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Multi-Objective Stock Portfolio Optimization Using NSGA-II: A Comparative Analysis of Conventional and Shariah Stocks in the U.S. Market

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ABSTRACT

This study analyzes and compares the performance of Conventional, Shariah, Intersection, and Combination stock portfolios in the United States stock market using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The study employs a quantitative empirical approach using daily stock closing price data from January 2022 to December 2025 obtained from Yahoo Finance. Portfolio optimization was conducted in Python and evaluated using the Efficient Frontier, Sharpe Ratio, Sortino Ratio, and Omega Ratio. The results show that the Combination portfolio achieved the best overall performance, followed by the Intersection portfolio. These findings indicate that broader diversification improves portfolio efficiency and supports Modern Portfolio Theory.

INTRODUCTION

The increasing complexity of global capital markets has intensified investors demand for investment strategies capable of generating optimal returns while maintaining manageable levels of risk (Henriques, 2021). The expansion of global economic integration, rapid developments in financial technology, and heightened market volatility have made portfolio construction increasingly challenging for investors seeking efficient asset allocation strategies (Asutay et al., 2022). Under these circumstances, portfolio optimization has become an essential approach for supporting rational investment decisions based on the trade-off between risk and expected return.

Modern Portfolio Theory, originally introduced by Markowitz, suggests that investment risk can be reduced through asset diversification without necessarily sacrificing expected returns (Yousefi & Aktaş, 2023). The theory highlights the importance of combining assets with low correlations in order to achieve a more efficient portfolio structure. Furthermore, the concept of the efficient frontier implies that investors possess different risk preferences, thereby requiring optimization techniques capable of generating multiple optimal portfolio alternatives simultaneously (Serrano-Monge, 2022).

Recent years, shariah-compliant investment has also experienced substantial growth alongside rising investor awareness regarding ethical and sustainable financial practices

(Ledhem & Mekidiche, 2022). Shariah stocks differ from conventional equities because they must comply with Islamic screening requirements, including restrictions on non-halal business activities and interest-based financial leverage (Tanin et al., 2025). Previous studies have indicated that shariah-compliant equities exhibit distinct risk-return characteristics compared to conventional stocks, thereby offering additional diversification opportunities for investors (Alkhazali & Lean, 2022).

Addition to conventional and shariah stocks, there is also a category of intersection stocks that simultaneously satisfy the criteria of both classifications. These stocks are generally associated with firms possessing strong and stable fundamentals, which may contribute to superior portfolio efficiency (Tu & Li, 2024). Diversification across conventional, shariah, and intersection stocks is therefore expected to enhance investment efficiency through the reduction of unsystematic risk (Saiti & Noordin, 2025).

Practice, portfolio optimization represents a multiobjective problem because investors aim not only to maximize returns but also to minimize investment risk at the same time (Kharrim, 2024). Conventional optimization approaches, such as Mean-Variance Optimization, often encounter limitations when dealing with non-linear problems involving large asset universes and highly complex datasets (Hidalgo-marín & Nebro, 2025). Consequently, metaheuristic approaches such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) have gained increasing attention due to their ability to generate Pareto-optimal solutions more effectively in multiobjective optimization problems (Weirstrass et al., 2025).

NSGA-II is an evolutionary optimization algorithm capable of extensively exploring solution spaces and identifying optimal portfolio compositions based on the trade-off between risk and return (Abdallah et al., 2025). Prior research has demonstrated that NSGA-II outperforms traditional optimization methods in portfolio construction problems (Gao & Kresta, 2024). Moreover, the integration of metaheuristic approaches with machine learning and evolutionary computation techniques has been shown to improve the efficiency of investment decision-making processes (Faridi, 2022).

Several previous studies have compared the performance of shariah and conventional stocks across different markets (Jabeen & Kausar, 2025; Kausar, 2021). However, research integrating conventional, shariah, and intersection stocks within a multiobjective optimization framework using NSGA-II in the context of the United States capital market remains relatively limited. Most earlier studies concentrated on a single stock category or employed single-objective optimization methods, which may not adequately capture the complexity of the risk-return relationship in modern portfolio management (Asgari & Behnamian, 2025).

Based on these considerations, this study aims to analyze and compare the performance of conventional, shariah, intersection, and combination stock portfolios using the NSGA-II approach in the United States capital market. The findings are expected to contribute to the development of the multiobjective portfolio optimization literature while also providing practical insights for investors in designing more efficient diversification strategies.

RESEARCH METHODOLOGY

This study employs an empirical quantitative approach using historical stock closing price data from January 2022 to December 2025 obtained from Yahoo Finance. A quantitative approach was adopted because the study focuses on the numerical analysis of the relationship between return and risk in portfolio construction and investment decision-making processes (Malhotra et al., 2023). The research focuses on stock portfolio optimization based on the trade-off between return and risk using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which can generate multiple optimal solutions simultaneously.

The optimization process is conducted in Python using supporting libraries such as yfinance, pandas, numpy, pymoo, matplotlib, and openpyxl. The research sample was selected through purposive sampling from the United States capital market and classified into three categories: conventional, sharia, and intersection stocks, to compare asset performance based on sharia compliance and sector characteristics.

Table 1. Stock Group Criteria

Groups	Main Criteria	Dominant Sectors	Quantity
Conventional	Non-Shariah	Banking, Tobacco, Defense	15
Shariah	Pass the business and business financial filters	Software, Green Energy, Semi-conductors	15
Intersection	*Blue Chip* dan *Dual-Compliance*	Consumer Technology, Healthcare, Retail	15
Total samples			45

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After obtaining the sample, the Coefficient of Variation (CV) was first calculated and used as the basis for stock selection, where stocks with lower CV values were prioritized as candidates. The selected stocks were then divided into three groups.

The conventional stock group consists of RTX (Raytheon Technogies), GS (Goldman Sachs), BK (BNY Mellon), PM (Philip Morris), JPM (JPMorgan Chase), AXP (American Express), C (Citigroup), ALL (Allstate Corp), MS (Morgan Stanley), MO (Altria Group), WFC (Wells Fargo).

The shariah stock group consists of FLEX (Flex Ltd), VRT (Vertiv Holdings), FSLR (First Solar), CSCO (Cisco Systems), MSTR (MicroStrategy), AMD (Advanced Micro Devices), SNPS (Synopsys Inc.), FFIV (F5 Inc.), CRM (Salesforce), TXN (Texas Instruments), NXPI (NXP Semiconductors).

The intersection stock group consists ofLLY (Eli Lilly & Co), WMT (Walmart), AVGO (Broadcom), NVDA (Nvidia Corp), GOOGL (Alphabet/Google), COST (Costco

Wholesale), MRK (Merck & Co), KO (Coca-Cola), JNJ (Johnson & Johnson), MSFT (Microsoft Corp), AAPL (Apple Inc.).

Eleven stocks with the lowest CV values in each sector were selected for the optimization process. This limitation aims to reduce computational complexity, maintain sector balance, and produce a more stable and manageable portfolio (Leybert et al., 2023).

To evaluate portfolio quality, this study used the Sharpe Ratio, Sortino Ratio, and Omega Ratio, which consider both return and risk characteristics (Malhotra et al., 2023). Since NSGA-II generates multiple optimal solutions, the study did not select a single portfolio directly. Instead, the minimum, median, and maximum values of each ratio were analyzed, with the median value chosen as the representative portfolio because it is more stable and less affected by extreme values (Weirstrass et al., 2025).

Data processing was conducted systematically through computational stages to transform the data into an optimal portfolio based on multiobjective optimization. The stages of data processing are as follows:

Price data transformation

Data processing is carried out by converting stock price data into returns using the log return approach, which is mathematically formulated as:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

Where $P_{i,t}$ represents the price of the i-th stock at time t, and $R_{i,t}$ denotes the logarithmic return. The use of log returns provides advantages in terms of distribution stability and time-additive properties, making them widely applied in modern financial analysis (Weirstrass et al., 2025).

Estimation of Statistical Parameters

After obtaining the return data, it then calculates the statistical parameters used as inputs in portfolio optimization.

The expected return of each asset is calculated as the average return:

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} R_{i,t}$$

The expected return of each asset was calculated using the average historical return, while portfolio risk was measured using the covariance matrix among assets (Yousefi & Aktaş, 2023).

Meanwhile, risk is measured using a covariance matrix between assets:

$$\Sigma ij = \mathrm{Cov}(Ri, Rj)$$

This covariance matrix represents the linear relationships between assets and is a key component in portfolio risk measurement (Weirstrass et al., 2025)

Portfolio Formation

The portfolio is formed through a combination of investment weights in each asset which is expressed as:

$$w = (w1, w2, \ldots, wn)$$

With constraints:

$$\sum_{i=1}^{n} wi = 1, \qquad 0 \leq wi \leq 1$$

This constraint ensures that all funds are fully invested without short selling (Weirstrass et al., 2025).

Portfolio Return and Risk Calculation

Portfolio return is calculated as a linear combination of the expected return of each asset:

$$R_p = \sum_{i=1}^{n} wi\mu i$$

The risk of the portfolio is calculated using the portfolio variance approach:

$$\sigma_p = \sqrt{w^T \Sigma w}$$

This formulation reflects that portfolio risk is not only affected by the variance of each asset, but also by the covariance between assets (Wang et al., 2026).

Multi-Objective Optimization Modeling with NSGA-II

The portfolio optimization problem is defined as the search for the asset weight (w) that optimizes two conflicting objectives functions:

Objective function 1 maximizing returns :

$$Minimize\ \ f\,1\,(w) = -\left(\sum_{i-1}^{n} wi\mu i\right)$$

Objective function 2 minimizing risk:

$$Minimize\ \ f\,2\,(w) = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} wiwj\sigma_{ij}}$$

The portfolio optimization process was conducted using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). This algorithm was selected because of its ability to generate Pareto-optimal solutions in multiobjective optimization problems by simultaneously maximizing expected return and minimizing portfolio risk (Abdallah et al., 2025).

Table 2. NSGA-II Parameter Settings

Parameter	**value**
Pupulation Size	400
Number of Generations	500
Crossover Operator	Simulated Binary Crossover (SBX)
Crossover Probability	0,9
Mutation Operator	Polynomial Mutation (PM)
Mutation Distributation Index (Eta)	20
Optimization Objectives	Maximize Return, Minimize Risk

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These parameter settings were intended to maintain solution diversity and improve the convergence capability of the algorithm in generating an optimal efficient frontier (Hidalgo-marı́n & Nebro, 2025).

Portfolio Performance Evaluation Metrics

The performance of the portfolio is evaluated using three main indicators:
Sharpe ratio measures excess return to total risk.

$$sharpe = \frac{E(R_P) - Rf}{\sigma_p}$$

The Sortino Ratio measures the return on downside losses (downside deviation).

$$sortino = \frac{E(R_P) - Rf}{\sigma_{downside}}$$

The Omega Ratio measures the ratio between financial profitability above the threshold to loss.

$$omega = \frac{\int_r^{\infty}[1 - F(x)]dx}{\int_{-\infty}^{r} F(x)dx}$$

Portfolio performance was evaluated using the Sharpe Ratio, Sortino Ratio, and Omega Ratio. The Sharpe Ratio measures return efficiency relative to total portfolio risk, whereas the Sortino Ratio focuses on downside risk that is more sensitive to potential investment losses (Jabeen & Kausar, 2025). Meanwhile, the Omega Ratio evaluates the overall return distribution, thereby providing a more comprehensive assessment of portfolio risk and return performance (Bulani & Bezbradica, 2025)

The final step is to compare the portfolio performance of the three data groups (Conventional, Sharia, Intersection). The results are displayed in the form of an Efficient Frontier curve that shows the optimal points where the lowest risk for a given level of profit is reached.

RESULTS AND DISCUSSION

This study analyzes the risk–return trade-off in stock portfolios using the Python-based NSGA-II algorithm. The optimization results include stock weights, expected returns, standard deviations, and performance indicators such as the Sharpe Ratio, Sortino Ratio, and Omega Ratio. The results are visualized through the Efficient Frontier, showing the relationship between risk and expected return from minimum-risk to maximum-return portfolios. The optimization therefore generates several efficient portfolios that investors can choose according to their risk preferences.

Conventional Stock Group

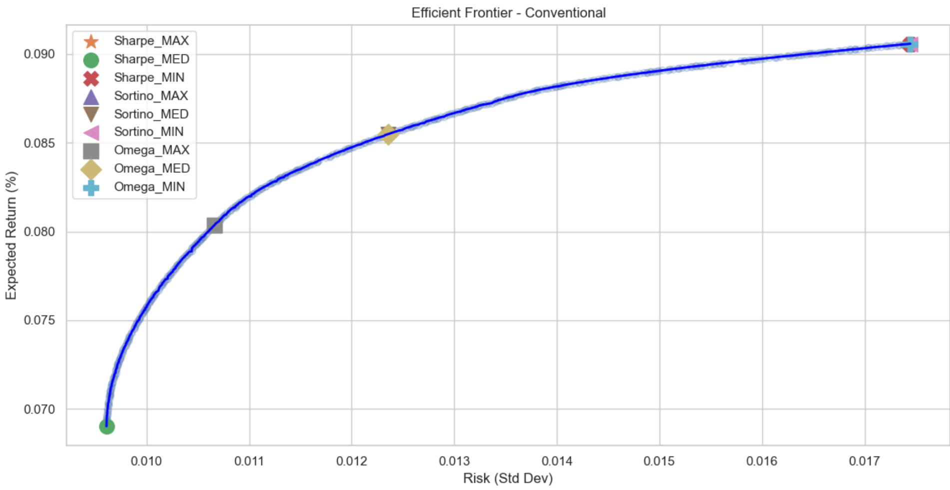
Table 3. optimal composition of conventional stocks

Conventional	Maxsimum Expected Return								Minimum Variance	
					Weight					
RTX	21,01	24,61	29,76	32,11	37,73	39,77	45,41	26,52	11,98	0,00
GS	3,15	9,57	14,78	18,87	32,96	47,28	53,73	73,44	88,00	99,99
BK	10,25	10,21	11,02	12,00	7,02	0,00	0,01	0,01	0,00	0,00
PM	18,28	22,36	28,50	30,76	22,27	12,91	0,84	0,00	0,01	0,00
JPM	7,60	5,48	3,65	3,01	0,00	0,01	0,00	0,00	0,00	0,00
AXP	0,00	0,78	0,00	0,22	0,01	0,03	0,01	0,03	0,01	0,00
C	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
ALL	6,93	5,54	1,34	3,02	0,00	0,00	0,00	0,00	0,00	0,00
MS	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MO	32,78	21,45	10,96	0,00	0,01	0,00	0,00	0,00	0,00	0,00
WFC	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Expected Return (%)	0,069	0,073	0,077	0,080	0,083	0,085	0,087	0,089	0,090	0,091
Standard Deviation	0,010	0,010	0,010	0,011	0,011	0,012	0,013	0,015	0,016	0,017
Coefficient of Variation (CV)	13,923	13,348	13,181	13,270	13,659	14,454	15,366	16,539	17,897	19,261
Sharpe	0,051	0,055	0,056	0,057	0,056	0,053	0,050	0,047	0,044	0,041
Sortino	0,067	0,073	0,076	0,076	0,076	0,073	0,070	0,066	0,062	0,058
Omega	1,213	1,223	1,228	1,228	1,222	1,211	1,199	1,183	1,168	1,155

Sourse: Processed by the outhor, 2026

The optimization results of the conventional stock portfolio indicate that fund allocation tends to concentrate on several dominant stocks, particularly MO, RTX, and PM in the maximum-return portfolio, while the minimum-risk portfolio is dominated by GS stocks with lower volatility. The maximum-return portfolio generates an expected return of approximately 0.091% with a risk level of 0.017, whereas the minimum-variance portfolio produces a return of around 0.069% with a risk level of 0.010. These findings reflect the trade-off between return and risk, where higher returns are associated with higher portfolio risk. This result is consistent with Modern Portfolio Theory, which states that portfolio optimization aims to balance expected returns and investment risk through diversification strategies (Yousefi & Aktaş, 2023).

Gambar 1. Efficient Frontier Conventional



Sourse: Processed by the outhor, 2026

The Efficient Frontier generated by the NSGA-II algorithm demonstrates that portfolios located in the middle region provide better risk-adjusted performance, as indicated by the highest Sharpe Ratio of 0.057, Sortino Ratio of 0.076, and Omega Ratio of 1.228. This finding supports (Weirstrass et al., 2025), who argued that balanced portfolios tend to achieve higher efficiency compared to overly aggressive portfolios. addition, the Coefficient of Variation (CV) ranges from 13.181 to 19.261, where lower CV values indicate greater portfolio stability and lower relative risk exposure.

Shariah Stock Group

Table 4. Optimal Composition of Shariah Stocks

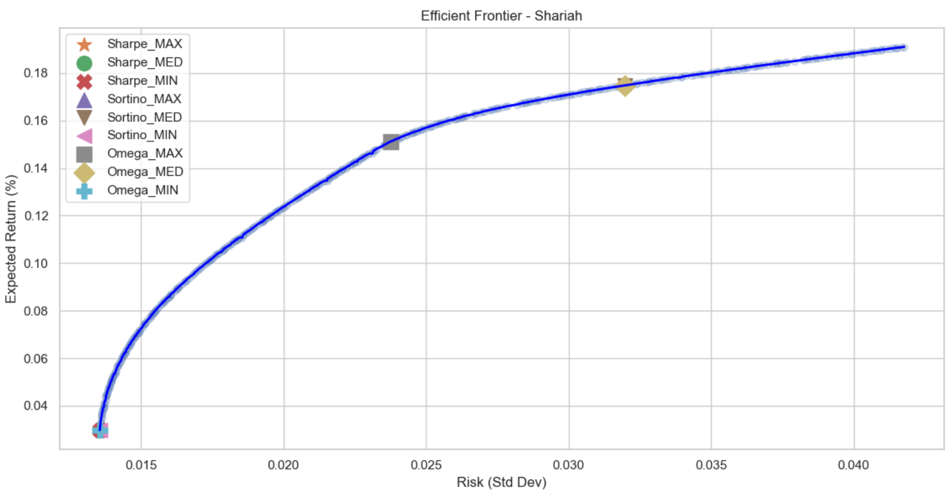
Shariah	Maxsimum Expected Return						Minimum Variance			
					Weight					
FLEX	0,02	17,83	35,77	49,80	63,98	73,92	60,46	37,67	17,92	0,00
VRT	0,00	0,02	1,54	6,04	9,58	16,19	39,49	62,26	82,06	100,00
FSLR	7,03	11,60	11,78	13,33	12,94	9,87	0,04	0,02	0,00	0,00
CSCO	60,92	61,58	50,65	30,77	13,49	0,01	0,00	0,00	0,00	0,00
MSTR	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AMD	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
SNPS	3,68	2,80	0,00	0,05	0,00	0,00	0,00	0,04	0,01	0,00
FFIV	11,50	3,22	0,19	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CRM	6,81	2,95	0,07	0,01	0,00	0,00	0,00	0,00	0,00	0,00

TXN	10,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
NXPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Expected Return (%)	0,030	0,060	0,085	0,110	0,132	0,151	0,165	0,175	0,183	0,191
Standard Deviation	0,014	0,014	0,016	0,018	0,021	0,024	0,027	0,032	0,037	0,042
Coefficient of Variation (CV)	45,493	23,848	18,675	16,696	15,965	15,712	16,631	18,286	20,101	21,867
Sharpe	0,007	0,028	0,041	0,049	0,053	0,055	0,053	0,048	0,044	0,041
Sortino	0,010	0,039	0,060	0,073	0,079	0,079	0,069	0,060	0,054	0,049
Omega	1,062	1,121	1,156	1,174	1,183	1,186	1,178	1,166	1,153	1,141

Sourse: Processed by the outhor, 2026

The optimization results of the shariah stock portfolio indicate that fund allocation is concentrated on several dominant stocks, particularly CSCO and FLEX in the maximum-return portfolio, while the minimum-risk portfolio is dominated by VRT stocks with lower volatility. The maximum-return portfolio generates an expected return of approximately 0.191% with a risk level of 0.042, whereas the minimum-variance portfolio produces a return of around 0.030% with a risk level of 0.014. These findings demonstrate the trade-off between return and risk, where higher returns are associated with greater portfolio volatility. This result is consistent with previous studies showing that shariah-compliant stocks tend to provide competitive returns due to their concentration in growth-oriented sectors, particularly technology-related industries (Alkhazali & Lean, 2022). However, the higher volatility observed in the shariah portfolio also indicates that sector limitations resulting from shariah screening may reduce diversification opportunities, thereby increasing portfolio risk (Tanin et al., 2025).

Gambar 2. Efficient Frontier Shariah



Sourse: Processed by the outhor, 2026

The evaluation results further show that the most efficient portfolio lies in the middle region of the Efficient Frontier, with the highest Sharpe Ratio of 0.055, Sortino Ratio of 0.079, and Omega Ratio of 1.186. This finding supports Modern Portfolio Theory, which emphasizes that balanced portfolios generally produce better risk-adjusted returns than highly aggressive portfolios (Yousefi & Aktaş, 2023). In addition, the Coefficient of Variation (CV) ranges from 15.712 to 45.493, where lower CV values indicate greater portfolio stability and lower relative risk exposure.

Intersection Stock Group

Table 5. Optimal Composition of Intersection Stocks

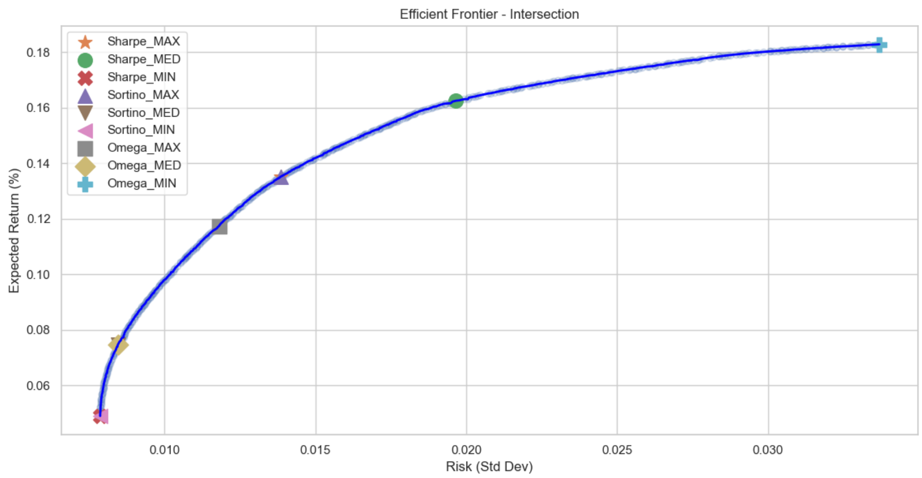
Intersection		**Maxsimum Expected Return**					**Minimum Variance**			
					Weight					
LLY	0,78	11,56	18,41	31,41	38,86	49,82	40,75	17,49	0,22	0,00
WMT	13,81	22,79	29,36	34,31	31,70	9,96	0,00	0,00	0,00	0,00
AVGO	4,69	8,62	12,14	17,27	21,24	28,72	38,19	42,71	41,56	0,08
NVDA	0,20	2,74	6,01	4,66	8,19	11,49	21,05	39,79	58,21	99,91
GOOGL	2,70	2,01	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00
COST	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MRK	8,54	6,06	5,67	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KO	32,51	23,14	8,60	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JNJ	30,00	23,07	19,80	12,10	0,00	0,00	0,00	0,00	0,00	0,00
MSFT	6,78	0,00	0,01	0,03	0,00	0,01	0,00	0,00	0,00	0,00
AAPL	0,01	0,00	0,00	0,22	0,00	0,00	0,00	0,00	0,01	0,00
Expected Return (%)	0,049	0,075	0,095	0,117	0,135	0,150	0,163	0,172	0,179	0,183
Standard Deviation	0,008	0,008	0,010	0,012	0,014	0,017	0,020	0,024	0,029	0,034
Coefficient of Variation (CV)	16,050	11,329	10,266	10,054	10,246	11,051	12,095	14,055	16,057	18,420
Sharpe	0,037	0,065	0,077	0,083	0,083	0,079	0,073	0,063	0,055	0,048
Sortino	0,054	0,094	0,113	0,122	0,123	0,117	0,107	0,092	0,081	0,074
Omega	1,181	1,270	1,302	1,307	1,301	1,278	1,252	1,215	1,184	1,158

Sourse: Processed by the outhor, 2026

The optimization results of the intersection stock portfolio indicate that fund allocation is concentrated on several dominant stocks, particularly KO, JNJ, and WMT in the maximum-return portfolio, while the minimum-risk portfolio allocates larger weights to NVDA and AVGO stocks with relatively more stable volatility. The maximum-return portfolio generates an expected return of approximately 0.183% with a risk level of 0.034, whereas the minimum-variance portfolio produces a return of around 0.049% with a lower risk level of

0.008. These findings reflect the trade-off between return and risk, as illustrated by the Efficient Frontier curve moving from the lower-left to the upper-right direction. This result supports diversification theory, which suggests that combining assets with different market characteristics can improve portfolio efficiency and reduce unsystematic risk (Saiti & Noordin, 2025). The strong performance of the intersection portfolio also indicates that stocks meeting both conventional and shariah criteria tend to possess stable fundamentals and balanced risk-return characteristics (Tu & Li, 2024).

Gambar 3. Efficient Frontier Intersection



Sourse: Processed by the outhor, 2026

The evaluation results further show that the most efficient portfolio lies in the middle region of the Efficient Frontier, with the highest Sharpe Ratio of approximately 0.083, Sortino Ratio of 0.123, and Omega Ratio of 1.307. These findings indicate that balanced portfolios provide superior risk-adjusted performance compared to highly aggressive or overly conservative portfolios, which is consistent with Modern Portfolio Theory (Yousefi & Aktaş, 2023). In addition, the Coefficient of Variation (CV) ranges from 10.054 to 18.420, where lower CV values indicate greater portfolio stability and lower relative risk exposure.

Combination Stock Group

Table 6. Optimal Composition of Stock Combination

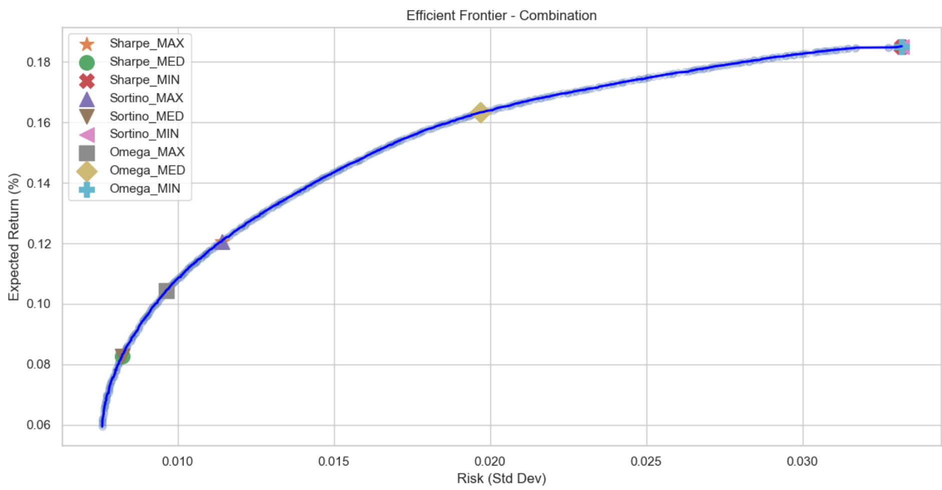
Combination	Maxsimum Expected Return					Minimum Variance				
					Weight					
RTX	8,44	9,37	12,14	12,86	0,02	0,04	0,01	0,02	0,00	0,02
GS	0,00	0,00	0,01	0,01	0,02	0,01	0,01	0,00	0,01	0,00
BK	1,46	0,03	0,06	0,04	0,05	0,01	0,00	0,00	0,02	0,01
PM	1,48	8,83	13,84	13,97	0,04	0,09	0,02	0,00	0,00	0,01
JPM	0,35	0,01	0,00	0,00	0,00	0,01	0,02	0,00	0,00	0,00
AXP	0,00	0,04	0,00	0,01	0,00	0,01	0,01	0,00	0,01	0,02

C	0,00	0,03	0,01	0,05	0,02	0,00	0,00	0,01	0,00	0,00
ALL	0,93	0,82	1,81	0,00	0,01	0,02	0,00	0,00	0,00	0,02
MS	0,02	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,01
MO	15,78	12,57	10,90	0,04	0,07	0,00	0,00	0,00	0,00	0,01
WFC	0,10	0,01	0,00	0,05	0,00	0,05	0,00	0,01	0,00	0,06
FLEX	1,48	4,19	5,52	10,41	12,91	15,57	0,46	0,18	0,27	0,10
VRT	0,00	0,01	0,01	0,14	3,25	1,77	9,43	20,45	23,07	60,65
FSLR	1,48	1,41	2,18	0,05	0,00	0,01	0,02	0,01	0,01	0,02
CSCO	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MSTR	0,00	0,00	0,01	0,00	0,00	0,01	0,00	0,00	0,01	0,00
AMD	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
SNPS	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01
FFIV	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00
CRM	0,01	0,00	0,01	0,01	0,01	0,00	0,00	0,00	0,00	0,00
TXN	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
NXPI	0,01	0,00	0,01	0,00	0,00	0,00	0,00	0,01	0,00	0,01
LLY	1,33	9,47	20,27	29,59	36,60	46,67	41,57	23,61	3,08	0,27
WMT	13,56	17,69	23,05	17,86	26,33	4,77	0,00	0,02	0,02	0,04
AVGO	2,05	7,95	8,34	12,54	15,65	25,07	30,74	27,36	36,96	23,46
NVDA	1,10	0,91	1,66	2,35	4,97	5,83	17,63	28,28	36,51	15,21
GOOGL	3,41	0,60	0,01	0,00	0,01	0,00	0,00	0,00	0,00	0,01
COST	0,11	0,04	0,01	0,00	0,00	0,02	0,01	0,00	0,00	0,01
MRK	6,37	6,33	0,07	0,01	0,01	0,00	0,00	0,01	0,00	0,00
KO	19,13	4,59	0,01	0,01	0,01	0,01	0,01	0,01	0,00	0,01
JNJ	19,09	15,07	0,04	0,00	0,01	0,00	0,01	0,01	0,01	0,03
MSFT	2,28	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,01
AAPL	0,00	0,00	0,00	0,00	0,00	0,01	0,01	0,00	0,00	0,01
Expected Return (%)	0,059	0,083	0,104	0,121	0,137	0,151	0,163	0,172	0,180	0,185
Standard Deviation	0,008	0,008	0,010	0,011	0,014	0,017	0,020	0,024	0,028	0,033
Coefficient of Variation (CV)	12,772	9,928	9,223	9,458	10,141	10,915	12,056	13,741	15,589	17,920
Sharpe	0,052	0,077	0,088	0,088	0,084	0,080	0,073	0,064	0,057	0,050
Sortino	0,073	0,108	0,125	0,127	0,121	0,115	0,104	0,088	0,078	0,062
Omega	1,236	1,316	1,344	1,334	1,306	1,283	1,252	1,219	1,191	1,169

Sourse: Processed by the outhor, 2026

The optimization results of the combination portfolio indicate that fund allocation is concentrated on several dominant stocks, particularly LLY, WMT, and AVGO in the maximum-return portfolio, while the minimum-risk portfolio distributes funds more evenly across stocks with relatively stable volatility. The maximum-return portfolio generates an expected return of approximately 0.185% with a risk level of 0.033, whereas the minimum-variance portfolio produces a return of around 0.059% with a risk level of 0.008. These findings demonstrate the trade-off between return and risk, as reflected by the upward movement of the Efficient Frontier curve from the lower-left to the upper-right direction. This result supports Modern Portfolio Theory, which states that diversification across assets with different characteristics can improve portfolio efficiency while reducing overall investment risk (Yousefi & Aktaş, 2023). The superior performance of the combination portfolio indicates that integrating conventional, shariah, and intersection stocks provides broader diversification benefits and enhances risk-adjusted returns (Saiti & Noordin, 2025).

Gambar 4. Efficient Frontier Combination



Sourse: Processed by the outhor, 2026

The evaluation results further show that the most efficient portfolio is located in the middle region of the Efficient Frontier, with the highest Sharpe Ratio of 0.089, Sortino Ratio of 0.127, and Omega Ratio of 1.344. These findings suggest that balanced portfolios tend to achieve better performance than overly aggressive or conservative portfolios, which is consistent with the findings of (Weirstrass et al., 2025). In addition, the Coefficient of Variation (CV) ranges from 9.223 to 17.920, where lower CV values indicate greater portfolio stability and lower relative risk exposure.

Performance Evaluation Comparative Ratio Analysis

This section compares portfolio performance using the Sharpe Ratio, Sortino Ratio, and Omega Ratio across four portfolio groups: Conventional, Shariah, Intersection, and Combination. These ratios are used to evaluate portfolio efficiency in generating returns relative to the risks incurred.

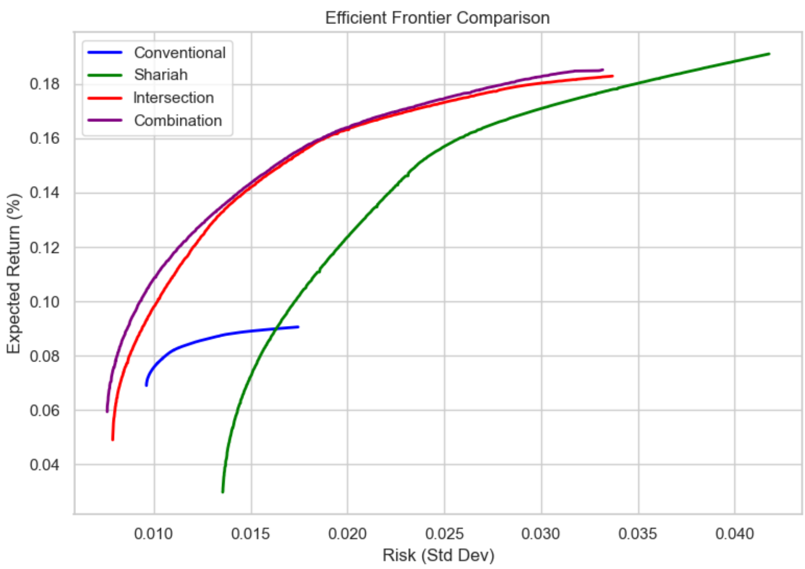
Table 7. Performance Ratio Comparison

Group	Metric	Max	Median	Min
Conventional	Sharpe	0,057	0,053	0,041
Conventional	Sortino	0,077	0,072	0,058
Conventional	Omega	1,229	1,215	1,155
Shariah	Sharpe	0,055	0,048	0,007
Shariah	Sortino	0,083	0,063	0,010
Shariah	Omega	1,187	1,166	1,062
Intersection	Sharpe	0,084	0,073	0,037
Intersection	Sortino	0,123	0,107	0,054
Intersection	Omega	1,311	1,268	1,158
Combination	Sharpe	0,089	0,076	0,050
Combination	Sortino	0,130	0,109	0,062
Combination	Omega	1,344	1,282	1,169

Sourse: Processed by the outhor, 2026

Based on the evaluation of the Sharpe Ratio, Sortino Ratio, and Omega Ratio, the Combination portfolio demonstrates the best performance among all groups. It has the highest ratio values, indicating better return efficiency, downside risk management, and profit potential relative to losses. The Intersection portfolio ranks second with relatively strong performance, while the Conventional and Shariah portfolios show lower ratio values, indicating lower efficiency compared to portfolios with broader diversification.

Gambar 5. Efficient Frontier Comparison



Sourse: Processed by the outhor, 2026

The Efficient Frontier chart illustrates the relationship between risk and expected return in the Conventional, Shariah, Intersection, and Combination portfolios generated through NSGA-II optimization. The Conventional portfolio has the lowest risk and return, reflecting a more conservative profile. The Shariah portfolio offers the highest returns but also carries greater risk. The Intersection portfolio provides a more balanced trade-off between risk and return than the Conventional portfolio. Meanwhile, the Combination portfolio shows the most efficient curve, generating relatively high returns with controlled risk through broader diversification.

CONCLUSION AND RECOMMENDATIONS

This study aims to optimize stock portfolios using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) across four portfolio categories: Conventional, Shariah, Intersection, and Combination portfolios. The findings demonstrate that NSGA-II successfully generates multiple optimal portfolios that form an Efficient Frontier, illustrating the trade-off between return and risk. Based on the optimization results, the Combination portfolio achieved the best overall performance, with the highest Sharpe Ratio of 0.089, Sortino Ratio of 0.130, and Omega Ratio of 1.344. The Intersection portfolio ranked second, followed by the Conventional and Shariah portfolios. These results indicate that broader diversification through combining stocks from different portfolio groups can improve portfolio efficiency and produce a more optimal balance between return and risk. The findings support Modern Portfolio Theory, which emphasizes that diversification across heterogeneous assets can reduce portfolio risk while maintaining attractive returns. In addition, this study confirms the effectiveness of NSGA-II in solving multi-objective portfolio optimization problems and generating Pareto-optimal investment solutions. This study is limited to historical stock price data and a specific observation period. Therefore, future research is recommended to include a larger number of stocks, longer observation periods, and additional risk measures such as Value at Risk (VaR) and Conditional Value at Risk (CVaR) to better capture extreme market risk (Han & Wang, 2022; Kei Nakagawa, 2021). Furthermore, future studies may explore alternative optimization techniques or hybrid approaches to compare the effectiveness of different algorithms in generating more efficient portfolios (Erwin & Engelbrecht, 2023).

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