JOMEFA

Journal of Management Economics and Financial Accounting

e-ISSN: 3110-4924
p-ISSN: 3110-5475

Optimization Of Portofolio Using NSGA-II Between Conventional and Shariah Stocks in Turkey

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Abstract: This study addresses the critical need for effective portfolio optimization in investment decision-making, particularly given the increasing complexity of stock types and classifications, such as conventional and Sharia-compliant indices in Turkey. This research aims to: (1)identify the optimal stock combinations across conventional, sharia, indexed in both, and combined, (2) analyze their efficient frontiers, and (3) compare performance ratios (Sharpe, Sortino, Omega) and expected returns for each group. Using a quantitative descriptive method, this study applies the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to optimize portfolios based on historical daily closing prices of BIST100 and KATILIM50 index stocks from January 3, 2022, to December 30, 2025. This finding indicates a trade-off between risk and return across all portofolio groups. A conventional portfolio alone offers the highest expected returns but also higher risk, while a Sharia-compliant portfolio alone provides lower returns and risk, suitable for investors who prioritize Sharia compliance. The combined portfolio group showed superior risk-adjusted performance, particularly in the Sharpe and Omega ratios, indicating better diversification potential with lower risk and competitive returns. Meanwhile, groups that are listed on both indices performed moderately. This research provides valuable academic references for technical and fundamental analysis in portfolio management, emphasizing that optimal portfolio selection is highly dependent on investor risk preferences.

Keywords: Portofolio Optimization; NSGA-II; Conventional Stocks; Sharia-Compliant Stocks; Efficient Ftontier

Received: April 20, 2026
Revised: April 23, 2026
Accepted: June 20, 2026
Published: June 30, 2026
Curr. Ver.: June 30, 2026

1. Introduction

Portfolio optimization is important information for investors in making investment decisions because it relates to selecting an asset combination with a specific level of risk and return [1]. On the other hand, every investor always wants maximum returns and minimal risk in their investment results, but this is a challenge for investors to manage [2]. One of the problems faced by investors is the management of their portfolios, as they have invested large sums of money without a clear purpose in unrelated areas such as securities, property, mortgages, and loans. Thus, the challenge faced by investors is when choosing a portfolio combination [3]. Diversification, therefore, offers an effective mechanism for reducing unsystematic risk while improving expected returns.

Another example that also becomes increasingly complex as the types and classifications of stocks become more varied. For example, in Turkey, there is an index that only measures companies based on market capitalization size, the BIST100, and another that is grouped based on compliance with Sharia rules, the KATILIM50. This reflects investors' preference for instruments that only consider market capitalization size and those that are Sharia-compliant. Over the past decade, the Islamic equity market has experienced substantial growth, driven by adherence to principles such as the prohibition of riba (interest), gharar (excessive uncertainty), and maysir (speculation), which form the foundation of Islamic capital markets [4].

Specifically in Turkey, evidence shows that the Borsa Istanbul stock market has grown rapidly in recent years [5]. In the context of the Sharia market, the development of a rating methodology for Sharia indices such as Katilim 50 indicates an increasing demand from investors for investment instruments that comply with Islamic principles. This includes qualitative and quantitative screening to ensure compliance with Sharia [6]. This phenomenon illustrates the evolution of Islamic finance as an ethical and sustainable alternative investment that can facilitate economic growth thru Sharia-compliant financing [7].

As a result, portfolio optimization faces challenges stemming from the distinction between conventional indices that are purely market capitalization based and Islamic indices that are required to comply with Sharia regulations. Other reasons include complex regulations, market fluctuations, and market uncertainty, where Sharia indices require additional screening to ensure compliance with Islamic principles, such as a maximum debt ratio of 33% and avoiding income from prohibited activities [8], [9]. This has a significant impact, especially in the E7 emerging countries, which include Turkey [10]. In this case, it differs from the usual, where calculating an optimal portfolio using classic methods like mean variance is felt to be less than optimal in the process. This is because comparing stocks from an index that is only measured by market capitalization, such as BIST100, and sharia compliance, such as KATILIM50, requires a method that can solve more complex problems and calculations [11].

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a relevant method that identifies optimal solutions by sorting the Pareto front at each generation and comparing these solutions across generations to obtain the final Pareto-optimal set [12]. This phenomenon is also related to the evolution of asset allocation models, where genetic algorithms are used to solve complex optimization problems in various fields, including investment portfolios, with the ability to find parallel and probabilistic solutions [13], [14]. In the context of the European Union, including Turkey, genetic algorithm models are also used to enhance competitive advantage thru capital investment and research and development. The research findings indicate that the best investments can enhance competitive positioning [15].

This research aims to meet the need for portfolio optimization that does not rely solely on one type of stock index, and to provide a comprehensive comparison between different stock groups, specifically between conventional stocks and Sharia-compliant stocks. This approach is expected to support both conventional and Sharia investors in making more informed investment decisions.

The objectives of this study are as follows: (1) to identify the optimal portfolio combinations for stocks listed only on the conventional index, listed only on the Sharia index, stocks listed on both indices, and a combined group consisting of all three categories; (2) to construct and analyze the efficient frontier for each of these stock groups, namely the conventional only, sharia only, both-indexed, and combined portfolios; and (3) to compare portfolio performance using the Sharpe ratio, Sortino ratio, and Omega ratio, as well as expected returns, across all portfolios derived from the conventional-only, Sharia-only, both-indexed, and combined stock groups.

The selection of Turkey as the research setting is grounded in its characteristics as an emerging market marked by high volatility and complex economic dynamics, making it an appropriate context for evaluating portfolio optimization models. In addition, NSGA-II was selected due to its capacity to efficiently address multi-objective optimization problems, generate a diverse set of Pareto-optimal solutions, and accommodate various constraints without relying on strict distributional assumptions.

2. Literature Review

2.1. Portfolio Optimization in Investment

Portfolio optimization is the process of selecting a combination of investment assets such as stocks, bonds, or commodities to maximize returns while minimizing risk, and it is the core of Modern Portfolio Theory (MPT), which emphasizes diversification to achieve a balance between risk and return [2]. In this theory, two things are considered: expected return and risk (volatility). Risk is the undesirable outcome for investors when investing. The metrics used are usually standard deviation or variance. One of the key assumptions of this theory is that the returns on investment assets always follow a normal distribution. This means that returns are considered to be symmetrically distributed around the mean, with most values clustered near the mean, and extreme events (very high or very low) having a very small and negligible probability.

However, empirical evidence suggests that the assumption of normality frequently fails to hold in real financial markets. This means that the probability of extreme events (very high or very low returns) is much higher than predicted by the normal model. Global empirical evidence shows that stock return distributions exhibit kurtosis levels three to ten times higher than those of a normal distribution [16]. This means that extreme stock drops or rises occur far more frequently than predicted by classical theory. Therefore, to achieve optimal results, research needs to be conducted using a different model [17].

2.2. NSGA-II

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is an evolutionary algorithm for multi-objective optimization that applies genetic principles, including selection, crossover, and mutation, to identify Pareto-optimal solutions, while employing non-dominated sorting and crowding distance to preserve population diversity [12]. Many studies rely on this method, and it is suitable for problems such as portfolio optimization where there is a trade-off between risk and return [14].

The working method includes the first step, which is to form a random initial population by ensuring diversity to prevent premature convergence to suboptimal solutions. The second step is to perform non-dominated sorting to classify the population into various groups based on Pareto dominance, and then each individual is ranked. The third step is to calculate the crowding distance for each individual on the frontier to maintain diversity and ensure that the solutions remain spread across the Pareto front area. In this section, the crowding distance prevents the clustering of solutions, encouraging exploration of the entire compromise space in multi-objective optimization [18]. In the fourth step, which is selection, crossover, and mutation. Mutations and crossovers help explore new regions in the search space, adapting to non-linear problems such as portfolio optimization [19]. The fifth step is that each combination is sorted again and the best individuals are selected for regeneration to maintain quality and dominance. The final step is to repeat the previous steps until a variety of Pareto-optimal solutions are found [20].

Evidence from prior research demonstrates that the generated portfolio outperforms the benchmark index; therefore, this study employs the NSGA-II method for portfolio optimization [21].

2.3 Efficient Frontier

Modern Portfolio Theory (MPT) introduces the concept of the efficient frontier, which represents the set of portfolios that either maximize returns for a given level of risk or minimize risk for a given level of return, thereby identifying the most efficient portfolios among all possible asset combinations [2]. It consists of two main components: the horizontal axis (X), which represents the level of risk accepted by investors, and the vertical axis (Y), which represents investment returns. The Efficient Frontier is depicted as a curve that bends upwards and to the right [2]. The efficient frontier curve establishes a trade-off relationship between risk and return [22].

The efficient frontier has been employed to compare the risk–return trade-offs between different stock indices. One study applied this approach by comparing the BIST30 and KATILIM30 indices using the mean–variance method to evaluate portfolio efficiency [23]. Cross-market comparative research further indicates that Sharia portfolios outperform the S&P 500 on a risk-adjusted basis, as evidenced by higher Sharpe ratios and greater resilience during periods of market downturn [24]. In addition, a comparative analysis of conventional and Sharia indices across four regions global, the United States, Europe, and Asia Pacific reveals that Sharia indices tend to achieve higher average returns while maintaining lower risk during specific crisis periods, particularly in 2007–2009 and 2013–2017, when compared to conventional indices [25].

2.4. Risk and Performance Measurement of Portfolio Investments

Portfolio performance measurement in investment must consider not only absolute returns but also the risks associated with those returns. As a result, various risk-adjusted performance measures are used to assess whether the returns earned are commensurate with the risk borne by investors [26]. Risk-based performance measures are widely used by individuals and institutions, and they confirm that the most common metrics in investment practice are the Sharpe and Sortino ratios [27]. The Sharpe ratio, in short, measures excess return per unit of total risk [28]. The Sharpe ratio is widely regarded as a key indicator in portfolio evaluation because it clearly reflects risk return efficiency, with higher values indicating better performance. Research on performance measurement using the Sharpe ratio has been conducted on the stocks of transportation and logistics companies in Indonesia, indicating that measurement with this index is relevant for investors who allocate only a portion of their investment funds to a portfolio [29]. In contrast, the Sortino ratio provides a more accurate assessment when return distributions are asymmetric by focusing solely on downside risk [30]. By focusing on the risk of loss, the Sortino ratio offers a different perspective on portfolio performance.

Furthermore, more modern measures like the omega ratio offer a more comprehensive approach because they calculate the entire probability distribution of returns by separating the probabilities of gains and losses based on a specific return threshold. The Omega ratio is considered an optimal portfolio performance measure because it incorporates both upside and downside outcomes relative to a specified threshold, rather than relying solely on excess returns or downside deviation, making it particularly suitable for non-normal return distributions [31]. Additionally, numerous studies employ standard deviation as a risk measure in performance evaluation, including research on thematic mutual funds in India [32]. Their findings indicate that standard deviation remains an explicit indicator for measuring risk exposure during volatile market periods. However, on the other hand, standard deviation does not reflect the true risk profile [33].

Another measure of risk employed in this study is the Coefficient of Variation (CV), calculated as the ratio of standard deviation to expected return. Unlike standard deviation, which measures absolute risk, the CV evaluates relative risk by indicating the amount of risk associated with each unit of expected return. Therefore, it is particularly useful for comparing the risk–return efficiency of different stocks. Comparative analysis study of risk and return between the Indonesian stock market and international benchmarks indicates that combining measures such as the coefficient of variation (CV) and the Sharpe ratio enables a more comprehensive evaluation of portfolio performance [34].

Previous Research:

a) A portfolio optimization with the similar model has been applied to major U.S. stock indices, specifically the S&P 500 and NASDAQ, demonstrating its effectiveness in improving portfolio performance within developed equity markets characterized by large-cap stocks [35].
b) Another previous studies have applied NSGA-II to stock level portfolio optimization using U.S. technology stocks, demonstrating its superiority over classical portfolio models in achieving higher returns with lower risk, which provides methodological support for extending NSGA-II to index based portfolio analysis in this study [36].
c) Previous research applies the NSGA-II algorithm to portfolio optimization by determining optimal asset allocation across various asset classes, including stocks, commodities, cryptocurrencies, and bonds. The results show that NSGA-II is capable of generating efficient frontier solutions that represent the optimal trade-off between risk and return. However, compared to other algorithms such as PSO, NSGA-II exhibits lower predictive accuracy, although it remains advantageous in terms of computational efficiency and solution diversity [37].
d) In the context of emerging markets, a similar optimization approach has been examined using Indonesian mutual funds, with the results indicating that the model is applicable

not only to developed markets but also to emerging economies and collective investment instruments [38].

Collectively, these studies provide a solid methodological and empirical foundation for portfolio optimization research across various markets and asset classes. However, none of them explicitly compares portfolio optimization outcomes between conventional stocks, Sharia-compliant stocks, and stocks indexed in both categories, particularly in the context of the Turkish stock market.

Furthermore, prior studies largely focus on optimization results without offering a comprehensive evaluation of portfolio performance ratios. Therefore, further research is required to not only optimize portfolios based on a single index type, but also to conduct a comprehensive comparison of stock groups such as conventional-only stocks , Sharia-only stocks, indexed by both stocks, and combined portfolios—in order to support more informed investment decisions for both conventional and Sharia investors.

3. Proposed Method

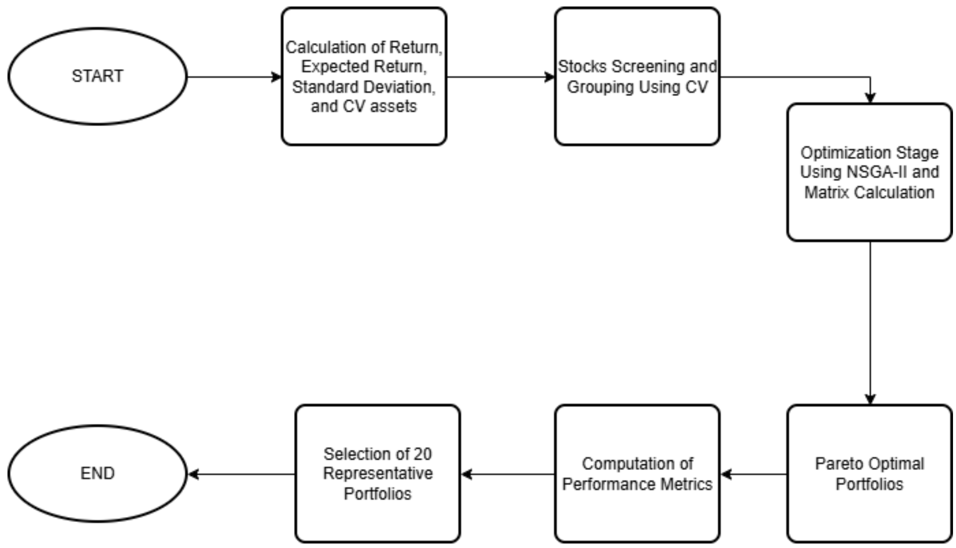

Figure 1. Algorithmic Framework of the Optimization Process Using NSGA-II
Source: Processed by the author, 2026

The data used in this study consist of daily closing stock prices for conventional stocks included in the BIST100 index and Sharia-compliant stocks listed in the KATILIM50 index, obtained from publicly available sources such as Yahoo Finance (yfinance). The dataset was downloaded on January 11, 2026, ensuring completeness and consistency of historical records. The dataset covers the period from January 3, 2022, to December 30, 2025. A purposive sampling method was employed to select samples that meet predefined criteria relevant to the research objectives [39].

The sample selection in this study is only for stocks that: (1) Have complete closing price data from January 3, 2022, to December 30, 2025, (2) Did not undergo delisting or listing during the period, (3) If there are incomplete closing prices or suspensions, they must not exceed seven consecutive days. This procedure was implemented to ensure data continuity and reliability, as such conditions may introduce bias in return estimation and distort risk measures due to discontinuities in the price series. The results of the screening can be visualized in a table like the one below:

Table 1. Population and Sample

Criteria	Total
Stocks indexed in BIST100 (Conventional index stocks)	100

Stocks indexed in KATILIM50 (Islamic index stocks)	50
Stocks indexed in both	38
Total Population	112
Stocks with incomplete daily closing price data, delisting, or data gaps exceeding seven consecutive days	24
Total Sampel	88

Source: Processed by the author, 2026

After the initial sample is obtained, the stocks are not immediately grouped. In the first step, expected returns and standard deviations are calculated using the Python programming language within the IDLE development environment. Stocks with negative expected returns are excluded from further analysis. For the remaining stocks, the coefficient of variation (CV) is computed and used as a ranking metric. Subsequently, the stocks are categorized into four groups: (1) conventional-only stocks, (2) Sharia-only stocks, (3) stocks listed on both indices, and (4) a combined group containing all stocks.

To ensure comparability across groups, the number of stocks is standardized based on the smallest group after filtering, namely the Sharia-only group, which consists of ten stocks. For groups containing more than ten stocks, the selection is performed by ranking stocks based on their CV values (from lowest to highest) and selecting the top ten stocks with the smallest CV. This procedure ensures that only stocks with positive expected returns are considered, using a consistent selection criterion across all groups. Such standardization helps reduce potential bias due to unequal sample sizes and improves the reliability of comparative quantitative analysis [40]. In addition, missing data observations are handled using the forward fill method by replacing missing values with the most recent available prices to maintain the continuity and consistency of the time series data. The results of the group division can be seen in the table below:

Table 2. Selected Stocks and Their Groups

Conventional Only Group	Sharia Only Group	Groups listed on both	Combined Group		
ANSGR	BERA	ASELS	ANSGR	BERA	ASELS
GARAN	FORMT	MAGEN	GARAN	FORMT	MAGEN
IEYHO	GOLTS	MAVI	IEYHO	GOLTS	MAVI
MGROS	IHLAS	MPARK	MGROS	IHLAS	MPARK
RALYH	JANTS	TUPRS	RALYH	JANTS	TUPRS
THYAO	KARSN	BIMAS	THYAO	KARSN	BIMAS
TURSG	KZBGY	KUYAS	TURSG	KZBGY	KUYAS
PGSUS	QUAGR	CIMSA	PGSUS	QUAGR	CIMSA
TAVHL	SELEC	ENJSA	TAVHL	SELEC	ENJSA
AKBNK	TMSN	GENIL	AKBNK	TMSN	GENIL

Source: Processed by the author, 2026

Table 2 shows the results of grouping based on stock code. The Conventional Only Group comprises ANSGR (Anadolu Anonim Türk Sigorta Şirketi), GARAN (Türkiye Garanti Bankası A.Ş.), AKBNK (Akbank T.A.Ş.), IEYHO (Işıklar Enerji ve Yapı Holding A.Ş.), RALYH (Ralyh Yatırım Holding A.Ş.), MGROS (Migros Ticaret A.Ş.), THYAO (Türk Hava Yolları

A.O.), PGSUS (Pegasus Hava Taşımacılığı A.Ş.), TAVHL (TAV Havalimanları Holding A.Ş.), and TURSG (Türkiye Sigorta A.Ş.).

The Sharia Only Group includes BERA (Bera Holding A.Ş.), FORMT (Formet Metal ve Cam Sanayi A.Ş.), GOLTS (Göltaş Göller Bölgesi Çimento Sanayi ve Ticaret A.Ş.), IHLAS (İhlas Holding A.Ş.), JANTS (Jantsa Jant Sanayi ve Ticaret A.Ş.), KARSN (Karsan Otomotiv Sanayii ve Ticaret A.Ş.), KZBGY (Kuzey Boru A.Ş.), QUAGR (Qua Granite Hayal Yapı ve Ürünleri Sanayi Ticaret A.Ş.), SELEC (Selçuk Ecza Deposu Ticaret ve Sanayi A.Ş.), and TMSN (Tümosan Motor ve Traktör Sanayi A.Ş.).

Groups listed on both indices consists of ASELS (Aselsan Elektronik Sanayi ve Ticaret A.Ş.), MAGEN (Margün Enerji Üretim Sanayi ve Ticaret A.Ş.), MAVI (Mavi Giyim Sanayi ve Ticaret A.Ş.), MPARK (MLP Sağlık Hizmetleri A.Ş.), TUPRS (Türkiye Petrol Rafinerileri A.Ş.), BIMAS (BİM Birleşik Mağazalar A.Ş.), KUYAS (Kuyas Yatırım A.Ş.), CIMSA (Çimsa Çimento Sanayi ve Ticaret A.Ş.), ENJSA (Enerjisa Enerji A.Ş.), and GENIL (Gen İlaç ve Sağlık Ürünleri Sanayi ve Ticaret A.Ş.). The Combined Group includes all stocks from the Conventional Only, Sharia Only, and Both Indexed Groups.

After the group is formed, the next process is to perform optimization using NSGA-II.

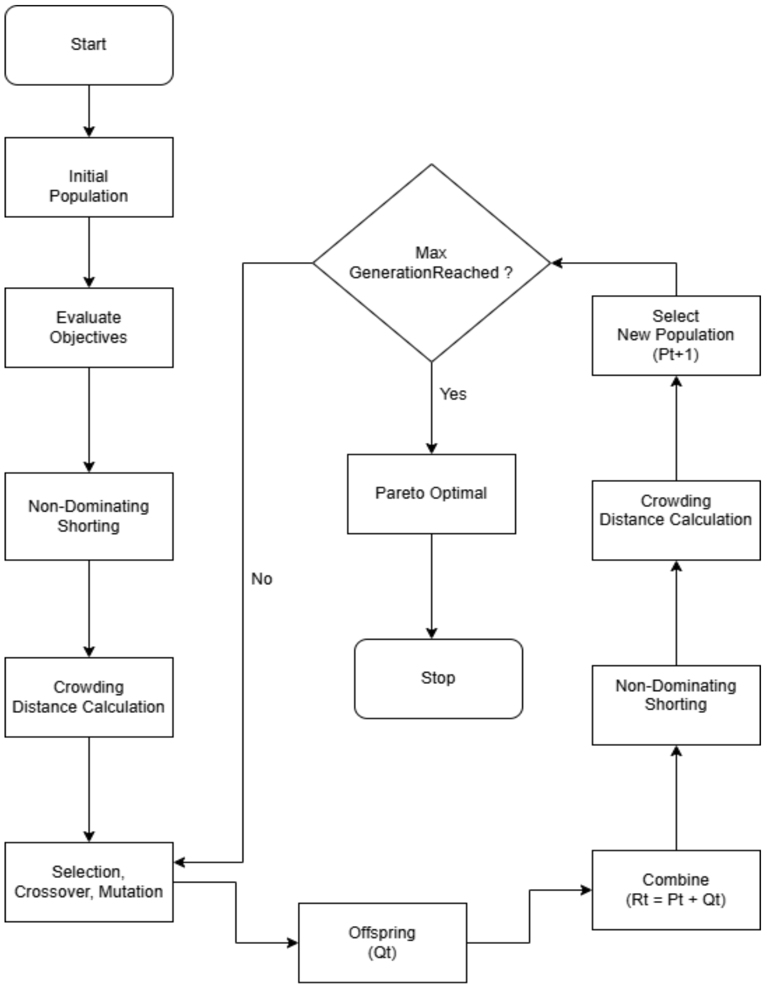

Figure 2. Algorithmic Framework of the NSGA-II
Source: Processed by the author, 2026

The implementation of the NSGA-II algorithm is illustrated in Figure 2, where the initial generations show a population characterized by a broad dispersion of risk return combinations, reflecting a high level of diversity among candidate solutions. As the evolutionary process advances, inferior (dominated) solutions are progressively filtered out through the application of non dominated sorting and selection procedures, allowing only the most competitive individuals to persist. Following the selection stage, genetic operators namely crossover and mutation are applied to generate a new set of offspring, which introduces additional diversity and enables the exploration of new regions in the solution space. These offspring are then evaluated and combined with the parent population to form a unified set, after which non dominated sorting is performed again to reclassify solutions based on Pareto dominance, followed by the recalculation of crowding distance to preserve solution diversity within each front. The next generation population is subsequently selected based on rank and crowding distance criteria. This iterative cycle continues as long as the maximum number of generations has not been reached and the population has not yet converged to a set of well-distributed optimal individuals. Consequently, over successive generations, the Pareto frontier becomes more stable, smoother, and evenly distributed, indicating that the algorithm is effectively converging toward optimal trade-offs between expected return and risk while maintaining diversity among the selected solutions.

After the optimization stage using NSGA-II, the resulting portfolios are evaluated using risk-adjusted performance metrics, namely the Sharpe ratio, Sortino ratio, and Omega ratio. These metrics provide a comprehensive assessment of portfolio efficiency by analyzing the relationship between returns and risk from various perspectives, extending the evaluation beyond the Pareto optimality framework [27], [41], [42]. The final results, including expected return, standard deviation, and coefficient of variation, were also calculated for each portfolio. It should also be noted that all final results have been annualized.

To further elaborate on the analytical framework, the mathematical formulations of return and risk measures are presented in the following section.

Table 3. Summary of Variables and Formulas

Calculation of asset returns and risk			
Component	Notation	Formula	Description
Asset Price	$\boldsymbol{Pit}$	_	Observed stock price
Daily Return Assets	$\boldsymbol{R_{i,t}}$	$\boldsymbol{R_{i,t} = \frac{Pi_{,t} - Pi_{,t-1}}{P_{i,t-1}}}$	Percentage return
Expected Return of Stock	μi	$\boldsymbol{\frac{1}{T}\sum_{t=1}^{T} R_{i,t}}$	Estimated return of the stock
Standard Deviation Assets	$\boldsymbol{\sigma_i}$	$\boldsymbol{\sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(R_{i,t} - \bar{R}_i)^2}}$	Volatility
Covariance matrix Assets	$\boldsymbol{\Sigma ij}$	$Cov(Ri,t,Rj,t)$	Risk structure
Coefficient of Variation Assets	$\boldsymbol{CV_i}$	$\boldsymbol{\frac{\sigma_i}{\mid \bar{R}_i \mid}}$	Risk per unit return

Source: Processed by the author, 2026

The formulas presented above are used both in the sample selection stage and during the NSGA-II optimization process. The core formulation of the NSGA-II algorithm is presented below.

Table 4. Formulas in the NSGA-II stage

NSGA-II			
Component	Notation	Formula	Description
Portofolio Weights	$\boldsymbol{w_i}$	$\boldsymbol{\sum_{i=1}^{n} w_i = 1}$	Allocation

Mean Return Vector	M	$(\mu 1,\ldots,\mu n)$	Vector of expected returns of all assets
Covariance Matrix	Σ	-	Risk Structure Assets
Portofolio Expected Return	$E(R_p)$	$\sum_{i=1}^{n} w_i \mu_i$	Portofolio Expected return
Portofolio Standard Deviation	σ_p^a	$\sqrt{w^T \Sigma w}$	portfolio risk
Objective 1	-	$\max E(R_p)$	Maximize Return
Objective 2	-	$\min \sigma_p^a$	Minimize Risk
Dominance	A<B	_	Pareto dominance rule
Non-Dominated Sorting	_	_	Ranking solutions
Crowding Distance	di	Diversity preservation	Spread of solutions
Selection	_	Tournament	Choose best individuals
Crossover	_	$w' = \alpha w_1 + (1-\alpha) w_2$	Combine solutions
Mutation	_	$w' = w + \epsilon$	Random variation

Source: Processed by the author, 2026

After the NSGA-II optimization, a Pareto-optimal set of portfolios is obtained. Performance metrics, including expected return, risk, Sharpe ratio, Sortino ratio, and Omega ratio, are computed for each portfolio in the Pareto set. Subsequently, 20 representative portfolios are selected for each group by uniformly sampling along the efficient frontier.

Table 5. Portfolio Performance Metrics Formulas

Performance Metrics & Annualization			
Component	Notation	Formula	Description
Portfolio Annual Expected Return	$\mu p^{(a)}$	$\mu_p \times 252$	Expected yearly return of the portfolio
Portfolio Annual Standard Deviation	$\sigma p^{(a)}$	$\sqrt{w^T \Sigma w} \times \sqrt{252}$	Yearly volatility of the portfolio
Portfolio Coefficient of Variation	CVp	$\frac{\sigma p^{(a)}}{\mu p^{(a)}}$	Risk per unit return of the portfolio
Portfolio Sharpe Ratio	SRp	$\frac{\mu p^{(a)} - Rf}{\sigma p^{(a)}}$	Risk-adjusted return of the portfolio
Portfolio Sortino Ratio	$SoRp$	$\frac{\mu p^{(a)} - MAR}{\sigma_{downp}{}^{(a)}}$	Downside risk-adjusted return of the portfolio
Portfolio Omega Ratio	Ωp	$\frac{\sum \max(R_a - \tau, 0)}{\sum \max(\tau - R_a, 0)}$	Gain-loss ratio of the portfolio

Source: Processed by the author, 2026

Table 5 shows the formulas used to calculate the metrics. The factor 252 reflects the approximate number of trading days in a year and is used to annualize daily measures. Daily returns are scaled linearly (×252), while volatility is scaled by $\sqrt{252}$, consistent with the time-scaling behavior of return variance. The Sharpe Ratio is calculated using a constant risk-free rate (Rf) of 34%, derived from the average yield of Turkey's 5-year government bond obtained from Investing.com over the study period. The same value is consistently applied as the Minimum Acceptable Return (MAR) for the Sortino Ratio and as the threshold return for the Omega ratio, ensuring comparability across performance measures. This approach provides a stable market-based proxy for the risk-free rate in Turkey's high-inflation environment while maintaining consistency in performance evaluation.

4. Results and Discussion

Analysis of each portfolio group shows that there is a trade-off relationship between risk and return, which varies across each group. The implementation of NSGA-II, applied to each group using the Python programming language, resulted in Excel file output and an efficient frontier curve. That Excel file contains a table with 20 representative portfolios from the efficient frontier (pareto). Inside, there is a composition of the weight allocation for each stock, expected return, standard deviation, CV, and performance ratio for each portfolio in each group.

The resulting efficient frontier curve contains 20 portfolio points that form it from each group. It also includes the max, median, and min points for the Sharpe, Sortino, and Omega ratios for each group, with dark blue representing the maximum point, light blue the median point, and white the minimum point. Each efficient frontier curve has a starting point on the left side and an ending point on the right side, which together determine its range of efficiency. The leftmost point represents the portfolio with the lowest risk level. Conversely, the rightmost point represents the portfolio with the maximum expected return.

4.1. Statistics on Returns and Risks of Selected Stock

Table 6. Stock Returns and Risks

Stocks	Expected Return	Standard Deviation	Coefficient of Variation
ANSGR	96.84%	42.97%	0.4437
GARAN	96.74%	46.82%	0.4839
IEYHO	191.10%	59.29%	0.3103
MGROS	97.38%	40.31%	0.4139
RALYH	210.95%	51.56%	0.2444
THYAO	90.94%	41.03%	0.4511
TURSG	114.56%	44.80%	0.3911
PGSUS	80.44%	43.91%	0.5458
TAVHL	73.63%	41.46%	0.5631
AKBNK	82.91%	48.82%	0.5888
BERA	39.89%	51.27%	1.2853
FORMT	45.30%	59.83%	1.3207
GOLTS	61.92%	50.35%	0.8132
IHLAS	41.70%	59.11%	1.4175
JANTS	23.77%	51.61%	2.1716
KARSN	25.73%	52.31%	2.0332
KZBGY	15.38%	60.14%	3.9102
QUAGR	26.76%	48.82%	1.8245
SELEC	62.89%	45.28%	0.7200
TMSN	49.53%	56.24%	1.1355
ASELS	116.51%	46.28%	0.3973
MAGEN	147.46%	55.44%	0.3760
MAVI	83.51%	41.17%	0.4930
MPARK	88.56%	41.55%	0.4692
TUPRS	85.83%	40.43%	0.4710
BIMAS	75.96%	39.09%	0.5145
KUYAS	148.64%	59.55%	0.4006
CIMSA	85.55%	48.32%	0.5648
ENJSA	72.33%	42.16%	0.5829
GENIL	93.80%	48.57%	0.5178

Source: Processed by the author, 2026

4.2. Optimization Results for the Conventional-Only Group

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14	p15	p16	p17	p18	p19	p20
ANSGR	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,11%	0,23%	0,51%	1,19%	1,94%	3,05%	4,05%	5,09%	6,22%	7,46%	8,92%	10,14%	12,39%	13,89%
GARAN	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,33%	1,00%	2,33%	3,47%	4,58%	5,97%	7,24%	8,00%	9,17%	8,21%	9,45%	9,16%	7,16%	7,36%
IEYHO	0,00%	4,50%	8,40%	14,99%	21,26%	30,23%	40,71%	37,92%	35,76%	33,91%	32,34%	30,35%	28,18%	25,90%	24,07%	21,77%	18,89%	16,24%	12,39%	10,97%
MGROS	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,15%	0,36%	0,80%	1,55%	2,45%	3,56%	4,65%	6,19%	7,00%	8,82%	10,77%	12,26%	13,01%	14,35%
RALYH	100,00%	95,50%	91,60%	85,01%	78,74%	69,77%	56,61%	54,30%	52,16%	50,25%	47,86%	45,21%	42,39%	40,18%	36,86%	34,25%	30,38%	28,10%	25,73%	20,33%
THYAO	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,05%	0,09%	0,21%	0,45%	0,75%	1,32%	1,83%	2,94%	3,25%	5,30%	6,61%	7,99%	9,50%	10,81%
TURSG	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	2,01%	6,04%	8,10%	9,01%	9,85%	10,12%	11,00%	10,63%	11,83%	10,45%	10,58%	10,12%	9,67%	10,32%
PGSUS	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,01%	0,04%	0,05%	0,06%	0,12%	0,20%	0,29%	0,54%	1,28%	1,46%	2,05%	3,84%	4,57%
TAVHL	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,01%	0,03%	0,04%	0,05%	0,11%	0,18%	0,25%	0,46%	1,08%	1,23%	1,73%	3,24%	3,84%
AKBNK	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,02%	0,03%	0,07%	0,08%	0,11%	0,19%	0,28%	0,54%	0,61%	1,38%	1,70%	2,21%	3,07%	3,57%
μ_p	127,30%	127,28%	127,27%	127,24%	127,22%	127,18%	125,99%	123,83%	121,87%	120,07%	118,16%	115,82%	113,36%	110,98%	108,46%	105,55%	102,05%	99,30%	95,65%	92,05%
σ_p	51,85%	49,72%	48,00%	45,40%	43,35%	41,24%	39,38%	37,99%	36,84%	35,86%	34,86%	33,73%	32,62%	31,66%	30,72%	29,83%	28,90%	28,34%	27,87%	27,62%
(CV)	0,407	0,391	0,377	0,357	0,341	0,324	0,313	0,307	0,302	0,299	0,295	0,291	0,288	0,285	0,283	0,283	0,283	0,285	0,291	0,300
Sharpe	1,888	1,968	2,038	2,154	2,256	2,371	2,452	2,485	2,510	2,528	2,546	2,562	2,573	2,576	2,573	2,552	2,514	2,466	2,377	2,267
Sortino	3,014	3,148	3,264	3,458	3,630	3,840	4,027	4,070	4,102	4,128	4,153	4,175	4,188	4,186	4,174	4,129	4,057	3,968	3,805	3,622
Omega	1,399	1,419	1,436	1,462	1,483	1,501	1,512	1,520	1,527	1,531	1,536	1,540	1,543	1,545	1,546	1,545	1,540	1,532	1,515	1,493

Figure 3. Optimal Composition of the Conventional-Only Group
Source: Processed by the author, 2026

The results for the conventional-only group show that the highest expected return among the 20 representative portfolios is 127.30% and the lowest is 92.05%. The portfolio with the highest expected return allocates 100% of its weight to RALYH (Rally Yatırım Holding A.Ş.) shares. Conversely, for portfolios with lower expected returns, the weight allocation for each share is more dispersed. The coefficient of variation (CV) value shows a decreasing pattern up to the medium-risk point, before increasing again at high risk.

4.3. Optimization Results for the Sharia-Only Group

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14	p15	p16	p17	p18	p19	p20
BERA	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,01%	0,02%	0,03%	0,18%	0,72%	1,41%	2,19%	3,05%	3,73%	4,54%	5,37%	6,23%
FORMT	0,00%	0,04%	0,05%	0,04%	0,04%	0,19%	0,65%	2,38%	4,69%	7,42%	10,04%	12,32%	14,44%	15,00%	14,48%	14,26%	13,76%	13,41%	12,86%	12,27%
GOLTS	100,00%	96,03%	91,80%	87,30%	82,41%	76,60%	70,41%	64,63%	59,25%	51,64%	44,95%	38,25%	31,49%	28,35%	25,73%	23,15%	20,57%	18,08%	15,11%	12,04%
IHLAS	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,01%	0,09%	0,12%	0,69%	2,58%	4,69%	7,11%	7,42%	7,16%	6,94%	6,71%	6,42%	6,18%	6,08%
JANTS	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,07%	0,15%	0,77%	1,85%	2,83%	3,90%	4,93%	6,12%	7,28%
KARSN	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,01%	0,05%	0,10%	0,48%	1,15%	1,76%	2,42%	3,06%	3,80%	4,55%
KZBGY	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,12%	0,30%	1,17%	2,60%	3,95%	5,33%	6,71%	8,30%	9,95%
QUAGR	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,14%	0,29%	1,44%	3,45%	5,28%	7,26%	9,16%	11,40%	13,68%
SELEC	0,00%	3,91%	8,13%	12,62%	17,53%	23,12%	28,78%	31,53%	33,01%	35,09%	35,56%	36,36%	36,41%	35,09%	32,87%	30,76%	28,56%	26,39%	23,89%	21,23%
TMSN	0,00%	0,02%	0,02%	0,03%	0,02%	0,08%	0,15%	1,36%	2,91%	5,11%	6,83%	7,83%	8,97%	8,86%	8,52%	8,02%	7,77%	7,31%	6,96%	6,69%
μ_p	66,16%	65,89%	65,61%	65,31%	64,99%	64,59%	64,16%	63,67%	63,17%	62,46%	61,72%	60,89%	59,95%	58,84%	57,32%	55,87%	54,38%	52,92%	51,22%	49,48%
σ_p	51,68%	50,11%	48,50%	46,88%	45,23%	43,44%	41,71%	40,11%	38,67%	36,91%	35,53%	34,41%	33,55%	32,95%	32,28%	31,73%	31,28%	30,93%	30,66%	30,55%
CV	0,7812	0,7604	0,7392	0,7178	0,6960	0,6725	0,6502	0,6300	0,6121	0,5910	0,5756	0,5652	0,5596	0,5600	0,5632	0,5680	0,5751	0,5845	0,5987	0,6174
Sharpe	0,8452	0,8665	0,8894	0,9138	0,9399	0,9696	0,9993	1,0269	1,0524	1,0831	1,1046	1,1161	1,1169	1,1036	1,0793	1,0524	1,0201	0,9842	0,9373	0,8839
Sortino	1,3380	1,3690	1,4018	1,4360	1,4718	1,5113	1,5492	1,5850	1,6170	1,6514	1,6690	1,6702	1,6546	1,6263	1,5830	1,5363	1,4826	1,4244	1,3503	1,2680
Omega	1,1598	1,1639	1,1683	1,1729	1,1777	1,1830	1,1879	1,1932	1,1985	1,2053	1,2103	1,2133	1,2139	1,2115	1,2068	1,2016	1,1952	1,1881	1,1788	1,1680

Figure 4. Optimal Composition of the Sharia-Only Group
Source: Processed by the author, 2026

The results for the Sharia-Only Group indicate a positive risk–return trade-off, where higher expected returns are associated with higher levels of risk, and vice versa. GOLTS (Göltaş Göller Bölgesi Çimento Sanayi ve Ticaret A.Ş.) shares consistently dominate portfolio weight, especially in high to medium expected return portfolios, indicating that these shares have the highest return profile within the sharia stock group. The expected return of the portfolio is in the range of approximately 66.17% to 49.48%, followed by a standard deviation in the range of 51.68% to 30.55%. The coefficient of variation (CV) value tends to be high for high-risk and lowest-risk portfolios, indicating that the relative efficiency of the sharia stock portfolio is most optimal at the medium risk level.

4.4. Optimization Results for Stocks Listed on Both Indices

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14	p15	p16	p17	p18	p19	p20
ASELS	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	1,28%	8,74%	15,08%	18,80%	19,83%	20,39%	19,05%	17,31%	15,20%	14,06%	12,06%	9,68%	7,57%	4,84%
MAGEN	0,00%	4,65%	10,53%	17,47%	24,77%	34,78%	47,86%	44,45%	42,13%	37,95%	35,87%	32,35%	30,19%	27,46%	24,78%	21,87%	18,72%	15,05%	11,54%	7,76%
MAVI	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,06%	0,08%	0,15%	0,39%	0,75%	1,01%	2,03%	3,28%	5,36%	7,01%	9,45%
MPARK	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,02%	0,27%	1,36%	3,32%	5,35%	6,89%	8,71%	10,53%	11,61%	12,30%	12,16%	12,51%	12,57%
TUPRS	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,04%	0,35%	0,49%	0,63%	2,43%	4,64%	7,02%	8,59%	10,36%	12,05%	13,71%	15,23%
BIMAS	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,04%	0,28%	0,40%	0,55%	1,93%	3,67%	5,43%	7,37%	9,64%	12,63%	15,21%	18,48%
KUYAS	100,00%	95,35%	89,47%	82,53%	75,23%	65,22%	50,84%	46,74%	42,00%	39,35%	35,18%	32,63%	30,24%	27,42%	25,22%	21,67%	19,36%	16,97%	14,58%	11,91%
CIMSA	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,03%	0,05%	0,09%	0,20%	0,37%	0,49%	1,01%	1,60%	2,60%	3,38%	4,27%
ENJSA	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,02%	0,04%	0,06%	0,17%	0,32%	0,42%	0,86%	1,38%	2,26%	2,95%	3,93%
GENIL	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,04%	0,41%	1,80%	4,74%	7,80%	8,52%	9,36%	9,90%	10,94%	11,30%	11,23%	11,54%	11,55%
μ_p	109,24%	109,11%	108,95%	108,75%	108,54%	108,26%	107,61%	106,09%	104,54%	102,73%	100,74%	98,78%	96,79%	94,35%	92,08%	89,36%	86,82%	83,88%	81,12%	77,95%
σ_p	60,13%	57,81%	55,05%	52,09%	49,39%	46,51%	43,98%	41,84%	40,01%	38,34%	36,65%	35,18%	33,89%	32,43%	31,22%	29,96%	29,01%	28,17%	27,64%	27,36%
CV	0,5504	0,5298	0,5053	0,4790	0,4551	0,4296	0,4087	0,3944	0,3828	0,3732	0,3638	0,3561	0,3501	0,3437	0,3391	0,3353	0,3341	0,3359	0,3407	0,3510
Sharpe	1,4430	1,4987	1,5708	1,6562	1,7425	1,8446	1,9359	1,9981	2,0509	2,0932	2,1354	2,1691	2,1930	2,2161	2,2293	2,2322	2,2183	2,1797	2,1220	2,0276
Sortino	2,3438	2,4322	2,5446	2,6756	2,8061	2,9606	3,1194	3,2299	3,3219	3,3852	3,4429	3,4780	3,5052	3,5259	3,5306	3,5123	3,4716	3,3937	3,2891	3,1307
Omega	1,2894	1,3019	1,3174	1,3357	1,3534	1,3733	1,3929	1,4100	1,4237	1,4340	1,4445	1,4520	1,4583	1,4647	1,4683	1,4684	1,4643	1,4556	1,4428	1,4218

Figure 5. Optimal Composition of Stocks Listed on Both Indices
Source: Processed by the author, 2026

Table 7 shows that, within the Both-Indexed Group, the portfolio with the highest expected return allocates 100% of its weight to KUYAS (Kuyas Yatırım A.Ş.). Conversely, the portfolio with the lowest expected return and risk exhibits a more diversified weight allocation.The highest expected return is 109.24%%, the lowest is 77.95%, the highest risk (standard deviation) is 60.13%, and the lowest is 27.36%. The resulting coefficient of variation (CV) value is smaller in the medium-risk portfolio.

4.5. Optimization Results for the Combined Group

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14	p15	p16	p17	p18	p19	p20
AKBNK	0,00%	0,02%	0,05%	0,07%	0,07%	0,07%	0,06%	0,06%	0,06%	0,06%	0,07%	0,18%	0,34%	0,48%	0,65%	0,79%	1,01%	1,21%	1,44%	1,71%
ANSGR	0,00%	0,01%	0,02%	0,02%	0,03%	0,03%	0,03%	0,04%	0,04%	0,05%	0,07%	0,45%	0,95%	1,42%	2,01%	2,46%	3,18%	3,87%	4,69%	5,69%
ASELS	4,88%	4,69%	4,50%	4,27%	3,90%	3,55%	3,10%	2,72%	2,16%	1,55%	1,01%	0,98%	1,03%	1,20%	1,41%	1,49%	1,74%	1,97%	2,28%	2,69%
BERA	1,96%	1,74%	1,50%	1,27%	1,16%	1,04%	0,92%	0,83%	0,66%	0,45%	0,29%	0,30%	0,34%	0,42%	0,50%	0,55%	0,66%	0,76%	0,88%	1,04%
BIMAS	0,00%	0,04%	0,08%	0,19%	0,61%	1,01%	1,56%	2,02%	2,69%	3,38%	4,03%	4,08%	4,05%	3,88%	3,65%	3,59%	3,33%	3,09%	2,73%	2,24%
CIMSA	0,00%	0,02%	0,03%	0,07%	0,22%	0,36%	0,56%	0,73%	0,97%	1,22%	1,45%	1,43%	1,37%	1,27%	1,13%	1,07%	0,90%	0,75%	0,54%	0,26%
ENJSA	0,00%	0,00%	0,01%	0,01%	0,02%	0,02%	0,02%	0,02%	0,02%	0,03%	0,05%	0,40%	0,87%	1,31%	1,87%	2,28%	2,97%	3,62%	4,41%	5,39%
FORMT	0,32%	0,29%	0,26%	0,22%	0,21%	0,19%	0,17%	0,16%	0,13%	0,10%	0,09%	0,26%	0,49%	0,72%	0,99%	1,20%	1,55%	1,87%	2,26%	2,73%
GARAN	1,62%	1,88%	2,16%	2,48%	2,99%	3,47%	4,10%	4,61%	5,38%	6,23%	6,97%	6,75%	6,34%	5,78%	5,09%	4,68%	3,84%	3,06%	2,05%	0,78%
GENIL	0,00%	0,07%	0,13%	0,31%	1,00%	1,65%	2,55%	3,30%	4,39%	5,52%	6,57%	6,73%	6,77%	6,58%	6,34%	6,31%	6,04%	5,79%	5,40%	4,86%
GOLTS	0,00%	0,01%	0,02%	0,03%	0,05%	0,08%	0,11%	0,15%	0,19%	0,23%	0,30%	0,70%	1,22%	1,70%	2,32%	2,78%	3,53%	4,24%	5,10%	6,17%
IEYHO	15,51%	15,07%	14,60%	14,18%	14,04%	13,90%	13,76%	13,67%	13,49%	13,20%	12,98%	12,49%	11,87%	11,32%	10,65%	10,09%	9,26%	8,47%	7,56%	6,47%
IHLAS	0,00%	0,14%	0,29%	0,42%	0,44%	0,47%	0,49%	0,50%	0,53%	0,59%	0,62%	0,60%	0,58%	0,55%	0,50%	0,49%	0,43%	0,39%	0,32%	0,23%
JANTS	0,00%	0,19%	0,39%	0,56%	0,52%	0,49%	0,42%	0,35%	0,27%	0,24%	0,18%	0,32%	0,53%	0,74%	1,00%	1,19%	1,51%	1,81%	2,18%	2,64%
KARSN	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,01%	0,01%	0,01%	0,01%	0,02%	0,02%	0,03%	0,03%	0,04%	0,04%	0,03%
KUYAS	16,76%	17,18%	17,63%	17,90%	17,25%	16,64%	15,74%	14,94%	13,87%	12,86%	11,80%	10,98%	10,07%	9,44%	8,66%	7,90%	6,92%	5,99%	4,99%	3,84%
KZBGY	0,00%	0,00%	0,01%	0,01%	0,01%	0,01%	0,02%	0,02%	0,02%	0,03%	0,04%	0,26%	0,55%	0,83%	1,18%	1,44%	1,87%	2,27%	2,75%	3,34%
MAGEN	0,87%	2,25%	3,71%	5,03%	5,42%	5,83%	6,19%	6,40%	6,90%	7,71%	8,23%	8,11%	7,89%	7,56%	7,16%	6,93%	6,45%	6,00%	5,43%	4,71%
MAVI	1,84%	1,63%	1,41%	1,21%	1,10%	1,00%	0,88%	0,79%	0,64%	0,44%	0,29%	0,30%	0,33%	0,39%	0,45%	0,49%	0,57%	0,64%	0,73%	0,82%
MGROS	2,62%	3,32%	4,07%	4,64%	4,29%	3,97%	3,43%	2,93%	2,31%	1,83%	1,25%	1,40%	1,70%	2,10%	2,60%	2,90%	3,50%	4,07%	4,79%	5,71%
MPARK	0,39%	0,82%	1,27%	1,74%	2,21%	2,66%	3,23%	3,67%	4,37%	5,19%	5,89%	6,16%	6,42%	6,50%	6,62%	6,80%	6,95%	7,10%	7,22%	7,33%
PGSUS	2,39%	2,28%	2,17%	2,04%	1,87%	1,70%	1,48%	1,31%	1,04%	0,75%	0,49%	0,54%	0,65%	0,81%	1,01%	1,13%	1,37%	1,60%	1,89%	2,26%
QUAGR	2,47%	2,18%	1,88%	1,59%	1,45%	1,30%	1,14%	1,03%	0,83%	0,56%	0,36%	0,56%	0,84%	1,16%	1,57%	1,84%	2,33%	2,80%	3,39%	4,13%
RALYH	43,94%	41,89%	39,75%	37,65%	36,08%	34,55%	32,72%	31,32%	29,02%	26,22%	23,89%	22,75%	21,59%	21,01%	20,29%	19,37%	18,45%	17,55%	16,73%	15,87%
SELEC	0,00%	0,22%	0,46%	0,65%	0,61%	0,57%	0,49%	0,41%	0,33%	0,29%	0,22%	0,41%	0,67%	0,93%	1,26%	1,50%	1,90%	2,27%	2,72%	3,27%
TAVHL	0,86%	0,79%	0,70%	0,68%	0,92%	1,15%	1,47%	1,75%	2,14%	2,52%	2,89%	2,81%	2,65%	2,41%	2,11%	1,94%	1,58%	1,24%	0,79%	0,22%
THYAO	0,00%	0,00%	0,00%	0,01%	0,01%	0,01%	0,01%	0,01%	0,01%	0,01%	0,01%	0,02%	0,03%	0,04%	0,05%	0,06%	0,07%	0,08%	0,08%	0,07%
TMSN	3,57%	3,15%	2,71%	2,30%	2,08%	1,88%	1,65%	1,48%	1,18%	0,79%	0,49%	0,42%	0,38%	0,41%	0,43%	0,41%	0,44%	0,47%	0,51%	0,58%
TUPRS	0,00%	0,00%	0,01%	0,01%	0,01%	0,02%	0,02%	0,02%	0,02%	0,02%	0,04%	0,22%	0,47%	0,70%	0,99%	1,21%	1,57%	1,90%	2,30%	2,78%
TURSG	0,00%	0,10%	0,18%	0,44%	1,43%	2,37%	3,67%	4,75%	6,31%	7,93%	9,44%	9,35%	9,00%	8,32%	7,47%	7,06%	6,05%	5,10%	3,81%	2,13%
μ_p	110,14%	109,53%	108,91%	108,23%	107,40%	106,60%	105,58%	104,76%	103,50%	102,08%	100,77%	99,21%	97,34%	95,84%	94,00%	92,37%	90,08%	87,90%	85,46%	82,55%
σ_p	32,31%	31,75%	31,23%	30,73%	30,19%	29,70%	29,13%	28,71%	28,13%	27,58%	27,18%	26,86%	26,51%	26,26%	25,98%	25,77%	25,51%	25,33%	25,20%	25,14%
CV	0,2933	0,2899	0,2868	0,2839	0,2811	0,2786	0,2759	0,2740	0,2717	0,2701	0,2698	0,2707	0,2723	0,2740	0,2764	0,2789	0,2832	0,2882	0,2948	0,3045
Sharpe	2,7135	2,7416	2,7674	2,7907	2,8129	2,8323	2,8532	2,8664	2,8809	2,8868	2,8802	2,8570	2,8244	2,7940	2,7525	2,7128	2,6497	2,5829	2,4997	2,3898
Sortino	4,3537	4,4009	4,4449	4,4840	4,5181	4,5472	4,5771	4,5945	4,6109	4,6111	4,5904	4,5406	4,4730	4,4119	4,3308	4,2544	4,1360	4,0130	3,8633	3,6706
Omega	1,5950	1,6018	1,6082	1,6138	1,6199	1,6254	1,6310	1,6350	1,6397	1,6416	1,6414	1,6378	1,6316	1,6257	1,6171	1,6079	1,5930	1,5766	1,5564	1,5299

Figure 6. Optimal Composition of the Combine Group
Source: Processed by the author, 2026

The combined group produces different outcomes because it contains all stocks included in the other groups. The expected return ranges from 110.14% to 82.55%, while the risk (standard deviation) ranges from 25.13% to 32.31%. The portfolio with the highest expected return also exhibits a more diversified allocation of weights. The coefficient of variation (CV) declines from high-return portfolios to medium-return portfolios, but rises again among portfolios with lower returns and lower risk, indicating that portfolios with lower expected returns tend to be less efficient.

4.6. Efficient Frontier and Its Comparison

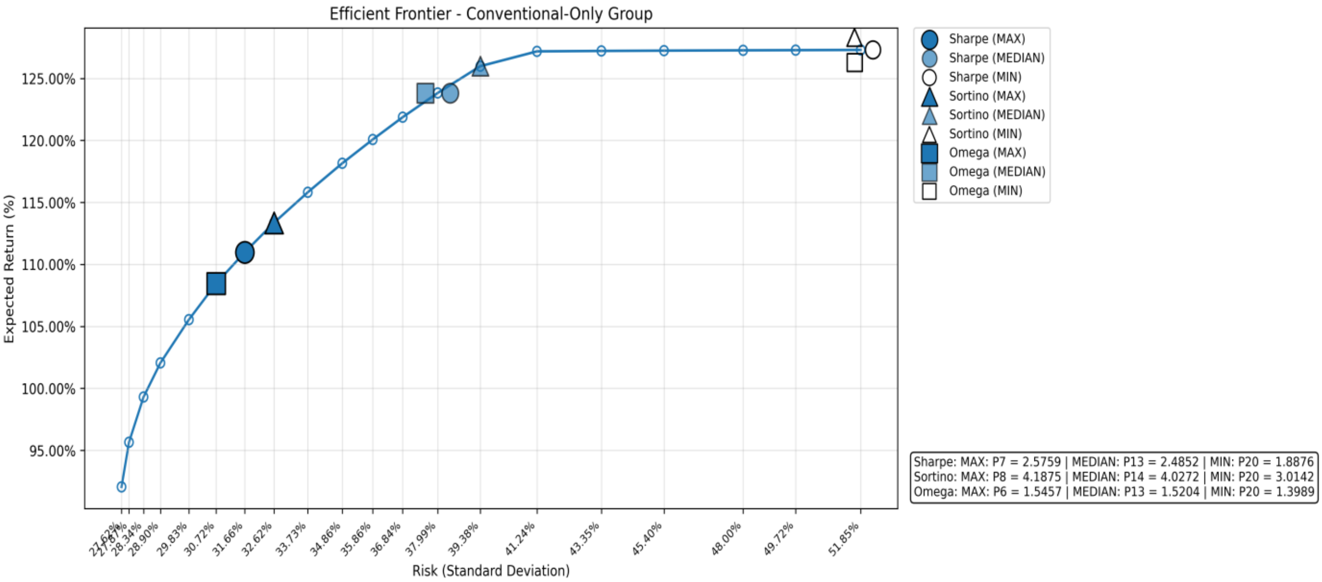

Figure 7. Efficient Frontier for Conventional-Only Group
Source: Processed by the author, 2026

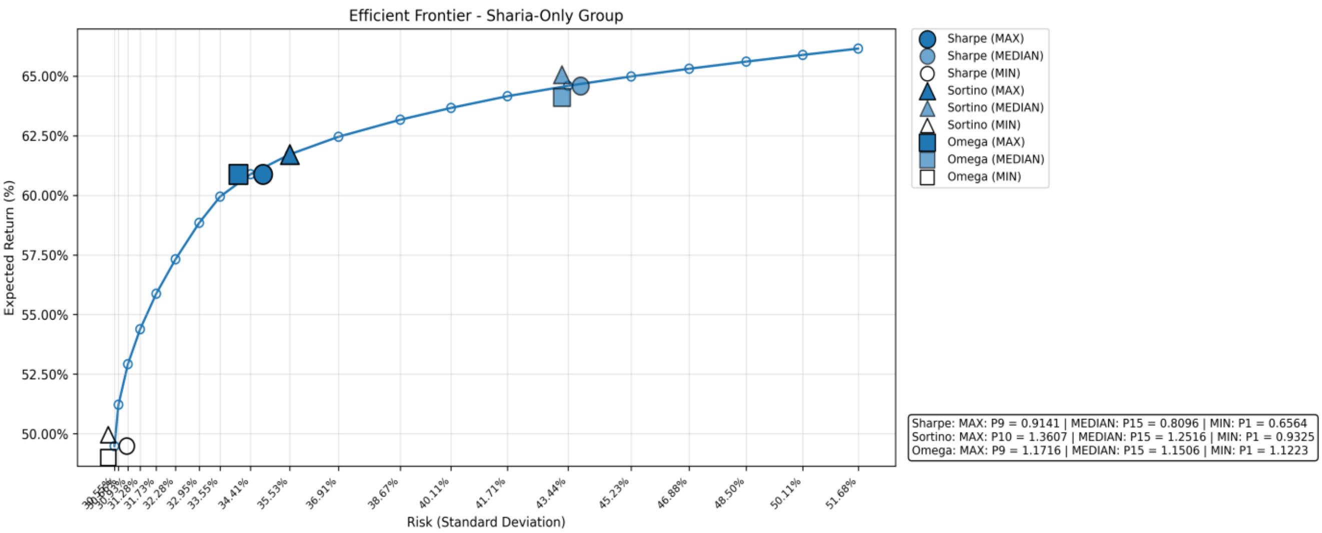

Figure 8. Efficient Frontier for Sharia-Only Group
Source: Processed by the author, 2026

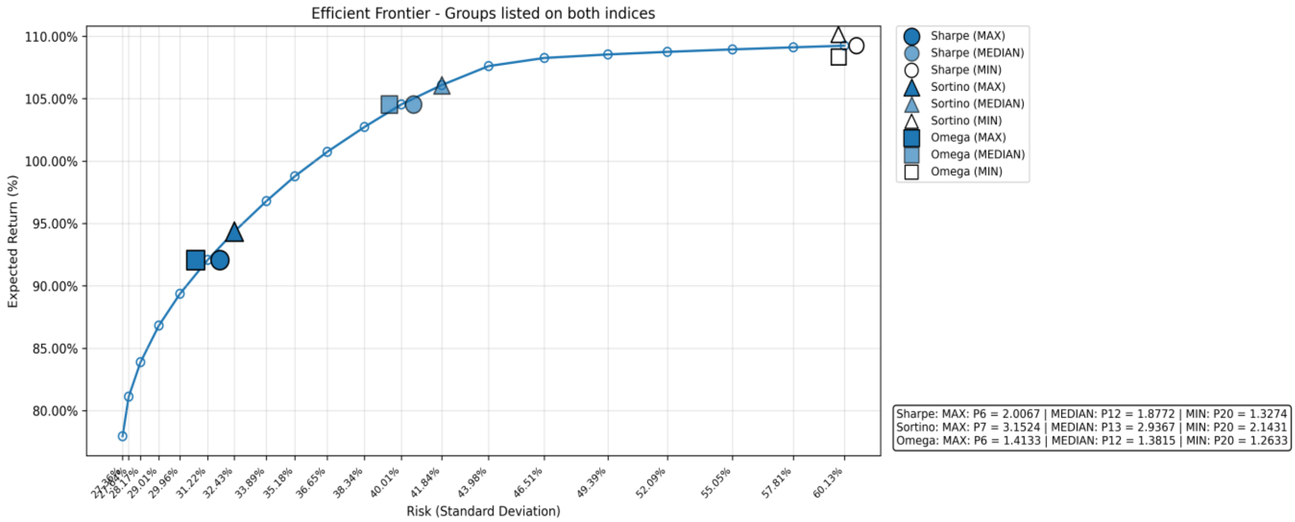

Figure 9. Efficient Frontier for the Group Listed in Both Indices
Source: Processed by the author, 2026

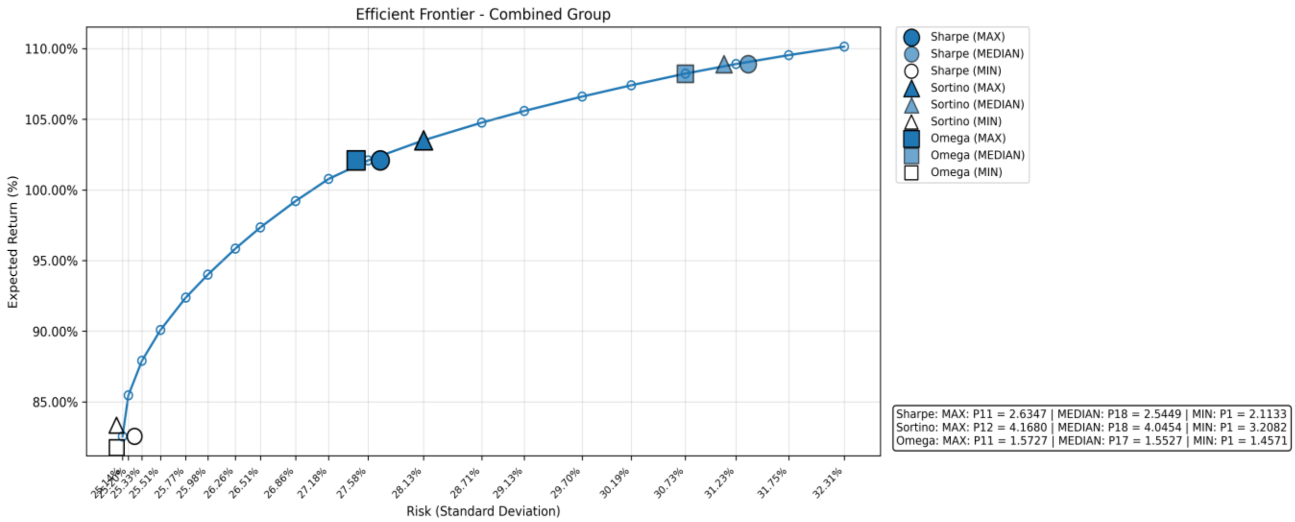

Figure 10. Efficient Frontier for the Combined Group
Source: Processed by the author, 2026

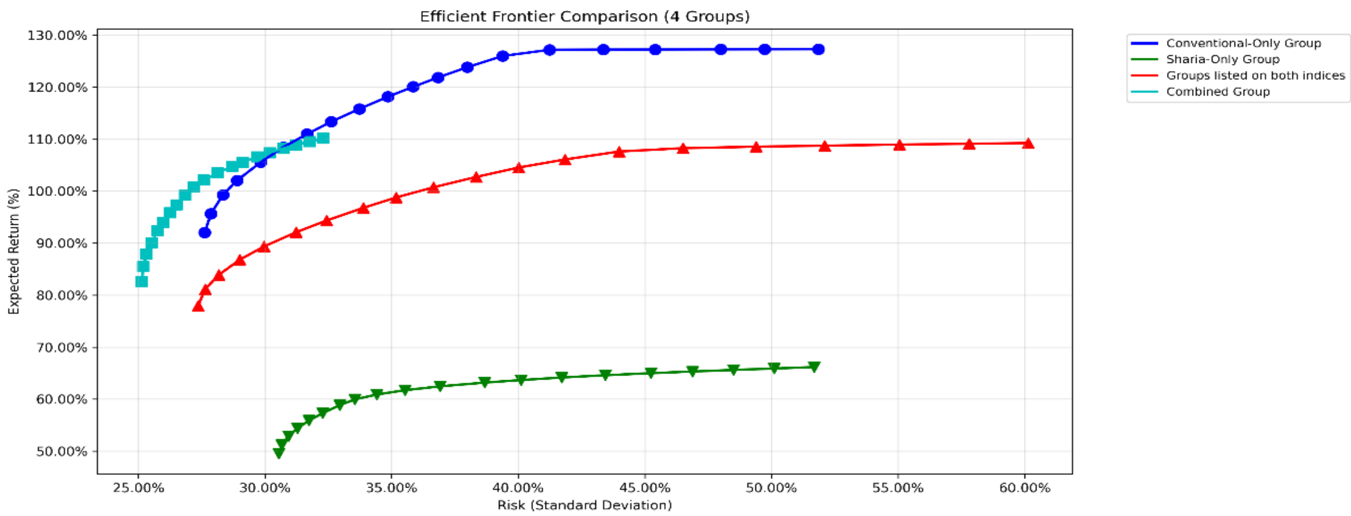

Figure 11. Efficient Frontier Comparison for each Groups
Source: Processed by the author, 2026

A comparison of the efficient frontiers across the different groups indicates that the Conventional-Only Group delivers the highest expected returns when compared to the other groups. In contrast, the Sharia-Only Group exhibits the lowest expected return among all categories. The Both Indexed Group lies between these two extremes, offering moderate expected returns but accompanied by relatively higher levels of risk. Meanwhile, the Combined Group demonstrates a more favorable risk–return trade-off, providing relatively high returns with lower associated risk, which highlights the advantages of diversification in mitigating overall portfolio risk.

In general, portfolios corresponding to the maximum performance ratios are located at intermediate levels of risk and return within each group. Conversely, portfolios positioned at the extreme ends of the efficient frontier those with either maximum or minimum expected returns tend to exhibit lower performance ratios, suggesting suboptimal risk-adjusted efficiency.

4.7. Intergroup Analysis Based on Risk-Adjusted Performance (Sharpe, Sortino, and Omega) Across Portfolio Groups

Table 7. Comparison of Adjusted Ratios Between Groups

Group	Max Sharpe	Max Sortino	Max Omega	Highest Expected Return	Lowest Standard Deviation	Lowest Coefficient of Variation (CV)
Conventional-Only Group	2.4329	3.9602	1.5469	127.30%	27.62%	0.2826
Sharia-Only Group	0.7812	1.1682	1.1724	66.15%	30.54%	0.5596
Groups listed on both indices	1.8608	2.9330	1.4144	109.24%	27.36%	0.3341
Combined Group	2.4712	3.9116	1.5741	110.15%	25.14%	0.2698

Source: Processed by the author, 2026

The portfolio analysis reveals clear differences in performance across groups when considering both risk-adjusted ratios and traditional risk-return measures. The Conventional-Only Group delivers the highest expected return at 127.30%, supported by relatively strong Sharpe (2.4329) and Sortino (3.9602) ratios, although its standard deviation (27.62%) and coefficient of variation (0,2826) remain moderate.

The Combined Group demonstrates the most balanced performance, achieving the lowest standard deviation (25.14%) and a low CV (0.2698), while simultaneously recording the highest Sharpe (2.4712) and Omega (1.5741) ratios, indicating superior efficiency in managing both total and downside risk. Portfolios listed on both indices show moderate outcomes, with an expected return of (109.24%) and a standard deviation of (27.36%).

In contrast, the Sharia-Only Group exhibits the weakest performance, with the lowest expected return (66.15%), the lowest standard deviation (30.54%), and the lowest CV (0.5596), reflecting inferior risk-adjusted efficiency.

5. Comparison

This study is closely related to prior research in multi-objective portfolio optimization using metaheuristics; however, it differs significantly in focus, scope, and contribution. Prior work [38] primarily emphasizes algorithmic improvement by introducing adaptive mutation in NSGA-II to enhance solution diversity and avoid premature convergence, with a focus on risk–return distribution. In contrast, this study employs the standard NSGA-II framework as a robust optimization tool and extends its application to a more practical setting by evaluating portfolio performance across distinct stock classifications, thereby generating insights that are more realistic for real-world investment decisions.

Similarly, previous research [35] incorporates constraints such as cardinality, pre-allocation, and budget constraints, and focuses on comparing hybrid metaheuristic methods in terms of risk–return efficiency. While methodologically rigorous, its contribution is largely algorithm-centric. This study, however, shifts the emphasis toward an application-oriented perspective by systematically comparing conventional, Sharia-compliant, overlapping, and combined portfolios, thus providing a more comprehensive understanding of how portfolio composition affects performance in practice.

Another study [36] integrates classical optimization models (mean-variance, mean semi-variance, MAD, and CVaR) with metaheuristics, but is limited to a small dataset and a short observation period. Such limitations may reduce the generalizability of the findings. In contrast, this research utilizes a broader and more representative dataset (BIST100 and KATILIM50) over a longer time horizon (2022–2025), enabling a more robust evaluation of portfolio behavior under varying market conditions.

Furthermore, prior research [37] analyzes portfolio optimization across multiple asset classes under global crises, highlighting the sensitivity of metaheuristics to macroeconomic shocks and investor preferences. While this provides valuable macro-level insights, it does not address intra-market segmentation. This study fills that gap by focusing on the structural differences between conventional and Sharia-compliant equities within the same market and demonstrates that combining these asset groups can significantly improve risk-adjusted performance, particularly in terms of Sharpe and Omega ratios.

Overall, unlike prior studies that are predominantly algorithm-driven or macro-focused, this research contributes a novel application-driven perspective by integrating portfolio classification, comprehensive performance metrics (Sharpe, Sortino, and Omega ratios), and empirical evidence from an emerging market, thereby offering more actionable insights for investors decision-making.

6. Conclusions

Research on portfolio optimization using NSGA-II shows that there is a clear trade-off between risk and return across all portfolio groups. The conventional-only portfolio group provides the highest return but is accompanied by higher risk, with a maximum expected return of 127.30%, making it more suitable for risk-seeking investors. In contrast, the Sharia-only group generates relatively lower returns and a narrower efficient frontier, reflecting a stronger focus on Sharia compliance rather than return maximization. The combined group demonstrates better diversification potential, with lower risk and relatively higher risk-adjusted returns compared to the other groups. Meanwhile, the both-indexed group occupies an intermediate position, where higher expected returns are generally associated with significantly increased risk, indicating suitability for investors with moderate risk preferences.

Within the Combined Group, the efficient frontier is positioned further to the left and exhibits greater stability compared to the other groups. This indicates that, for a comparable level of expected return, the group achieves lower risk levels, making it particularly attractive to risk-averse investors who prioritize capital stability and downside risk control. The Both-Indexed Group, on the other hand, occupies an intermediate position along the efficient frontier, offering competitive returns but with increasing risk at higher return levels. This suggests suitability for moderately risk-tolerant investors who are willing to accept higher volatility in exchange for improved returns. The Conventional-Only Group is located toward the upper-right region of the efficient frontier, reflecting a combination of high return and high risk, consistent with aggressive investment behavior. In contrast, the Sharia-Only Group remains more constrained in its risk–return space, making it more appropriate for investors prioritizing Sharia compliance over return maximization.

Overall, the findings confirm that optimal portfolio selection is strongly driven by investor risk preferences rather than expected return alone. It should be emphasized that the portfolio configurations are derived from an academic optimization framework using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) applied to historical data from January 3, 2022, to December 30, 2025. Therefore, the results should be interpreted as analytical insights rather than direct investment recommendations.

7. Limitations and Future Research Directions

In this study, several limitations should be acknowledged. First, the dataset is limited to daily closing prices of stocks in the BIST100 and KATILIM50 indices over the period from January 3, 2022, to December 30, 2025, which may limit the generalizability of the findings across different time periods or markets. Second, the portfolio optimization relies solely on the NSGA-II method without comparison to alternative optimization techniques, which may lead to different efficient frontier solutions. Third, the determination of the number of stocks across groups is based on the smallest group (the Sharia-only group), resulting in other groups with more than 10 stocks being filtered using the lowest coefficient of variation (CV). This procedure may automatically exclude stocks with higher expected returns that are typically preferred by risk-seeking investors, thereby introducing a potential selection bias. Furthermore, this study applied the forward fill method to handle missing values in the dataset. While this approach preserves the continuity of time series data, it may underestimate actual market volatility by carrying forward previous price information during missing periods. In addition, stocks with trading suspensions or missing observations exceeding seven consecutive trading days were excluded from the analysis to maintain data quality and consistency. Consequently, the sample may be biased toward more actively traded and liquid stocks. Moreover, the values of the risk-free rate (Rf), Minimum Acceptable Return (MAR), and threshold were assumed to be constant at 34%, based on the average yield of Turkey's 5-year government bond during the research period. Although this approach simplifies the analysis and ensures consistency in performance evaluation, it may not fully reflect time-varying market conditions and interest rate fluctuations, potentially affecting the accuracy of risk-adjusted performance measurements. Finally, the study does not incorporate external factors such as macroeconomic conditions, regulatory changes, or geopolitical events that may influence market performance.

Additionally, the performance and risk measurement in this study is limited to the Sharpe ratio, Sortino ratio, and Omega ratio, each of which has inherent limitations in fully capturing the complexity of portfolio risk and return dynamics. The Sharpe ratio assumes symmetric risk distribution, the Sortino ratio only accounts for downside risk while ignoring upside volatility, and the Omega ratio is sensitive to the choice of threshold, which may affect comparability across studies. Therefore, future research is encouraged to incorporate additional performance measures such as the Treynor ratio, Jensen's alpha, Value at Risk (VaR), Conditional Value at Risk (CVaR), or drawdown-based metrics to provide a more comprehensive assessment of portfolio performance and risk.

Further research could explore the use of alternative metaheuristic algorithms, such as Particle Swarm Optimization (PSO) and Differential Evolution (DE), as benchmarks to evaluate the consistency and robustness of portfolio optimization results [43]. In particular, NSGA-III may provide advantages in handling many-objective optimization problems and maintaining solution diversity in complex portfolio allocation scenarios. Other models could consider integrating Machine Learning methods to improve the estimation of input parameters, such as asset return and risk prediction, prior to the portfolio optimization stage [44].

Funding: This research received no external funding.

Data Availability Statement: Data were obtained from publicly available financial databases, specifically Yahoo Finance, which provides historical market data on asset prices. The dataset used in this study can be accessed directly from the platform or is available from the author upon reasonable request.

Acknowledgement: The author would like to express sincere gratitude to the academic supervisor and examiners for their valuable guidance, constructive feedback, and continuous support throughout the research process. The author also acknowledges the use of publicly available financial data from Yahoo Finance and Investing.com, as well as all parties who contributed to the completion of this study.

Conflicts of Interest: The authors declare no conflict of interest.

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