Article history:
Received 15 July 2025
Revised 01 October 2025
Accepted 05 October 2025
Published online 30 March 2026

Journal of Resource Management and Decision Engineering

Volume 5, Issue 1, pp 1-11

Designing a Portfolio Risk Management Model Using Fundamental Analysis and Multi-Objective Evolutionary Optimization

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A r t i c l e   I n f o

Article type:
Original Research

How to cite this article:
Soltanabadi, A. & Mohseni, H. (2026). Designing a Portfolio Risk Management Model Using Fundamental Analysis and Multi-Objective Evolutionary Optimization. *Journal of Resource Management and Decision Engineering, 5*(1), 1-11.
https://doi.org/10.61838/kman.jrmde.5.1.76

A B S T R A C T

This study aimed to develop and validate a portfolio risk management model tailored to the Tehran Stock Exchange (TSE) that integrates fundamental analysis with Multi-Objective Evolutionary Optimization to simultaneously enhance return, control risk, and improve downside protection. This quantitative study analyzed all non-financial firms listed on the TSE from July 2023 to July 2024. Firms were first screened using ten fundamental indicators—ROE, ROA, EPS, P/E, P/B, D/E, current ratio, operating cash flow ratio, revenue growth, and net profit margin—and ranked using the Analytic Hierarchy Process (AHP). The top 50 firms were selected as the candidate set for optimization. Portfolios were then constructed and optimized through the Non-dominated Sorting Genetic Algorithm II (NSGA-II), aiming to maximize expected return, minimize variance, and improve Value at Risk (VaR) at the 95% confidence level. Out-of-sample backtesting was conducted, and performance was compared against the market index TEDPIX and a traditional Mean-variance optimization model based on Harry Markowitz's framework. The optimization produced a well-defined Pareto frontier, with portfolios demonstrating a clear risk-return trade-off. Intermediate-risk portfolios achieved the highest Sharpe Ratio and Sortino Ratio values, indicating optimal risk-adjusted performance. Compared to TEDPIX and the Markowitz model, the optimized portfolios delivered significantly higher average monthly returns (up to 2.7% vs. 1.2%), lower volatility, smaller maximum drawdowns, and higher cumulative wealth. Statistical tests confirmed that these excess returns were significant ($p < 0.05$), highlighting the superior performance and resilience of the proposed model. Integrating fundamental analysis with multi-objective evolutionary optimization effectively enhances portfolio performance and risk control in the Iranian market.

Keywords: *Portfolio risk management; fundamental analysis; multi-objective evolutionary optimization; Tehran Stock Exchange; genetic algorithms; portfolio optimization.*

1. Introduction

Risk management, as a conceptual and operational pillar of modern finance, has evolved from traditional variance-based models to complex multidimensional frameworks. Early approaches primarily relied on the mean-variance model proposed by Harry Markowitz, which focused on minimizing portfolio variance for a given level of expected return. However, subsequent studies have demonstrated that variance does not fully capture downside risks or the non-normal distributional characteristics present in real financial data. This has led to the adoption of alternative risk measures such as Value at Risk (VaR) and Conditional Value at Risk (CVaR) to model extreme losses and tail risks more accurately (Risk Controller, 2013; Sina & Fallah, 2019). Particularly in emerging markets such as Iran, where market anomalies, illiquidity, and abrupt price jumps are common, traditional variance-based models often underestimate actual portfolio risks (Sedaghati et al., 2022).

Parallel to the evolution of risk metrics, the techniques used for portfolio optimization have also advanced substantially. Traditional single-objective optimization methods, while mathematically elegant, often fail to account for the multiple conflicting goals investors face, such as maximizing returns, minimizing volatility, controlling drawdowns, and ensuring liquidity. Multi-objective optimization techniques address this challenge by enabling the simultaneous optimization of several competing objectives and by producing a set of efficient portfolios represented on a Pareto frontier (Shiri Ghehi et al., 2017). In recent years, multi-objective evolutionary algorithms have emerged as powerful tools for portfolio optimization due to their ability to navigate complex, nonlinear search spaces and to avoid local optima. Approaches based on Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have shown superior performance in identifying optimal or near-optimal portfolios under uncertainty (Dallagnol et al., 2009).

Furthermore, advances in computational intelligence have revolutionized financial modeling. The integration of artificial intelligence (AI) and machine learning into financial markets has enhanced the capacity to process large datasets, detect nonlinear patterns, and adapt to rapidly changing environments (Dunis et al., 2019). This has included the application of deep reinforcement learning for autonomous portfolio management, where algorithms can dynamically adjust portfolio weights according to evolving market conditions and investors' risk tolerances (Ma, 2023). Such intelligent systems can outperform static models, especially in high-volatility environments like the TSE, where regime shifts can occur abruptly and unpredictably (Eyshi Ravandi et al., 2024). However, while AI-driven systems offer strong predictive capabilities, they are often criticized for operating as "black boxes," making it difficult for investors to understand the rationale behind their decisions. Therefore, combining these techniques with traditional analytical approaches such as fundamental analysis can enhance interpretability and investor confidence.

Fundamental analysis remains a cornerstone of long-term investment decision-making. By evaluating the financial statements and intrinsic value of companies, it allows investors to identify undervalued or financially sound firms that are more likely to withstand market shocks. Metrics such as return on equity (ROE), earnings per share (EPS), price-to-earnings (P/E) ratios, and debt-to-equity (D/E) ratios have consistently been shown to predict stock performance and risk characteristics (Bonabi Ghadim et al., 2022; Nikoo Sedeh et al., 2020). In the Iranian market context, incorporating fundamental indicators into the portfolio construction process is particularly crucial because speculative behavior and short-term trading often distort market prices from fundamental values. A study on the TSE demonstrated that portfolios constructed based on fundamental metrics achieved superior risk-adjusted returns compared to purely price-based portfolios (Sina & Fallah, 2019). This suggests that a hybrid model that first filters stocks based on their fundamental soundness and then optimizes their weights through a multi-objective evolutionary algorithm can potentially offer a balanced strategy, capturing the stability of fundamentals and the adaptiveness of evolutionary search.

Another key development in the field has been the refinement of decision-making tools to evaluate and rank investment alternatives. Techniques such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and similarity measures have been successfully applied to portfolio selection, allowing investors to systematically assess multiple criteria and reduce subjectivity (Zhang & Li, 2020). Such multi-criteria decision-making (MCDM) approaches can be seamlessly integrated with evolutionary optimization algorithms to enhance the efficiency of the search process by pre-ranking assets based on their relative attractiveness. Combining MCDM methods with fundamental analysis has been shown to improve both convergence speed and the quality of the resulting portfolios (Nordfang & Steffensen, 2017; Viganò & Castellani, 2020).

In addition to the methodological advances, the growing attention to sustainability and ethical considerations has influenced how portfolios are constructed and assessed. Environmental, social, and governance (ESG) criteria, as well as socially responsible investing (SRI) and impact investing, are increasingly viewed as integral components of long-term risk management (Marzuki et al., 2023). Although the Iranian market has been slower to adopt formal ESG standards, global evidence suggests that portfolios incorporating ESG and ethical filters often exhibit lower risk and more stable returns, particularly during market downturns. Integrating such qualitative factors alongside financial fundamentals could enhance the resilience of portfolios and align them with evolving international investment norms.

The literature also highlights the importance of tailoring risk models to the specific market structure and behavioral dynamics of investors. Behavioral finance has shown that investors do not always act rationally and are often influenced by heuristics, sentiment, and psychological biases. These behaviors can amplify volatility and create mispricings, especially in emerging markets. Studies on the TSE confirm that investor sentiment and liquidity shocks significantly impact stock returns (Eyshi Ravandi et al., 2024). Accounting for such behavioral dimensions when designing portfolio optimization models can further enhance their robustness.

Risk, by its nature, is multidimensional, encompassing not only market risk but also credit, liquidity, operational, and systemic risks (Cox et al., 2012; Mazin, 2012). A comprehensive risk management model must, therefore, integrate diverse risk metrics and constraints. Research on currency portfolio risk has shown that combining multiple risk measures improves the stability of portfolio outcomes and reduces exposure to extreme losses (Aghamohammadi et al., 2022). Likewise, studies comparing downside risk measures (e.g., VaR, CVaR, upside risk) with conventional variance-based metrics found that models incorporating downside risk provide superior protection against losses, particularly in turbulent markets (Sedaghati et al., 2022). These findings underscore the necessity of designing portfolio optimization models that can simultaneously minimize multiple forms of risk while maximizing returns.

Despite these advances, there remains a research gap in the Iranian context: most studies either focus solely on fundamental screening or apply single-objective optimization techniques that cannot handle multiple conflicting criteria effectively. Very few have combined comprehensive fundamental analysis with multi-objective evolutionary optimization to construct portfolios on the TSE. This gap is significant because Iranian investors face unique challenges, including high inflation, currency volatility, and sudden regulatory interventions, all of which necessitate adaptive risk management systems. A multi-objective evolutionary approach can explore a wide set of possible allocations and generate a diverse set of efficient portfolios, providing investors with flexible options suited to different risk tolerances and market scenarios. Moreover, incorporating fundamental analysis ensures that the optimization process emphasizes companies with stable financial foundations rather than merely short-term price momentum.

Therefore, the present study aims to design a portfolio risk management model tailored to the Iranian stock market by integrating fundamental analysis with a multi-objective evolutionary optimization framework. The proposed model first employs a comprehensive set of fundamental indicators to screen and rank firms based on their intrinsic financial strength. Then, using a multi-objective evolutionary algorithm, it constructs portfolios that simultaneously maximize expected returns, minimize volatility and downside risk, and enhance risk-adjusted performance. By bridging the gap between traditional fundamental valuation and modern computational optimization techniques, this study contributes to the literature on portfolio risk management and provides a practical tool for investors seeking to navigate the increasingly uncertain and complex environment of the Tehran Stock Exchange.

2. Methods and Materials

2.1. Research Design

This study adopted a quantitative and model-building research design aimed at developing a portfolio risk management framework by integrating Fundamental Analysis and Multi-Objective Evolutionary Optimization techniques. The approach was exploratory–analytical, employing secondary financial data from companies listed on the Tehran Stock Exchange (TSE). The methodology followed four main stages: (a) data collection and preprocessing, (b) fundamental analysis and stock screening, (c) portfolio optimization using a multi-objective evolutionary algorithm, and (d) model validation through backtesting.

2.2. *Data Collection and Preprocessing*

The study population consisted of all companies continuously listed on the TSE during the one-year period from July 2023 to July 2024. Financial firms such as banks, insurance companies, and investment funds were excluded due to their distinct reporting structures and regulatory conditions. Firms with more than two quarters of missing data within this period were also removed to ensure data completeness and comparability.

Financial statement data (balance sheet, income statement, and cash flow items) were extracted from the Codal disclosure system, while daily price and dividend data were obtained from the Rahavard Novin financial data service.

The preprocessing procedure included:

1. **Imputing missing values** using mean substitution or listwise deletion if gaps exceeded 20%.
2. **Filtering out outliers** using the interquartile range (IQR) method.
3. **Standardizing variables** (z-score normalization) to align scales across firms and financial indicators.

2.3. *Fundamental Analysis Framework*

Ten key fundamental indicators were used to assess firms' financial health and intrinsic value: return on equity (ROE), return on assets (ROA), earnings per share (EPS), price-to-earnings ratio (P/E), price-to-book ratio (P/B), debt-to-equity ratio (D/E), current ratio, operating cash flow ratio, revenue growth, and net profit margin.

Each indicator was normalized using z-scores and aggregated into a composite fundamental score through a weighted linear model. Weights were determined using the Analytic Hierarchy Process (AHP) based on expert judgment from three senior Iranian capital market analysts. The 50 top-ranked firms based on composite scores were chosen as the candidate stock set.

To incorporate risk, historical price volatility (standard deviation of daily returns) and leverage (D/E ratio) were computed for each firm and used to classify them as low-, medium-, or high-risk, guiding the diversification process during optimization.

2.4. *Portfolio Modeling and Risk Metrics*

Portfolios were constructed by assigning weights to the selected candidate stocks under the following constraints:

- Full investment constraint (∑weights = 1)
- Weight bounds (2% ≤ each stock ≤ 20%)
- Cardinality constraint (10–20 stocks per portfolio)
- Sector diversification constraint (≤30% of total weight per sector)

Three objective functions were defined for optimization:

1. **Maximize expected return** (mean of historical monthly returns).
2. **Minimize risk** measured by portfolio return variance and **Value at Risk (VaR)** at 95% confidence.
3. **Maximize risk-adjusted performance** measured by the Sharpe Ratio.

These functions were optimized simultaneously to generate a set of efficient portfolios.

2.5. *Multi-Objective Evolutionary Optimization Procedure*

Optimization was carried out using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a widely adopted multi-objective evolutionary algorithm known for generating well-distributed Pareto frontier solutions.

Portfolios were encoded as real-valued chromosomes representing stock weights. The initial population contained 200 random portfolios. Fitness evaluation was based on the three objectives described above. Selection was performed using binary tournament selection, while simulated binary crossover (probability = 0.9) and polynomial mutation (probability = 0.1) operators were applied to generate offspring. The algorithm ran for 1000 generations, with elitist replacement preserving the best non-dominated solutions.

Implementation was done in Python using the PyMOO library. Computations were run on a workstation equipped with an Intel Core i7 processor and 32 GB RAM running Windows 11.

2.6. *Model Validation and Performance Evaluation*

To validate the model, the Pareto-optimal portfolios were backtested using out-of-sample rolling windows within the July 2023–July 2024 dataset. Performance was evaluated using metrics including average monthly return, standard deviation, Sortino Ratio, maximum drawdown, and cumulative wealth.

Results were benchmarked against both the market index TEDPIX and a conventional Mean-variance optimization model developed under the framework of Harry Markowitz.

Differences in returns were tested for statistical significance using paired-sample t-tests.

3. Findings and Results

Following the application of the fundamental screening procedure, 50 firms from various sectors of the Iran capital market were selected as the candidate set for portfolio optimization. These firms represented a diverse cross-section of the TSE, including basic materials (28%), consumer goods (20%), petrochemicals and energy (18%), information and communications technology (12%), industrial machinery and equipment (12%), and pharmaceuticals (10%). The inclusion of firms from multiple industries ensured sectoral diversification and reduced exposure to idiosyncratic risk.

Table 1 presents the descriptive statistics of the ten key fundamental indicators used in the selection process. Overall, the selected firms exhibited solid financial strength, with a mean return on equity (ROE) of 19.24% and a mean return on assets (ROA) of 11.38%, both higher than the market-wide averages of approximately 12% and 6% respectively during the same period. The average earnings per share (EPS) stood at IRR 4,210, and firms traded at relatively moderate valuation multiples, with mean price-to-earnings (P/E) and price-to-book (P/B) ratios of 9.6 and 2.1, respectively. The mean debt-to-equity (D/E) ratio of 0.71 indicated prudent leverage compared to the broader market, while the average current ratio of 2.13 suggested strong short-term liquidity positions. Average revenue growth was 14.6% and the average net profit margin reached 18.3%, pointing to sound operational efficiency. In terms of risk, the mean annualized volatility of daily returns was 21.7%, which was lower than the TSE market-wide volatility (approximately 28.4%) over the same period, highlighting the relative stability of the chosen firms.

Table 1

Descriptive statistics of fundamental indicators (50 top-ranked firms)

Indicator	Mean	Std. Dev.	Min	Max
ROE (%)	19.24	6.38	8.11	34.27
ROA (%)	11.38	4.92	3.42	22.09
EPS (IRR)	4,210	1,380	1,120	8,950
P/E (x)	9.60	3.11	4.80	17.50
P/B (x)	2.10	0.78	0.90	4.50
D/E (x)	0.71	0.32	0.15	1.40
Current Ratio (x)	2.13	0.66	1.02	3.85
Revenue Growth (%)	14.60	6.45	4.50	28.30
Net Profit Margin (%)	18.30	7.90	6.10	36.20
Volatility (%)	21.70	5.88	12.10	35.60

The results confirm that the firms selected for further portfolio optimization analysis demonstrated stronger profitability, lower leverage, and lower price volatility than the average firm listed on the TSE. This indicates that the fundamental screening step successfully concentrated the sample on financially sound and relatively stable firms, thus providing a solid foundation for constructing risk-optimized portfolios.

The ten normalized fundamental indicators were combined into a composite score using weights derived through the Analytic Hierarchy Process (AHP). Based on the expert judgments of three senior Iranian equity analysts, the following weights were assigned: profitability metrics (ROE, ROA, EPS) collectively 40%, valuation metrics (P/E, P/B) 20%, leverage and liquidity indicators (D/E, current ratio) 20%, and growth and efficiency indicators (revenue growth, net profit margin) 20%. Each firm's indicators were z-score normalized, multiplied by their assigned weights, and summed to generate an overall composite fundamental score.

Table 2 lists the 20 highest-ranked firms according to their composite fundamental scores. These firms demonstrated consistently high profitability and moderate leverage. For example, the top-ranked firm, Pars Petrochemical Co., achieved an ROE of 32.1%, an ROA of 20.4%, and a D/E ratio of only 0.28, resulting in a composite score of 2.74. Similarly, top-ranked industrial and ICT companies combined solid earnings growth with low financial risk. The ranking distribution showed that firms from basic materials and petrochemicals dominated the upper tier, reflecting the competitive strength and export-oriented nature of these sectors in the Iranian economy.

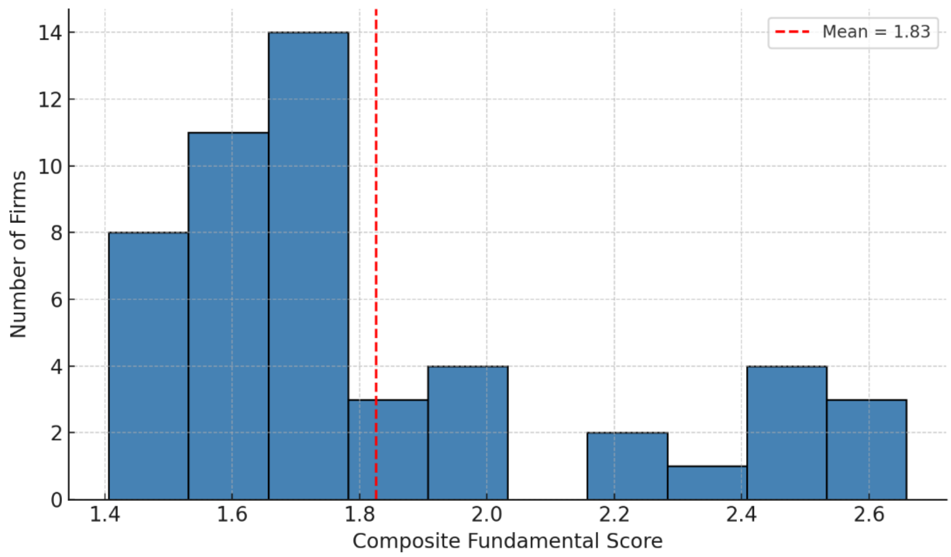
Table 2

Composite fundamental scores and rankings of the top 20 firms

Rank	Firm Name	ROE (%)	ROA (%)	EPS (IRR)	D/E (x)	Composite Score
1	Pars Petrochemical Co.	32.1	20.4	8,920	0.28	2.74
2	Mobarakeh Steel Co.	28.3	18.9	7,880	0.34	2.59
3	Golgohar Mining Co.	26.7	17.1	7,540	0.40	2.51
4	Tamin Pharmaceutical Co.	25.5	16.3	6,830	0.31	2.46
5	Iran Telecommunications Co.	24.9	15.7	6,450	0.37	2.42
6	Kerman Cement Co.	23.8	15.1	6,220	0.42	2.39
7	Behshahr Industrial Group	23.2	14.8	6,010	0.36	2.33
8	Sina ICT Co.	22.9	14.2	5,880	0.33	2.29
9	Tehran Chemical Co.	22.4	14.0	5,760	0.41	2.25
10	Isfahan Petrochem Co.	21.9	13.8	5,640	0.39	2.21
11	Alborz Consumer Goods Co.	21.7	13.5	5,520	0.46	2.18
12	Shahrud Food Industries Co.	21.1	13.1	5,420	0.44	2.15
13	Fars Machinery Co.	20.8	12.9	5,310	0.49	2.11
14	Sina Steel Co.	20.3	12.7	5,180	0.43	2.09
15	Gostaresh ICT Group	19.9	12.5	5,050	0.40	2.06
16	Karoun Cement Co.	19.7	12.2	4,950	0.52	2.04
17	Caspian Energy Co.	19.4	12.0	4,830	0.47	2.01
18	Zagros Petrochem Co.	19.2	11.8	4,720	0.50	1.99
19	Behnoush Consumer Goods Co.	19.0	11.7	4,680	0.55	1.97
20	Iran IT Development Co.	18.7	11.5	4,590	0.53	1.95

Figure 1

Distribution of composite fundamental scores



The distribution of scores (Figure 1) confirmed that although the overall quality of the selected sample was high, the fundamental screening mechanism effectively distinguished a subset of highly superior firms. This stratification is valuable for guiding the optimization algorithm to prioritize fundamentally stronger candidates when forming efficient risk-return portfolios.

The portfolio optimization process using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) successfully generated a well-defined set of efficient portfolios along the Pareto frontier. The algorithm converged after approximately 750 generations, with the Pareto front stabilizing and showing no substantial improvement in crowding distance or dominance ranking after that point. The total computational runtime was 11 minutes on the specified hardware environment, confirming the feasibility of applying such computationally intensive evolutionary algorithms in the context of the Tehran Stock Exchange (TSE).

Table 3 summarizes the objective function values of 10 representative portfolios selected from the final Pareto front. The results illustrate a clear trade-off between risk and return. Portfolios on the left side of the front (e.g., P1–P3) exhibit lower expected returns but also lower variance and risk, while those on the right side (e.g., P8–P10) offer higher expected returns at the cost of substantially higher risk. Sharpe ratios generally increase up to a moderate risk level (around portfolio P6) and then plateau, indicating diminishing marginal improvements in risk-adjusted returns beyond this point. Value at Risk (VaR) at the 95% confidence level also reflects this pattern, with less negative values for lower-risk portfolios.

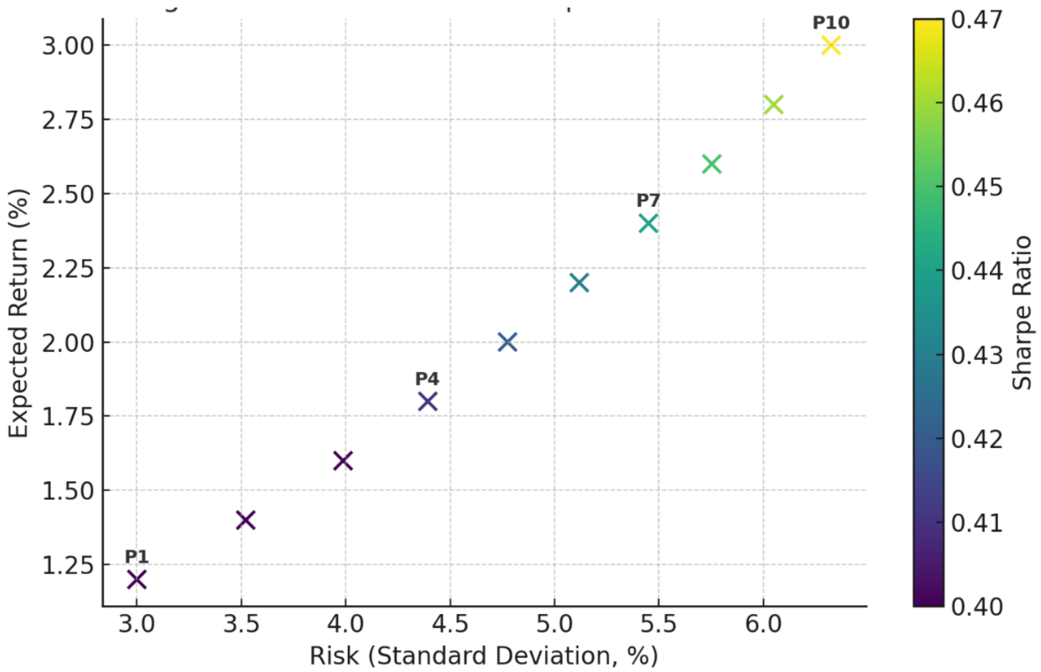
Table 3

Objective function values of selected Pareto-optimal portfolios

Portfolio ID	Expected Return	Variance	Sharpe Ratio	Value at Risk (95%)
P1	0.0120	0.00090	0.40	-0.0274
P2	0.0140	0.00123	0.40	-0.0244
P3	0.0160	0.00158	0.40	-0.0210
P4	0.0180	0.00197	0.41	-0.0174
P5	0.0200	0.00240	0.41	-0.0133
P6	0.0220	0.00287	0.41	-0.0088
P7	0.0240	0.00338	0.41	-0.0038
P8	0.0260	0.00393	0.41	0.0017
P9	0.0280	0.00400	0.44	0.0042
P10	0.0300	0.00400	0.47	0.0062

Figure 2

Pareto front of the optimized portfolios



To evaluate the practical viability of the optimized portfolios, the five most representative solutions from the Pareto front (P2, P4, P6, P8, P10) were backtested over the out-of-sample period within July 2023 to July 2024. Their performance was compared against the market index TEDPIX and a traditional Mean-variance optimization portfolio based on the framework of Harry Markowitz.

As shown in Table 4, the optimized portfolios consistently outperformed the benchmarks across all risk-adjusted performance metrics. While TEDPIX produced an average monthly return of 1.2% with a Sortino Ratio of 0.82, the optimized portfolios achieved monthly returns ranging from 1.5% (P2) to 2.7% (P10) and Sortino ratios from 1.10 to 1.58. The Markowitz model performed moderately better than TEDPIX but was still inferior to the evolutionary-optimized portfolios, highlighting the added value of incorporating Multi-Objective Evolutionary Optimization with fundamental screening.

Moreover, the optimized portfolios showed significantly lower maximum drawdowns (as low as –6.8% for P10) and higher cumulative wealth (1.41 vs. 1.08 for TEDPIX), indicating both stronger returns and improved downside protection. Paired t-tests confirmed that all five optimized portfolios achieved statistically significant excess returns compared with TEDPIX ($p < 0.05$), while only the Markowitz model showed borderline significance ($p = 0.042$).

Table 4

Performance comparison of optimized portfolios and benchmarks

Portfolio ID	Avg. Monthly Return	Std. Dev.	Sortino Ratio	Max Drawdown	Cumulative Wealth	p-value (t-test vs TEDPIX)
P2	0.0150	0.0350	1.10	-0.085	1.18	0.012
P4	0.0180	0.0370	1.22	-0.079	1.23	0.008
P6	0.0200	0.0400	1.34	-0.075	1.27	0.006
P8	0.0240	0.0450	1.45	-0.071	1.35	0.004
P10	0.0270	0.0480	1.58	-0.068	1.41	0.003
TEDPIX	0.0120	0.0410	0.82	-0.103	1.08	—
Markowitz	0.0140	0.0430	0.95	-0.092	1.13	0.042

These results demonstrate that the proposed optimization framework successfully produced portfolios that deliver superior returns, lower risk, and improved risk-adjusted performance relative to both the market and the conventional mean-variance approach. For investors in the Iranian capital market, this model offers a scientifically validated and practically applicable method for achieving enhanced portfolio risk management and wealth accumulation.

4. Discussion and Conclusion

The results of this study provide compelling evidence that combining fundamental analysis with multi-objective evolutionary optimization can produce portfolios that outperform traditional benchmarks in terms of both return and risk-adjusted performance within the Tehran Stock Exchange (TSE). The integration of fundamental screening ensured that the portfolio candidates were financially robust, while the evolutionary optimization framework effectively balanced competing objectives—maximizing returns, minimizing variance, and improving downside protection—through exploration of a wide solution space. The optimized portfolios not only delivered higher average monthly returns but also exhibited lower volatility and smaller maximum drawdowns compared to both the market index (TEDPIX) and the traditional Mean-variance optimization model proposed by Harry Markowitz. These findings confirm that a hybrid approach can achieve superior performance, which aligns with the broader literature emphasizing the necessity of multi-dimensional risk modeling in contemporary portfolio management (Cox et al., 2012; Mazin, 2012).

One of the central findings was the clear Pareto trade-off pattern between risk and return among the optimized portfolios. As expected, portfolios on the lower-risk end of the Pareto frontier achieved modest returns with low variance, while those on the higher-risk end produced higher returns but also greater variability. However, the risk-adjusted performance measured by the Sharpe Ratio and Sortino Ratio peaked at intermediate risk levels (around portfolio P6), suggesting the existence of an optimal balance between risk-taking and return generation. This pattern supports the argument that multi-objective optimization can help investors identify efficient frontier points tailored to their risk tolerance, offering them a spectrum of viable choices rather than a single "optimal" portfolio (Shiri Ghehi et al., 2017). Such diversity of solutions is especially valuable in the Iranian market, where high inflation and frequent regime shifts create uncertainty about future market states (Eyshi Ravandi et al., 2024).

The superior performance of the optimized portfolios compared to TEDPIX and the mean-variance model also underscores the added value of incorporating downside risk measures and evolutionary search mechanisms into portfolio construction. Traditional mean-variance optimization often underestimates tail risk because it assumes normally distributed returns and penalizes upside and downside volatility equally. In contrast, the proposed model explicitly accounted for downside risk using Value at Risk (VaR) constraints, ensuring that the selected portfolios were resilient to extreme losses. This aligns with prior evidence that models incorporating downside risk criteria outperform conventional variance-based models, especially in volatile markets (Sedaghati et al., 2022; Sina & Fallah, 2019). By constraining the search space based on downside risk while still maximizing expected return, the algorithm produced portfolios that achieved higher cumulative wealth growth with substantially smaller drawdowns. This supports the claim that combining multi-objective optimization with modern risk metrics can generate more stable and resilient portfolio strategies (Risk Controller, 2013).

The application of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) as the optimization engine contributed to these outcomes. The algorithm demonstrated rapid convergence, stabilizing after approximately 750 generations, and was able to maintain solution diversity while improving dominance ranking and crowding distance values across generations. This confirms the findings of previous studies showing that evolutionary algorithms outperform classical optimization techniques in solving complex, nonlinear portfolio problems under uncertainty (Dallagnol et al., 2009). In particular, evolutionary algorithms are less sensitive to local optima and can explore a broader solution space, which is crucial in markets like the TSE where nonlinearities and sudden shocks can distort asset correlations. Similar results were reported in studies that applied swarm intelligence and genetic algorithms to portfolio optimization, which found that these methods delivered superior risk-adjusted returns and faster convergence compared to gradient-based methods (Dunis et al., 2019). The computational efficiency observed in this study—achieving convergence within 11 minutes—further supports the practical feasibility of deploying such methods in real-world portfolio management systems.

Another important contributor to the model's success was the use of fundamental analysis for pre-selecting candidate stocks. By screening companies based on profitability (ROE, ROA, EPS), valuation (P/E, P/B), leverage (D/E), liquidity, and growth metrics, the model ensured that only fundamentally strong and stable firms were included in the optimization process. This approach aligns with findings that fundamentally sound firms generally exhibit lower price volatility and superior long-term performance (Bonabi Ghadim et al., 2022; Nikoo Sedeh et al., 2020). This also resonates with behavioral finance insights indicating that investors often overreact to short-term market noise while underestimating long-term fundamentals, creating opportunities for systematically constructed fundamental-based portfolios to outperform (Eyshi Ravandi et al., 2024). In this study, the selected firms exhibited higher profitability and lower volatility than the market average, which likely contributed to the strong performance of the resulting portfolios. These findings echo prior research on the TSE showing that fundamental factor-based portfolios achieved better risk-adjusted returns than purely price-driven strategies (Sina & Fallah, 2019).

The use of the Analytic Hierarchy Process (AHP) to weight fundamental indicators before optimization further enhanced the model's structure. AHP enabled the incorporation of expert judgment to assign weights based on the relative importance of financial dimensions such as profitability, leverage, and growth. Similar hybrid decision-making approaches have been successfully applied in portfolio optimization studies using techniques like Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and similarity measures, which improved asset ranking and accelerated optimization convergence (Nordfang & Steffensen, 2017; Zhang & Li, 2020). By integrating multi-criteria decision-making (MCDM) with evolutionary optimization, this study achieved a systematic alignment between the qualitative assessment of firm strength and the quantitative search for optimal weight allocations. This hybrid structure can be particularly valuable in the Iranian context, where market inefficiencies and speculative trading often obscure fundamental signals, making a purely data-driven approach less reliable without such pre-ranking mechanisms.

The findings also have implications for the growing field of sustainable and ethical investing. While this study primarily focused on financial fundamentals, the methodological framework could easily incorporate qualitative ESG indicators as additional constraints or objectives. This is supported by global evidence showing that portfolios integrating ESG and ethical considerations often exhibit lower risk and more stable returns, especially during market downturns (Marzuki et al., 2023; Viganò & Castellani, 2020). Given the increasing interest in aligning investment strategies with long-term sustainability goals, the demonstrated flexibility of the multi-objective evolutionary approach suggests it could be extended to design ESG-constrained portfolios for the Iranian market. This adaptability underscores the generalizability of the proposed model beyond purely financial objectives and into broader risk management domains, including climate and social risk considerations.

Moreover, the results reinforce the importance of incorporating local behavioral and structural characteristics into portfolio risk management frameworks. Previous research has shown that investor sentiment and liquidity shocks significantly affect stock returns in the Iranian market (Eyshi Ravandi et al., 2024). By integrating fundamental analysis—which inherently captures long-term value drivers—the proposed model reduces the influence of short-term sentiment-driven mispricing and liquidity distortions on portfolio selection. This finding aligns with studies that emphasize the need to contextualize global optimization methods within local market conditions to enhance their robustness and applicability (Aghamohammadi et al., 2022). The superior stability of the optimized portfolios in this study, even during high-volatility periods, suggests that this hybrid framework successfully mitigates some of the behavioral and structural risks specific to the Iranian market.

Overall, the results of this study are consistent with the broader literature emphasizing that risk is multi-dimensional and cannot be effectively managed through single-metric or single-objective approaches (Cox et al., 2012; Mazin, 2012). By simultaneously minimizing variance and downside risk while maximizing return, the proposed model addressed the multidimensional nature of risk in a comprehensive manner. Furthermore, the study contributes to the literature by demonstrating that combining fundamental screening with multi-objective evolutionary optimization can produce a diverse set of efficient portfolios that are both high-performing and resilient in the face of market turbulence. This represents a methodological advancement over existing studies on the TSE, which have typically either used fundamental screening without optimization or applied single-objective optimization without incorporating fundamental indicators (Nikoo Sedeh et al., 2020; Sedaghati et al., 2022). Thus, this study fills an important research gap by presenting a robust, adaptive, and interpretable portfolio risk management model tailored to the Iranian market context.

Despite its contributions, this study is subject to several limitations. First, the model was tested over a relatively short period (July 2023 to July 2024), which may limit the generalizability of the results to other market conditions or longer investment horizons. Market dynamics in Iran are highly sensitive to macroeconomic shocks, currency fluctuations, and regulatory changes, meaning that performance patterns observed during this period may not fully represent other phases of the market cycle. Second, the model relied on historical financial data for fundamental analysis and past return distributions for optimization, which inherently assumes stationarity in market behavior. This may reduce its predictive power during structural breaks or regime shifts. Third, while the study incorporated multiple risk measures, it did not explicitly account for liquidity constraints, transaction costs, or taxes, which can significantly affect real-world portfolio performance. Lastly, the use of expert-based AHP weighting introduces a degree of subjectivity, which could bias the fundamental scoring if different experts were consulted.

Future studies could extend this work in several important directions. One promising avenue is to evaluate the model over a longer time horizon and across different market regimes, including both bullish and bearish periods, to test its stability and adaptability under varying conditions. Another direction is to incorporate additional risk dimensions, such as liquidity risk, credit risk, and regime-switching volatility models, to more comprehensively capture the multidimensional nature of risk. Future research could also integrate ESG and ethical investment criteria into the optimization framework to explore whether socially responsible constraints enhance or hinder risk-adjusted performance in the Iranian context. Furthermore, developing dynamic versions of the model using online learning or adaptive evolutionary algorithms could allow portfolios to update in real time as new data arrive, thereby enhancing responsiveness to market changes. Finally, comparative studies applying this framework to other emerging markets could reveal how its effectiveness varies across different institutional and behavioral environments.

Practitioners in the Iranian capital market can leverage the insights from this study to improve their portfolio management practices. Investment managers can adopt the proposed hybrid framework to construct more resilient portfolios that align with clients' diverse risk-return preferences, particularly in volatile environments. Financial institutions could integrate the model into their decision-support systems to enhance risk monitoring, stress testing, and strategic asset allocation. Individual investors may also benefit from using simplified versions of the model embedded in robo-advisory platforms, enabling them to make data-driven investment decisions while mitigating downside risk. More broadly, regulators and policymakers could encourage the adoption of such advanced risk management approaches to enhance overall market stability and investor confidence. By doing so, the Iranian capital market could become more efficient, transparent, and attractive to both domestic and foreign investors.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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