{i-1}^{(m)}$ *are the neighboring objective values of individual i in objective m,*
- $f_{max}^{(m)}$ *and* $f_{min}^{(m)}$ *are the maximum and minimum values of objective m,*
- ϵ *is a small constant to avoid division by zero,*

M is the number of objectives.

This enhanced formula improves solution diversity and avoids selection bias in closely packed solutions on the Pareto front.

Enhanced NSGA-II Algorithm Procedure

1. Initialize parameters, including population size, crossover and mutation probabilities, archive size (if used), and learning or diversity preservation parameters.
2. Generate an initial population using a hybrid or guided random initialization method (e.g., Latin Hypercube Sampling or seeding with solutions from classical methods) to improve diversity and convergence.
3. Perform non-dominated sorting on the initial population to assign Pareto fronts and rank.
4. Calculate improved crowding distance or use diversity enhancement metrics (e.g., epsilon-dominance or reference-point-based niching) to better distribute solutions along the Pareto front.
5. Apply an improved selection mechanism, such as adaptive binary tournament selection, decomposition-based selection, or reference-point-guided selection, to maintain pressure toward both convergence and diversity.
6. Apply crossover and mutation operators optionally enhanced by:
   - Adaptive mutation rates that decrease over generations,
   - Problem-specific crossover strategies, or
   - Hybridization with local search techniques (e.g., gradient-based refinement or differential evolution).

7. Generate offspring population and merge with the parent population.

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8. Perform fast non-dominated sorting and recalculate diversity measures.
9. Select individuals for the next generation based on improved dominance ranking, diversity indicators, or reinforcement learning-based scoring (in advanced versions).
10. Optionally update an external archive to store elite non-dominated solutions if elitism or archiving is used.
11. Repeat steps 4–10 until the stopping criterion is met (e.g., maximum generations or no improvement over N iterations).
12. Return the final Pareto-optimal solution set, possibly enhanced using local refinement or solution clustering.

Through this process, ENS-NSGA-II effectively identifies a diverse set of non-dominated portfolios, balancing risk and return while adhering to real-world investment constraints.

Research Methodology

The target population of this study includes all companies listed on the Tehran Stock Exchange (TSE). From the list of publicly traded firms as of 2025, a sample of 135 companies was selected for analysis. The variables used in this study consist of monthly stock prices covering the period from 2013 to 2024. The primary objective of this research was to effectively apply the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for portfolio optimization.

In the implementation of the NSGA-II algorithm, the mutation operator was applied with a low mutation rate of 0.02, in accordance with values commonly adopted in previous studies. The number of generations was set to 1,000, and the population size for each generation was fixed at 25 individuals. The entire optimization process, including the modeling and algorithmic procedures, was implemented using MATLAB software. This setup ensured a balance between exploration and exploitation in the search for Pareto-optimal solutions, allowing for the generation of efficient portfolios that reflect real market behavior under multiple constraints and objectives.

Data Analysis and Empirical Evaluation Results

Multi-Objective Optimal Portfolio Using Classical Methods

To perform multi-objective portfolio optimization using classical approaches, three key risk measures were applied: Value at Risk (VaR), Conditional Value at Risk (CVaR), and the Mean Semi-Variance. These criteria were used to calculate portfolio risk, and the resulting optimal portfolio is presented below.

In the Pareto front chart, various performance metrics are considered for each company, including profitability, revenue growth, return on investment, return on equity, and other financial indicators. For example, the stock of the company Shamla, located on the efficient frontier, implies superior performance across these metrics. This placement indicates that the company has demonstrated strong performance management and has achieved results that surpass its competitors or the industry average.

In other words, the company's stock holds a dominant position, having outperformed others in key financial dimensions. This status is of significant importance to shareholders and potential investors, as it signals a successful strategy and operational strength, implying a relatively safer and more reliable investment. Furthermore, such a favorable position can attract new investors and enhance the confidence of existing shareholders.

Overall, the presence of a stock on the efficient frontier reflects the superior financial performance of the associated company and can serve as a strong indicator of future growth potential and strategic excellence.

Multi-Objective Optimal Portfolio Using Intelligent Methods (Stability Evaluation of the ENS-NSGA-II Algorithm)

Stability testing is one of the most important validation procedures in portfolio optimization, particularly for verifying the reliability of an algorithm like ENS-NSGA-II. This test assesses whether the algorithm consistently produces similar and stable results across multiple runs and whether the optimal solution is unique.

To perform this test, the algorithm was executed multiple times, and the resulting outputs were compared. A 10-asset portfolio was selected as the test case, and the outputs of 10 independent executions were recorded.

The results of the stability assessment are presented in Table 2, Table 3 and illustrated in Figure 1.

The results from Table 2, Table 3 and Figure 1 indicate only minor differences between repeated runs of the algorithm. The extremely low variance value of 0.000000205444 demonstrates a high degree of stability in the NSGA-II algorithm across 1,000 iterations.

Impact of Portfolio Size on the Objective Function, Risk, and Return in NSGA-II

As shown in Table 4, the ENS-NSGA-II algorithm is capable of optimizing stock portfolios of varying sizes. It is observed that the objective function values vary only slightly across different portfolio sizes. As the number of assets in the portfolio increases, both the risk and efficiency (performance) of the portfolio tend to increase proportionally. Conversely, reducing the portfolio size results in decreased risk and performance metrics.

In the classical approach, the criteria of Value at Risk (VaR), Conditional Value at Risk (CVaR), and Mean Semi-Variance were used for optimization. These metrics are commonly applied to evaluate the risk and return of companies.

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Based on this method, the company with the highest potential return and the lowest associated risk according to these criteria is selected as the optimal investment choice. The results demonstrate the optimal investment distribution across 132 companies, with specific investment weights determined using the NSGA-II algorithm. For each defined investment weight, the algorithm calculates the corresponding allocation to each company. NSGA-II employs multiple techniques, particularly genetic algorithms, to identify the Pareto-optimal population, which reflects the most efficient investment distributions across companies.

In this distribution, each company is assigned a weight representing its share of the total investment relative to others. This approach enables investors to generate an optimal investment portfolio by adjusting weight configurations according to their preferences.

To analyze this distribution, one may examine how investment allocations shift across companies when investment weights are modified. Companies that consistently receive higher allocations under increased investment weights may change depending on risk-return profiles. By observing such changes, investors can assess the strengths and weaknesses of different allocation strategies.

In some cases, increasing the investment weight in high-return companies may also lead to elevated portfolio risk. Conversely, increasing allocation to low-risk companies might reduce the expected return. Additionally, by analyzing the Pareto-optimal points generated by ENS-NSGA-II, one can identify companies that consistently maintain superior positions across all optimal distributions. These companies can be considered strong candidates for inclusion in an optimized investment portfolio.

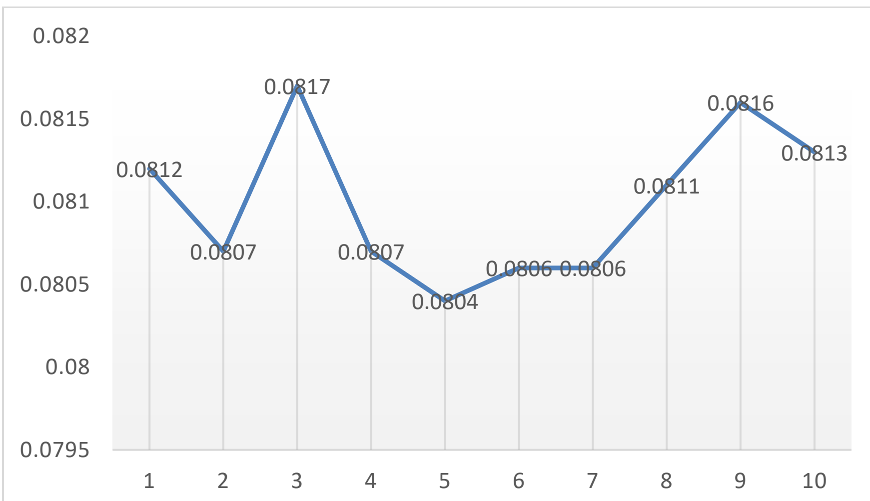

Fig. 1 Stability Assessment and Sensitivity Analysis of the ENS-NSGA-II Algorithm Across 10 Executions

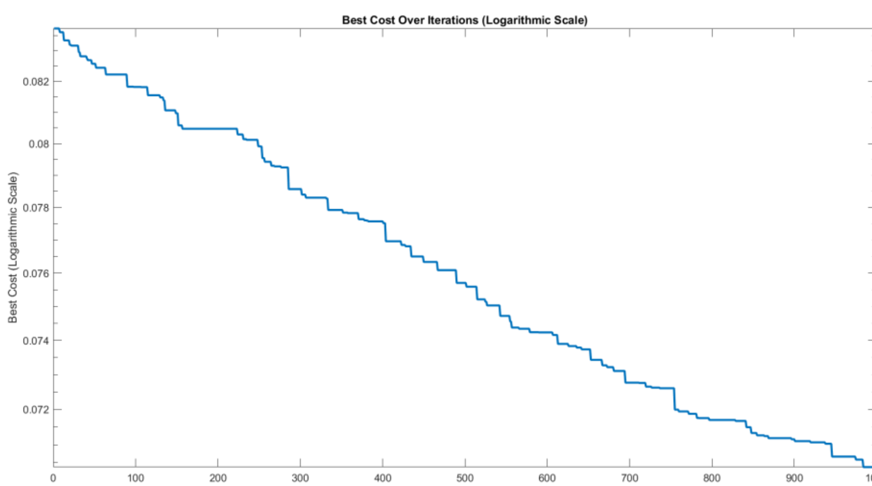

Fig.2 Error Reduction and Optimization Process of the ENS-NSGA-II Algorithm Over 1000 Iterations

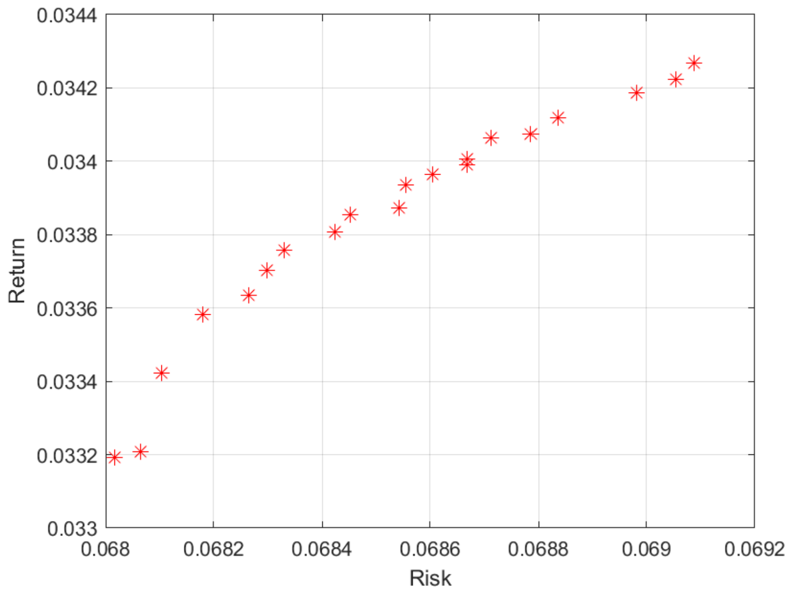

Fig.3 Pareto Front: Efficient Frontier of the Optimal Portfolio Using the ENS-NSGA-II Algorithm Over 1000 Iterations

Table 1. Risk and Return Evaluation of Shamla Company

Method	Risk Value	Return
Value at Risk (VaR)	0.146521	0.0412256
Conditional Value at Risk (CVaR)	0.185863	0.0412256
Mean–Semi-Variance	0.146521	0.0412256

Table 2. Mean Objective Function Values Across Five Executions of the ENS-NSGA-II Algorithm

Execution 1	Execution 2	Execution 3	Execution 4	Execution 5	Mean
0.0704	0.0707	0.0717	0.0707	0.0712	0.07094

Table 3. Objective Function Values from Executions 6 to 10 and Standard Deviation (ENS-NSGA-II Algorithm)

Execution 6	Execution 7	Execution 8	Execution 9	Execution 10	Standard Deviation
0.0613	0.0616	0.0611	0.0606	0.0606	0.00029

Note: The standard deviation indicates a high level of consistency across repeated runs of the algorithm.

Table 4. Effect of Portfolio Size on Objective Function, Mean Return, Portfolio Efficiency, and Variance Using ENS-NSGA-II

Portfolio Size	10 Assets	20 Assets	30 Assets
Objective Function	0.1005	0.0913	0.0967
Portfolio Risk	0.0910	0.0931	0.0959
Portfolio Return	0.0231	0.0228	0.0264

Note: The results highlight that ENS-NSGA-II remains consistent in its optimization capability across varying portfolio sizes while balancing risk and return.

Conclusion and Recommendations

This study aimed to contribute to the portfolio optimization literature by integrating innovative algorithmic approaches alongside classical and intelligent methods. Classical techniques employed well-established mathematical models frequently used in previous research, focusing on minimizing the expected risk-return trade-off for effective portfolio evaluation. To incorporate intelligent optimization, this study addressed the complexities of financial markets and investor goals by replacing variance, the conventional risk measure in the mean-variance Markowitz model, with semi-variance. A risk minimization objective function was formulated accordingly. By introducing additional real-world constraints, a modified mean–semi-variance model was developed as the foundational framework for the study. The Enhanced Non-Dominated Sorting Genetic Algorithm II (ENS-NSGA-II) was then applied to this model to solve the portfolio selection and optimization problem.

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A numerical example was also included to empirically demonstrate the algorithm's effectiveness. Findings revealed that ENS-NSGA-II significantly outperforms classical optimization approaches in identifying efficient portfolios. The algorithm quickly converges to Pareto-optimal solutions in a single run, offering all required decision-making information while maintaining computational efficiency. Key differences between metaheuristic algorithms and classical methods in portfolio optimization can be observed across several dimensions. Classical approaches are rooted in rigid mathematical formulations and rely on analytical models such as linear, nonlinear, and integer programming. These methods are well-regarded for their high precision and theoretical rigor but often struggle with complex, nonlinear, and ill-defined constraints, especially in dynamic environments. In contrast, metaheuristic algorithms are inspired by natural processes and employ iterative, stochastic search mechanisms that allow them to effectively navigate vast and irregular solution spaces. Their inherent flexibility, scalability, and ability to be parallelized make them suitable for large-scale, real-world problems. Moreover, metaheuristics are better equipped to handle dynamic and uncertain market conditions, as they can adapt to changing input variables and integrate real-time data. Unlike classical models, which operate on static assumptions, metaheuristics can learn and evolve over time, improving their performance as conditions change. The ENS-NSGA-II algorithm, as demonstrated in this study, offers a robust and efficient alternative for portfolio selection and optimization in today's complex

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