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Portfolio optimization with cardinality and minimum return constraints on the LQ45 index using genetic algorithm

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ABSTRACT

Traditional mean-variance portfolio optimization often faces limitations in accommodating practical investment constraints, particularly in restricting the number of selected assets while ensuring a minimum expected return. To address these limitations, this study proposes a Genetic Algorithm (GA)-based portfolio optimization framework that simultaneously incorporates cardinality and minimum return constraints for constructing efficient portfolios. The main contribution of this study is the integration of these practical investment constraints into a GA framework to improve portfolio optimization under realistic investment scenarios using LQ45 stocks. Historical daily stock price data of LQ45 constituents were collected from Yahoo Finance and used to estimate portfolio returns, portfolio risk (standard deviation), and Sharpe ratios. The optimization process minimizes portfolio risk while enforcing cardinality and minimum return constraints through penalty function. Experimental results show that the proposed framework successfully generated efficient portfolios under various parameter settings. The best portfolio was obtained using a cardinality constraint of three stocks and a minimum return target of 10%. This portfolio achieved a return of 14.17%, a risk (standard deviation) of 0.1670, and a Sharpe ratio of 0.4867. In comparation, the equal-weighted LQ45 portfolio produces a return of -16.64% with a Sharpe ratio of -1.2710, indicating substantially lower investment performance. These findings demonstrate that the proposed GA-based framework provides an effective and practical portfolio optimization strategy under realistic investment constraints while highlighting the potential of evolutionary optimization methods for improving risk-adjusted portfolio performance in dynamic market environments.

1. Introduction

Investment is a long-term process conducted everywhere to build wealth and increase the value of money. It can contribute to economic growth, protect asset values from inflation, and gain profits from investment returns according to the type of investment chosen [1]. Indonesian Law No. 8 of 1995 on the capital market serves as the legal basis for the capital market in Indonesia which guarantees legal protection for all parties involved in capital market activities. Various financial instruments traded in the capital market such as stocks, bonds, mutual funds, and other instruments have different characteristics. Among the various investment instruments, stocks are the most favored instrument by investors because they offer the potential for higher returns. However, large profits are always proportional to the risks that must be faced [2].

Stocks are a form of ownership in a company that entitles the holder to receive dividends and participate in the company's decision making [3]. Stocks in the LQ45 index are one of the best choices because they offer high liquidity and good company quality. As seen in Fig. 1, the LQ45 index is an index consisting of 45 companies that have been selected based on certain criteria such as high liquidity levels, large market capitalization, good fundamental conditions, growth prospects, and other criteria set by the Indonesia Stock Exchange. The purpose of the LQ45 index is to complement the Composite Stock Price Index (JCI) by providing objective and reliable information for financial analysts, investment managers, investors and market observer [4]. So that the LQ45 index has a significant role for both the capital market and the economy as a whole because it is considered a barometer or indicator of the performance of the Indonesian stock market.

Fig. 1. Changes in LQ45 index stocks April 2024 - May 2025

Investing in stocks offers the potential for attractive returns. However, to maximize returns and reduce risk, it is important for investors to have an understanding of diversification and portfolio management. Diversification is a strategy to build an investment portfolio by spreading funds to various companies. Thus, portfolio risk can be minimized [5]. A stock portfolio is a combination of two or more types of stock securities invested in a certain period of time and conditions [3]. Forming a portfolio is one strategy to reduce the risk of loss [6]. Portfolio management on stock financial assets is done by balancing risk and return. Asset selection for portfolios with regard to minimum risk has been a problem since Markowitz [7] introduced in a paper entitled “Portfolio Selection”, and has become the basis for managing investment portfolios. This method then known as ‘mean-variance’ portfolio optimization model, since it uses the variance of asset return as a measure of investment risk.

Markowitz mean-variance model has become the foundation of modern portfolio optimization. However, its practical implementation faces several limitations. The model assumes continuous asset allocation and becomes computationally difficult when practical investment constraints, such as cardinality constraints, are incorporated. In real-word investment scenarios, investors often limit the number of selected assets to reduce transaction costs, simplify portfolio management, and improve investment efficiency [8]. However, introducing cardinality constraints transform the optimization problem into a combinatorial optimization problem that cannot be efficiently solved using conventional quadratic programming approaches [9]. Consequently, more adaptive optimization techniques are required to overcome these computational challenges.

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Heuristic optimization methods have attracted increasing attention because of their capability to efficiently explore large and nonlinear search spaces. Among these methods, the GA has demonstrated strong performance in solving complex optimization problems through evolutionary operators such as selection, crossover, and mutation [10], [11]. Optimization algorithms such as Genetic Algorithm (GA) are used to find more adaptive and effective solutions in determining the optimal portfolio. The Genetic Algorithm introduced by Holland [12] is based on the principle of evolution. In this approach, possible solutions are represented by structures called chromosomes that consist of several genes. Each chromosome then evaluated using a fitness function, which represent the objective function. To manipulate the chromosomes, two processes are conducted, namely crossover and mutation. These processes are conducted iteratively, while the elitism principle is used to maintain the best solution during the process. In this context, asset weights are represented by genes contained in the chromosome [13].

Previous studies have demonstrated the effectiveness of Genetic Algorithm in mean-variance portfolio optimization. Rosadi et al. implement the genetic algorithm in portfolio optimization with transaction lot using modified variance measure [14]. Syahla et al. [15] optimized a mean-variance portfolio using GA and obtained an optimal allocation for five LQ45 stocks. Moreover, empirical studies applying evolutionary portfolio optimization models to the Indonesian LQ45 stock market remain relatively limited compared with studies conducted on major international markets [16]. Nevertheless, most existing studies primarily focus on maximizing returns and minimizing risk using the classical mean-variance framework, while practical investment constraints, such as limiting the number of selected assets and guaranteeing a minimum return threshold, remain insufficiently explored.

Despite these advances, empirical studies integrating cardinality and minimum return constraints simultaneously within a Genetic Algorithm framework remain limited, particularly for the Indonesian LQ45 stock market [17]. Many existing studies primarily focus on optimizing the risk-return trade-off or cardinality constraints individually, while fewer studies integrate multiple practical investment constraints within a single optimization framework [18], [19]. Therefore, there is a need for portfolio optimization framework capable of balancing return, risk, and realistic investment constraints within a unified optimization process.

The contribution of this research is the development of a GA-based portfolio optimization framework that simultaneously integrates cardinality and minimum return constraints for LQ45 stock portfolios. By incorporating these practical investment constraints, the proposed framework provides a more flexible approach to portfolio construction while maintaining competitive risk-adjusted performance compared with conventional portfolio optimization methods. Unlike conventional mean-variance optimization approaches, the proposed framework is designed to accommodate practical investment constraints while maintaining competitive risk-adjusted portfolio performance [20]. Therefore, this study aims to evaluate the effectiveness of the proposed optimization framework by comparing its portfolio performance with an equal-weighted portfolio using return, portfolio risk, and Sharpe ratio as evaluation metrics [21], [22]. The findings are expected to enrich the application of evolutionary optimization techniques in portfolio management and provide practical insights for investors seeking efficient portfolio allocation under realistic investment constraints.

2. Method

2.1. Problem Statement

The genetic algorithm portfolio optimization approach was chosen because of its ability to solve non-linear and complex optimization problems that are difficult to solve with conventional methods, especially when there are constraints such as the maximum number of shares (cardinality) and minimum return [23], [24]. In the context of a dynamic stock market, a flexible and adaptive optimization strategy is needed so that the portfolio can remain efficient, even when market conditions are unfavorable. Therefore, genetic algorithms are a good choice because they are able to explore the solution space widely and find optimal solutions.

The research method used is quantitative with a case study approach on stocks that are members of the LQ45 index. Daily historical stock data is taken from Yahoo Finance and used to calculate return [25]. The optimization process is carried out with the stages of random population initialization, selection based on the objective function, crossover to produce new combinations of solutions, and mutation to maintain the diversity of solutions. The objective function is designed to minimize risk and provide a penalty if the portfolio does not meet the minimum return limit or the number of shares exceeds the maximum limit [26].

The Genetic Algorithm parameters used in this study were selected based on configurations commonly adopted in previous portfolio optimization studies to achieve a balance between solution quality and computational efficiency. The population size was set to 100 to balance solution diversity and computational efficiency. A larger population generally increases the exploration capability of the search process and reduces the risk of premature convergence, but it also increases computational cost [27]. The crossover probability was fixed at 0.8 because crossover is the primary mechanism for combining high-quality genetic information from parent solutions, thereby improving the exploration of promising regions in the search space. A relatively high crossover probability has been widely adopted in evolutionary optimization studies to accelerate convergence while preserving solution quality [28].

The maximum number of generations was set to 200 following configurations commonly reported in evolutionary portfolio optimization studies to provide sufficient evolutionary iterations for convergence without excessive computational cost. A penalty coefficient was incorporated into the fitness function to discourage infeasible solutions violating the minimum return and cardinality constraints. The penalty value was selected to ensure that feasible portfolios consistently received higher fitness values than infeasible solutions without excessively dominating the optimization objective [29], [30].

The analysis techniques were implemented using Python to ensure computational efficiency and reproducibility of the optimization process. The effectiveness of the proposed framework was evaluated by comparing the optimized portfolio with an equal-weighted portfolio, a commonly adopted benchmark in portfolio optimization studies. In addition, experiments were conducted under multiple parameter configurations to assess the robustness and consistency of the proposed approach.

2.2. Genetic Algorithm (GA)

Genetic Algorithm (GA) is one of the first proposed heuristic optimization methods. This method was developed by John Holland in the 1960s and popularized by David Goldberg in the 1980s. The optimization process in Genetic Algorithm mimics natural Darwinian evolutionary mechanisms such as selection, reproduction, and mutation to find the optimal solution to a problem [10]. Following Arkeman et al. [31], [32] the genetic algorithm is explained as follows.

1. Basic concept of Genetic Algorithm

Genetic Algorithm (GA) is a population-based optimization technique that operates on encoded candidate solutions rather than directly manipulating the decision variables of an optimization problem. This encoding process represents each candidate solution as a chromosome composed of smaller units called genes, which define the search space of the optimization process [33], [34]. In binary encoding, chromosomes are represented as strings of 0s and 1s, where each gene corresponds to a decision variable or selection status within the optimization problem. The effectiveness of GA lies in its ability to evaluate the quality of each chromosome through a fitness function without requiring explicit knowledge of the underlying problem structure. This evolutionary mechanism enables the algorithm to efficiently explore the search space and identify high-quality solutions for complex optimization problems [35], [36].

2. Chromosome Representation

Genetic algorithms require encoding the problem solution into chromosomes with the commonly used binary (0 and 1) representation.

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3. Fitness Function and Objective Function

Genetic algorithms evaluate the quality of solutions (chromosomes) using a fitness function that reflects the goal of the problem. Chromosomes with high fitness values are considered better and have a greater chance of surviving for the next generation. The fitness function can be equal to or modified from the objective function.

4. Chromosome Selection

The selection process in genetic algorithms mimics natural selection where chromosomes with high fitness values have a greater chance of being selected as parents and surviving the next generation. One commonly used selection method is roulette wheel selection where each chromosome has a chance of being selected partly by its fitness value [37].

5. Crossover

Crossover is the main operation in genetic algorithms that swap parts of the parent chromosomes to produce child chromosomes. The crossover rate (Pc) determines the frequency of these exchanges. A high Pc speeds up the search for the optimal solution but too high can waste time. The appropriate Pc value depends on the problem. The one-point crossover introduced by Holland is suitable for binary chromosomes [38].

6. Mutation

Mutation is an additional operation in genetic algorithms that randomly changes the chromosome structure to create new variations (mutants). Mutation is important to prevent losing good genes and introducing new genes that might improve the solution. The mutation rate (Pm) is usually low to maintain stability but should not be too low or high. The right mutation can help the algorithm find the optimal solution. There are different types of mutations that are tailored to the chromosome representation.

2.2.1. Objective Function

The objective function in this optimization aims to minimize portfolio risk by considering the penalty if the portfolio return does not meet the minimum target and if the number of shares exceeds the maximum limit. Before optimization using genetic algorithms, the approach is done with Mean-Variance Optimization (Markowitz Portfolio Theory) with the following objective function in Equation (1).

$$\min(\mathrm{w}) = \mathrm{w}^{\mathrm{T}}\Sigma\mathrm{w} \tag{1}$$

subject to:

$\boldsymbol{\Sigma \mathrm{w} = 1}$
$0 \leq w_i \leq 1$
w: Vector of stock weights,
Σ: Covariance matrix.

The objective function in GA combines a risk measure (from return covariance) with a penalty when the portfolio return is below the target or the number of active stocks exceeds the limit in Equation (2).

$$\min f(w) = \sigma_p - 10 \cdot \min\,(R_p - R\min, 0) + \max\,(k - u, 0) \tag{2}$$

subject to:
σ_p : Portfolio risk (standard deviation)
R_p: *Portfolio return over a certain period*
R_{min}: *Minimum return set*
u: Maximum limit of stocks allowed in the portfolio
k : Number of active stocks in the period

2.2.2. Portfolio Return

The portfolio return is calculated by the formula compounded arithmetic return portfolio during time t in Equation (3).

$$R_p = \left(1 + \sum_{i=1}^{n} w_i \cdot R_i\right)^t - 1 \tag{3}$$

Dengan,
R_i : The daily return of the i-th stock
t : Number of trading days in optimization period i

2.2.3. Cardinality Constraint

The maximum number of shares allowed is expressed as follow in Equation (4).

$$k = \sum_{i=1}^{n} [\delta_i] \leq u \tag{4}$$

u: The maximum number of stocks allowed in the portfolio
δ_i: Indicator (0 or 1) to indicate whether the i-th stock is included in the portfolio.

$$\delta_i = \begin{cases} 1, & jika\ w_i > 0{,}001 \\ 0, & jika\ w_i \leq 0{,}001 \end{cases} \tag{5}$$

As seen in Equation (5), each element in the chromosome has a value of 1 or 0, where.
1 indicates the stock is selected in the portfolio.
0 indicates the stock is not selected in the portfolio.

2.2.4. Stock Weight

Portfolios before using genetic algorithms are generally formed using a more mathematical approach, weighting is done using the equal-weight method or all stocks have equal weights. To evaluate the effectiveness of the proposed Genetic Algorithm-based portfolio optimization framework, an equal-weighted portfolio (EWP) was employed as the benchmark. The equal-weighted portfolio is one of the most widely adopted benchmark strategies in portfolio optimization because it allocates identical weights to all assets without relying on optimization procedures or parameter estimation, thereby providing a simple and transparent investment strategy [39]. Unlike optimized portfolios, the EWP does not explicitly consider expected return, portfolio risk, or asset covariance, making it an unbiased baseline for evaluating the additional value of optimization methods. Therefore, comparing the proposed Genetic Algorithm framework with the EWP enables an objective assessment of its ability to generate superior risk-adjusted portfolio performance. Formulated as follows in Equation (6).

$$\mathrm{w_i} = \frac{1}{\mathrm{n}} \tag{6}$$

$\mathrm{w_i}$: Weight of the i-th stock
n: Number of stocks in the portfolio
Stock weights are initially chosen randomly and then normalized to make the total equal to 1 in Equation (7).

$$w_i = \frac{x_i}{\sum_{j \in S} x_j}, untuk\ i \in S \tag{7}$$

x_i: Random value of the selected stock
x_j: Initial representative value of stock j generated by genetic algorithm
S: The set of selected stocks

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2.2.5. Stock Weight Limitation

The total weight must be equal to 1 (100%), formulated as follows in Equation (8).

$$0 \leq w_i \leq 1$$
$$\sum_{i=1}^{n} w_i = 1 \tag{8}$$

2.2.6. Portfolio Risk

$$\sigma_p = \sqrt{w^T \cdot \sum \cdot w} \tag{9}$$

$\sum$: Covariance matrix of returns between stocks. In Equation (9).

2.2.7. Sharpe Ratio

Sharpe ratio is used to measure portfolio efficiency Equation (10).

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{10}$$

R_f: Risk-free return

2.2.8. Fitness Function

Chromosomes (stock weight vectors) in genetic algorithms represent candidate portfolio solutions. The chromosome is formed randomly and from all available stocks, a random number of stocks are selected according to a specified limit. Then the weights are randomly divided and normalized so that the total weight = 1.

For example, if there are 10 stocks, the chromosome will be in Equation (11).

$$w = [0{,}1; 0{,}15; 0; 0{,}2; 0; 0; 0{,}25; 0{,}1; 0{,}2; 0] = 1 \tag{11}$$

If the return is smaller than the target, it is given a large penalty and if there are too many active stocks, it is also given a penalty. So fitness = risk + penalty, and minimize fitness. The chromosome with the best fitness (smallest value) will be more likely to be selected for reproduction. In the crossover process, two parents (P) will be combined to produce children in Equation (12). Mutations are performed to keep the population varied such as changing the stock weights to random numbers, adding or subtracting certain stock weights, and activating or deactivating new stocks. After mutation, the weights are adjusted again so that the total remains 1. Each time a new chromosome is created (either from crossover or mutation), it will be assigned a fitness score using the function in Fig. 2.

$$f(w) = \sigma_p - 10 \cdot \min\,(R_p - R\min, 0) + \max\,(k - u, 0) \tag{12}$$

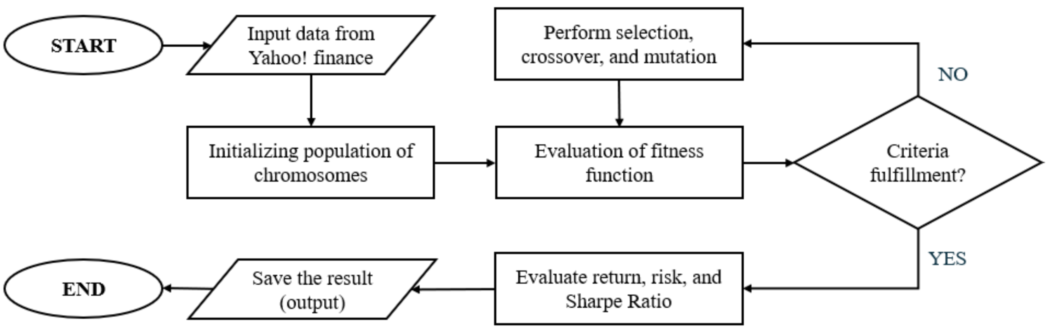

Fig. 2. Research Flowchart

3. Results and Discussion

This section presents the results of portfolio optimization using the proposed Genetic Algorithm (GA) framework under various combinations of cardinality and minimum return constraints. The optimization was performed using daily closing prices of LQ45 constituent stocks over a one-year observation period. Portfolio performance was evaluated based on expected return, portfolio risk (standard deviation), and Sharpe ratio to assess the effectiveness of the proposed optimization framework compared with the equal-weight portfolio benchmark.

The implementation of genetic algorithms is carried out using the Python programming language and DEAP library to compile GA components, as well as Yahoo Finance to obtain historical stock price data. Historical daily closing prices of LQ45 constituent stocks were collected from Yahoo Finance covering the period from 1 April 2024 to 31 March 2025 (252 trading days). The crossover used is one point crossover, where two parents are cut at a certain point, then the left part of the first parent is combined with the right part of the second parent to form an offspring. Meanwhile, the mutation used is a combination of swap and perturbation, which serves to maintain diversity and explore new solutions. Solution evaluation is based on the number of shares, portfolio return value, portfolio risk (standard deviation), and Sharpe Ratio value. The optimization process generated a set of feasible portfolios satisfying the imposed constraints, from which the portfolio with the highest Sharpe ratio was selected as the optimal solution in Table 1. The following subsections present the optimization results under different portfolio cardinalities and minimum return levels, followed by an analysis of the portfolio performance.

An example of manual calculation is done with the following steps.

1. Problem definition

Input : 1-year daily return data (252 days)

Output : Optimal portfolio with a limit of 3 stocks and a minimum return of 4%

2. Data Preparation

Table 1. Example of stock return average data

Stocks	**A**	**B**	**C**	**D**	**E**
Return	0.0012	0.0010	0.0008	0.0007	0.0009
Stocks	**F**	**G**	**H**	**I**	**J**
Return	0.0011	0.0005	0.0006	0.0004	0.0006

3. Creating Individual (Random Portfolio)

Initial portfolio P(1). Suppose the selected random stocks are stocks A. C. and F. Then the weights are randomly generated. (0.5; 0.3; 0.4; 0; 0; 0; 0; 0; 0; 0) =1.2.

Then the weights are normalized so that they become = 1.

$$w_i = \frac{0.5}{1.2} = 0.4167$$

$(0.42; 0.25; 0.33; 0; 0; 0; 0; 0)$

This means.

A: 42%. B: 25%. C: 33%. Others: 0%.

4. Calculate the portfolio return

$$Return = (0.42 \times 0.0012) + (0.25 \times 0.0008) + (0.33 \times 0.0011) = 0.001067$$

$$R_{252} = (1 + 0.0001067)^{252} - 1 \ = 1.1659 - 1 = 0.1659$$

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5. Calculate Portfolio Risk

The variance-covariance matrix is assumed to be simple.

$$\sum \boldsymbol{w} = \begin{bmatrix} 0.0025 & 0.0012 & 0.0009 \\ 0.0012 & 0.0036 & 0.0011 \\ 0.0009 & 0.0011 & 0.0041 \end{bmatrix} \cdot \begin{bmatrix} 0.42 \\ 0.25 \\ 0.33 \end{bmatrix} \approx \begin{bmatrix} 0.001647 \\ 0.001767 \\ 0.002006 \end{bmatrix}$$

$$\boldsymbol{w}^{\boldsymbol{T}}(\sum \boldsymbol{w}) = [0.42 \quad 0.25 \quad 0.33] \cdot \begin{bmatrix} 0.001647 \\ 0.001767 \\ 0.002006 \end{bmatrix} = 0.00179549$$

$$\sigma_p = \sqrt{0.00019792} \approx 0.04239$$

6. Calculate Sharpe Ratio

The risk-free rate used is 6.04% (0.0604) set based on the average BI-Rate during the study period.

$Return = 0.1659$

Risk = 0.04239

$Sharpe\ Ratio = \frac{0.1659-0.0604}{0.04239} = 0.2489$

7. Evaluate Fitness Function

$f(w) = \sigma_p - 10 \cdot \min\,(R_p - R\_\min. 0) + \max\,(k - 5.0)$

$\sigma_p = 0.04239$

$R_p = 0.1659$

$R_{min} = 0.04$

Calculating the difference in stock returns and penalties.

$f(w) = 0.04239 - 10 \cdot 0 + 0 = 0.04239$

8. Crossover and Mutation Process

Crossover of two portfolio. For example. *Parent* 1: [A. C. F]. *Parent* 2: [B. D. H]. Combines some stocks from Parent 1 and Parent 2 and creates a new child portfolio. Example of crossover result. [A. D. F].

Mutation or small random changes. Mutations can include replacing stock B with J. changing B's weight from 25% to 30%. and adding new stocks (if less than 3). Example: Discard stock B. replace with J. Change the weight slightly. then normalize (total number = 1). For example: (0.36; 0.27; 0.49). Then repeat the calculation of return. risk. and fitness as before. After crossover or mutation. the total weight can be more than 1. Then it must be normalized. Example of random weights from crossover.

[0.6; 0.5; 0.2] = 1.3

Then it needs to be normalized with the formula:

$w_i^{new} = \frac{w_i}{\sum w_i}$

$w_i = \frac{0.6}{1.3} . \frac{0.5}{1.3} . \frac{0.2}{1.3}$

Then the result is obtained:

[0.46; 0.38; 0.16] = 1

9. Best Portfolio

Each resulting portfolio will be calculated portfolio return, risk, number of shares, and fitness. The best portfolio in this algorithm is a portfolio of stocks that provides an optimal balance between return and risk (standard deviation) by meeting two restrictions namely the maximum number of shares selected (limited diversification) and the minimum return that must be achieved.

3.1. Portfolio Optimization Case Study

The implementation of genetic algorithm (GA) is used to perform portfolio optimization using several predetermined parameters. The parameters used include population size 100 number of generations 100 crossover rate 0.8 and mutation rate 0.2. The number of stocks in the portfolio was determined by the researcher with a varied range (3. 5. 8. 10) and minimum return (7%. 8%. 9%. 10%). Optimization was carried out 10 times, and the best results were taken from each number of shares and minimum return. The optimal solution is a portfolio that has the lowest possible risk value and meets the minimum return limit.

Table 2. Best Portfolio Optimization Results with 3 Stock Restrictions

Minimum Return	Selected stocks and weight	Return	Standard Deviation	Sharpe Ratio
7%	ITMG.JK (37.41%). EXCL.JK (32.38%). INDF.JK (30.21%)	0.0760	0.1517	0.1026
8%	INDF.JK (34.30%). ITMG.JK (33.67%). EXCL.JK (32.03%)	0.0842	0.1541	0.1542
9%	INDF.JK (38.96%). ITMG.JK (31.65%). EXCL.JK (29.39%)	0.0912	0.1569	0.2020
10%	ITMG.JK (40.23%). INDF.JK (40.14%). PGAS.JK (19.63%)	0.1417	0.1670	0.4867

Table 2 above is the result of the best portfolio optimization at a minimum return of 7%. 8%. 9%. and 10% with restrictions on 3 stocks based on the Sharpe ratio value and the resulting risk. The optimization results indicate that ITMG.JK, INDF.JK, and PGAS.JK consistently formed the optimal portfolio under different minimum return levels. This suggests that these stocks possess favorable combinations of expected return, volatility, and correlation with other selected assets enabling the Genetic Algorithm to construct portfolios with higher risk-adjusted performance while satisfying the imposed cardinality and minimum return constraints. The optimization results obtained a return of up to 14.17% and a risk of 0.1670. The portfolio has the highest Sharpe ratio value with a value of 0.4867 which provides the most efficient return compared to the risk taken. The optimization results demonstrate the fundamental risk-return trade-off in portfolio theory. where portfolios targeting higher expected returns are generally associated with greater levels of risk. This pattern is consistent with Modern Portfolio Theory. which states that investors must accept higher risk to obtain higher expected returns [3].

This also has an impact on the resulting Sharpe ratio value. The resulting Sharpe ratio value shows the efficiency of the portfolio. If investors want a more stable portfolio, then they can choose a portfolio with a target return of 7% with a low risk (volatility) of 0.1517 because it is suitable for investors who avoid sharp fluctuations and want fund stability. However, if investors dare to take a little extra risk for the sake of a large potential return. Then a portfolio with a target return of 10% is worth considering even though the risk is slightly higher. Thus, investors can choose a combination of stocks with a minimum return according to the risk taken. The consistent selection of stocks from different industrial sectors also reflects the role of diversification in portfolio optimization. ITMG.JK represents the energy sector. PGAS.JK operates in the natural gas industry while INDF.JK belongs to the consumer goods sector. Combining stocks from different sectors potentially reduces portfolio risk because the price movements of these assets are not perfectly correlated. Consequently, the Genetic Algorithm not only identifies stocks with attractive expected returns but also seeks combinations that improve overall portfolio efficiency through diversification. This finding is consistent with modern portfolio theory which emphasizes that diversification among assets with different risk characteristics contributes to better risk-adjusted portfolio performance. Experiment results with 10 trials at 3, 5, 8, and 10 stock limits can be seen in the appendix.

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Table 3. Best Portfolio Optimization Results with 5 Stocks Restriction

Minimum Return	Selected stocks and weight	Return	Standard Deviation	Sharpe Ratio
7%	EXCL.JK (24.37%). INDF.JK (23.60%). ITMG.JK (22.80%). MTEL.JK (15.48%). PGAS.JK (13.75%)	0.0958	0.1517	0.2471
8%	ITMG.JK (26.05%). EXCL.JK (20.46%). INDF.JK (20.24%). PGAS.JK (17.47%). MTEL.JK (15.77%)	0.0985	0.1430	0.2665
9%	INDF.JK (26.09%). ITMG.JK (23.08%). MTEL.JK (20.77%). PGAS.JK (16.71%). EXCL.JK (13.35%)	0.1012	0.1470	0.2774
10%	EXCL.JK (23.36%). INDF.JK (21.50%). ITMG.JK (20.03%). PGAS.JK (18.29%). MTEL.JK (16.83%)	0.1054	0.1459	0.3083

Table 3 show that the best-performing portfolio consists of EXCL.JK, INDF.JK, ITMG.JK, PGAS.JK, and MTEL.JK. Among the selected assets ITMG.JK, PGAS.JK, and INDF.JK appeared consistently across several portfolio configurations. This indicates that these stocks possess favorable combinations of expected return. Volatility and correlation with other assets, making them attractive candidates for portfolio optimization under cardinality and minimum return constraints. The optimized portfolio achieved an expected return of 10.54% with a portfolio risk of 0.1459, resulting in the highest Sharpe ratio of 0.3083 among the evaluated five-stock portfolios. These results indicate that the proposed optimization framework successfully balanced return and risk under the imposed investment constraints. The frequent selection of several stocks in the optimized portfolios suggests that the Genetic Algorithm consistently identified assets with favorable risk-return characteristics under the imposed constraints. Rather than selecting stocks solely based on high expected returns. The optimization process also considered portfolio diversification through covariance among assets allowing the resulting portfolio to achieve a higher risk-adjusted performance. Furthermore, the selected portfolio consists of companies operating in different sectors, including telecommunications (EXCL.JK and MTEL.JK), energy (ITMG.JK and PGAS.JK), and consumer goods (INDF.JK).

The combination of assets from multiple sectors enhances diversification by reducing concentration risk and limiting the impact of sector-specific market fluctuations on overall portfolio performance. This demonstrates that the Genetic Algorithm not only prioritizes attractive individual asset performance but also identifies diversified asset combinations that improve portfolio efficiency. These findings are consistent with the fundamental risk-return trade-off in portfolio theory. which states that investors seeking higher expected returns must generally be willing to accept higher levels of investment risk [40]. Overall, these findings demonstrate the capability of the proposed Genetic Algorithm framework to efficiently explore a large solution space and identify diversified portfolios that satisfy both cardinality and minimum return constraints while maintaining competitive risk-adjusted performance. The 8-stock portfolio optimization experiment was conducted with over 10 independent runs. and the best-performing portfolio based on the highest Sharpe ratio was selected for further analysis as presented in Table 4. The optimal portfolio consists of EXCL.JK, INDF.JK, ITMG.JK, PGAS.JK, MTEL.JK, ASII.JK, SIDO.JK, and ADRO.JK. Among the evaluated scenarios. the portfolio with a minimum target returns of 10% achieved the highest Sharpe ratio of 0.2948 with an expected return of 10.17% and a portfolio risk (standard deviation) of 0.1401. These results indicate that the proposed Genetic Algorithm successfully balanced return and risk while satisfying the imposed portfolio constraints. The selected portfolio combines stocks from multiple industrial sectors including telecommunications (EXCL.JK and MTEL.JK), energy (ITMG.JK. PGAS.JK. and ADRO.JK), consumer goods (INDF.JK and SIDO.JK), and the automotive industry (ASII.JK).

Table 4. Best Portfolio Optimization Results with 8 Stocks Restriction

Minimum Return	Selected Stock and Weight	Return	Standard Deviation	Sharpe Ratio
7%	INDF.JK (20.13%). EXCL.JK (14.10%). ITMG.JK (13.94%). SIDO.JK (11.13%). PTBA.JK (10.41%). BBCA.JK (10.26%). PGAS.JK (10.19%). MTEL.JK (9.83%)	0.0711	0.1382	0.0771
8%	INDF.JK (19.18%). EXCL.JK (18.53%). ITMG.JK (14.30%). MTEL.JK (11.92%). PGAS.JK (10.53%). ASII.JK (9.45%). SIDO.JK (8.92%). ICBP.JK (7.17%)	0.0817	0.1394	0.1529
9%	EXCL.JK (21.52%). INDF.JK (20.34%). ITMG.JK (18.64%). PGAS.JK (12.70%). SIDO.JK (8.37%). MTEL.JK (7.95%). ASII.JK (6.91%). BBCA.JK (3.59%)	0.0924	0.1388	0.2303
10%	EXCL.JK (20.33%). INDF.JK (19.21%). ITMG.JK (17.00%). PGAS.JK (12.48%). MTEL.JK (11.31%). ASII.JK (9.08%). SIDO.JK (8.03%). ADRO.JK (2.55%)	0.1017	0.1401	0.2948

This diversified sector composition indicates that the Genetic Algorithm does not merely prioritize assets with high expected returns but also considers the interaction among assets through their covariance structure. As a result, the optimization process is able to construct a more balanced portfolio that achieves competitive returns while maintaining portfolio risk at an acceptable level. Consistent with the principles of Modern Portfolio Theory. Increasing the minimum target return generally shifts portfolio allocation toward assets with higher expected returns and greater volatility. Thereby increasing the overall portfolio risk. Therefore, the choice of portfolio should be aligned with the investor's risk tolerance. Conservative investors may prefer portfolios with minimum return targets of 7–8% due to their lower volatility. Whereas aggressive investors may benefit from portfolios targeting returns of 9–10%. Despite the associated increase in investment risk [41].

As presented in Table 5, the optimal portfolio consisting of ten diversified stocks achieved an expected return of 10.09%. This represents the best performing portfolio among the evaluated ten-stock configurations. The optimized portfolio assigns the largest weights to ITMG.JK (21.77%), EXCL.JK (20.12%), and INDF.JK (18.47%). This indicates that these assets contribute substantially to the portfolio's expected risk-adjusted performance. Their relatively high allocation suggests that the Genetic Algorithm identified these stocks as having favorable combinations of expected return, volatility, and covariance with other portfolio constituents.

Together these three stocks account for nearly 60% of the total portfolio weight reflecting a concentration on assets with strong optimization characteristics while the remaining stocks enhance diversification by reducing unsystematic risk through exposure to different sectors and asset correlations. This allocation strategy demonstrates the ability of the Genetic Algorithm to balance concentration in high-performing assets with diversification benefits to improve overall portfolio efficiency. For the portfolio with a minimum return target of 10%. The Sharpe ratio reached 0.2923, this indicates that the portfolio achieved a favorable balance between expected return and investment risk. Although increasing the number of selected stocks slightly reduced the portfolio return compared with portfolios containing fewer assets. The diversification effect contributed to maintaining competitive risk-adjusted performance. The distribution of portfolio weights further illustrates that the proposed Genetic Algorithm does not simply maximize returns by concentrating investment in a single asset.

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Table 5. Best Portfolio Optimization Results with 10 Stocks Restriction

Minimum Return	Selected Stocks and Weight	Return	Standard Deviation	Sharpe Ratio
7%	EXCL.JK (18.92%). MTEL.JK (11.47%). ICBP.JK (10.72%). ITMG.JK (10.36%). INDF.JK (9.69%). UNTR.JK (9%). PGAS.JK (8.79%). SIDO.JK (8.54%). ASII.JK (7.22%). ANTM.JK (5.28%)	0.0767	0.1372	0.1189
8%	EXCL.JK (14.07%). PGAS.JK (12.19%). INDF.JK (11.51%). MTEL.JK (10.65%). ITMG.JK (10.41%). UNTR.JK (8.44%). BBCA.JK (8.39%). ANTM.JK (8.37%). ICBP.JK (8.25%). SIDO.JK (7.72%).	0.0811	0.1375	0.1508
9%	ITMG.JK (16.8%). EXCL.JK (15.89%). INDF.JK (15.22%). PGAS.JK (13.21%). MTEL.JK (10.12%). UNTR.JK (7.64%). BBCA.JK (7.23%). SIDO.JK (6.97%). ASII.JK (4.66%). ADRO.JK (2.26%).	0.0914	0.1364	0.2250
10%	ITMG.JK (21.77%). EXCL.JK (20.12%). INDF.JK (18.47%). PGAS.JK (13.99%). ANTM.JK (7.31%). MTEL.JK (6.57%). BBCA.JK (6.23%). SIDO.JK (2.16%). KLBF.JK (1.75%). GOTO.JK (1.63%).	0.1009	0.1364	0.2923

Instead, it allocates capital across multiple assets according to their contribution to the overall portfolio objective. thereby satisfying both the cardinality and minimum return constraints while preserving portfolio diversification. These findings demonstrate the effectiveness of the proposed optimization framework in constructing practical investment portfolios under realistic investment constraints in Fig. 3.

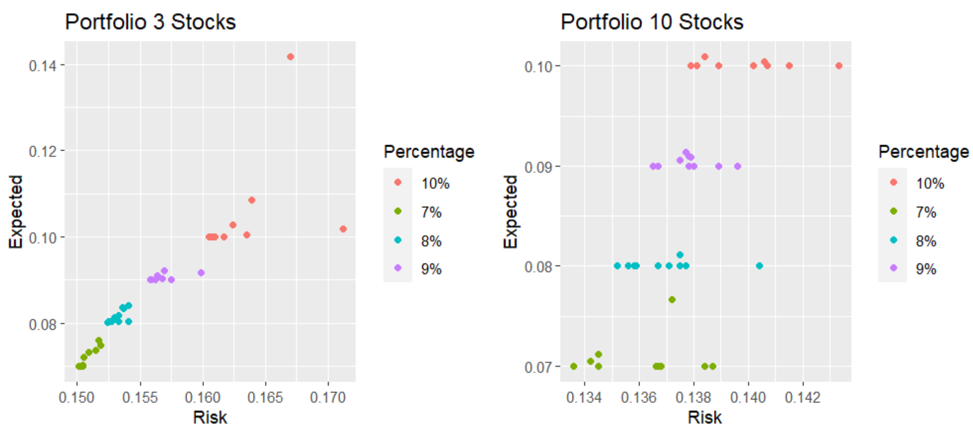

Fig. 3. Efficient Frontier of Portfolio 3 and 10 Stocks

A comparison between portfolios consisting of 3 stocks and 10 stocks illustrates the impact of portfolio cardinality on the optimization process. The 3-stock portfolio exhibits a relatively structured solution distribution, indicating that the Genetic Algorithm (GA) can explore the solution space more efficiently when the number of selected stocks is limited. Conversely, the 10-stock portfolio entails a larger and more complex search space, thereby increasing the likelihood of the algorithm converging to a local optimum rather than a global optimum. This can lead to greater variation in the risk-return combinations obtained from the optimization process as the number of stocks increases. Therefore, it is advisable to run the Genetic Algorithm independently multiple times to mitigate the risk of becoming trapped in a local optimum and to enhance the chances of obtaining a more optimal portfolio solution.

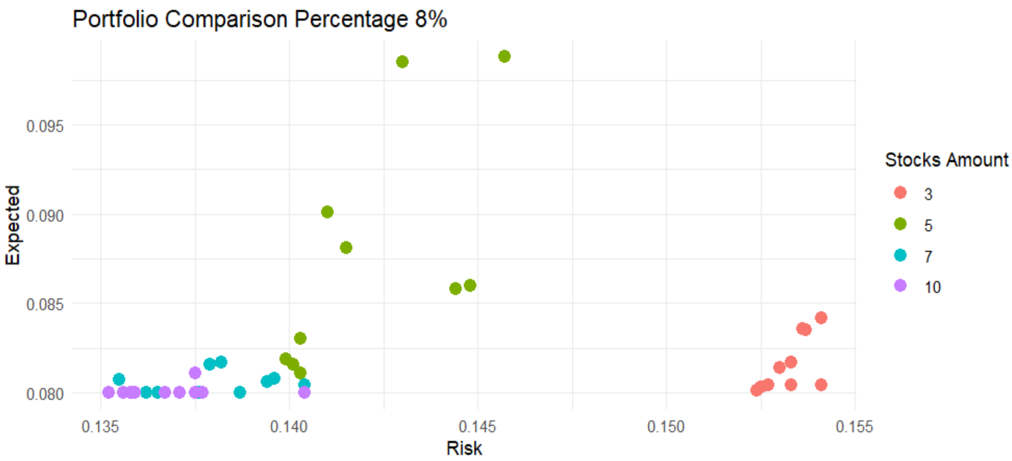

Fig. 4. Portfolio Comparison Percentage 8%

At a fixed minimum return of 8% in Fig. 4. Portfolios with different numbers of stocks show different risk–return characteristics. The 3-stock portfolio tends to have the highest risk. The 5-stock portfolio provides higher expected returns with relatively moderate risk. The 7- and 10-stock portfolios show lower risk and more concentrated risk–return distributions. This indicates that increasing the number of stocks can improve portfolio diversification and reduce risk; however. The larger search space may also increase the possibility of the Genetic Algorithm becoming trapped in a local optimum. So multiple runs are recommended.

Table 6. Portfolio Results of 45 LQ45 Index Stocks

Portfolio	Return	Standard Deviation	Sharpe ratio
LQ45 (all 45 stocks)	-0.1664	0.12710	-1.2710

The results of the proposed Genetic Algorithm (GA) optimization framework demonstrate superior portfolio performance compared with the equal-weighted LQ45 portfolio. The optimized portfolios consistently outperformed the equal-weighted LQ45 portfolio because the proposed framework simultaneously considers cardinality and minimum return constraints while optimizing asset allocation using the Sharpe ratio as the objective function. In contrast, the equal-weighted portfolio allocates identical weights to all constituent stocks without considering differences in expected return. risk or asset covariance. The optimized portfolios successfully achieved all predefined minimum return targets (7%. 8%. 9%. and 10%), whereas the equal-weighted LQ45 portfolio generated a negative return of −16.64% over the same observation period.

These findings indicate that incorporating practical investment constraints within the Genetic Algorithm framework enables more effective portfolio construction under unfavorable market conditions. Furthermore, the equal-weighted LQ45 portfolio exhibited a portfolio risk of 0.1785 and a negative Sharpe ratio of −1.2710 in Table 6. Indicating that the portfolio failed to generate adequate returns relative to the level of risk undertaken. This result highlights the limitation of passive equal-weight allocation during periods of unfavorable market performance as all constituent stocks receive identical investment proportions regardless of their individual risk-return characteristics. Overall, the comparison demonstrates that the proposed Genetic Algorithm framework is capable of constructing more efficient portfolios by selectively allocating capital to assets with favorable return, risk, and covariance characteristics while satisfying cardinality and minimum return constraints. These findings are consistent with previous studies reporting that evolutionary optimization techniques are

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more effective than passive allocation strategies in solving complex portfolio optimization problems because they can efficiently explore a large solution space and identify near-optimal asset combinations under multiple investment constraints.

This study proposed a Genetic Algorithm (GA)-based portfolio optimization framework by simultaneously incorporating cardinality and minimum return constraints. Portfolio optimization was performed using historical daily prices of LQ45 constituent stocks over a one-year observation period with portfolio performance evaluated using return, portfolio risk, and the Sharpe ratio. The discussion focuses on interpreting the optimization results and their implications for portfolio construction under practical investment constraints.

The optimization results consistently demonstrate that the proposed Genetic Algorithm framework was capable of constructing efficient portfolios across different cardinality constraints. Although the portfolio composition and asset weights varied depending on the imposed minimum return targets, all optimized portfolios achieved positive returns with favorable Sharpe ratios. The highest portfolio performance was obtained under the three-stock configuration with a minimum return target of 10% indicating that a more concentrated portfolio may generate higher risk-adjusted returns under certain market conditions [18].

Furthermore, the analysis was conducted using 45 stocks of the LQ45 index to compare the performance of the selected portfolio with the limitation of the number of stocks and the minimum return using genetic algorithms with all stocks. The portfolio results gave a return of -16.64% with a risk value of 0.1785. The analysis is done by dividing the number of weights equally. The resulting Sharpe ratio value is -1.2710, which indicates that the portfolio in that period has decreased. This is evidenced by the decline in stock prices on the LQ45 index which can be seen in the attachment. Thus, in that period, the portfolio performance over the past 1 year suffered a loss. The resulting fluctuations or risks are quite high but not accompanied by commensurate returns.

The superior performance of the optimized portfolios compared with the equal-weighted portfolio demonstrates the effectiveness of incorporating practical investment constraints into the optimization process. Unlike passive equal-weight allocation. the proposed framework selectively allocates capital based on expected return, portfolio risk, and covariance among assets, enabling more efficient portfolio construction [42]. These findings support previous studies reporting that evolutionary optimization techniques outperform traditional allocation strategies when solving constrained portfolio optimization problems [16].

The findings of this study demonstrate that incorporating cardinality and minimum return constraints within a Genetic Algorithm framework provides a practical approach to portfolio optimization under realistic investment conditions. In contrast to traditional mean-variance optimization. which often assumes unconstrained asset allocation. the proposed framework allows investors to limit the number of selected assets while ensuring that the portfolio satisfies a predefined return target [18]. Consequently, the resulting portfolios are not only computationally efficient but also more applicable to real-world investment decision-making. These findings reinforce the growing role of evolutionary optimization techniques in addressing complex financial optimization problems characterized by nonlinear objective functions and multiple investment constraints.

The findings obtained in this study are consistent with previous research reporting the effectiveness of Genetic Algorithms in solving constrained portfolio optimization problems. Similar to those studies. The proposed framework successfully balanced return and portfolio risk through adaptive optimization. However, unlike previous studies that primarily focused on unconstrained portfolio optimization. This research simultaneously incorporates cardinality and minimum return constraints within the context of LQ45 stocks. thereby providing a more practical portfolio optimization framework for investors operating in the Indonesian capital market [43].

4. Conclusion

This study demonstrates that Genetic Algorithm-based portfolio optimization incorporating cardinality and minimum return constraints is capable of constructing efficient stock portfolios with favorable risk-adjusted performance. The performance of genetic algorithms shows good adaptive capabilities in exploring complex solutions. Among the evaluated scenarios the three-stock portfolio with a minimum return target of 10% achieved the highest Sharpe ratio (0.4867), indicating that a more concentrated portfolio may provide superior risk-adjusted performance under the observed market conditions. This shows that the GA approach is capable of finding optimal solutions that balance return and risk under certain market conditions. The optimized portfolio generated an expected return of 14.17% with a portfolio risk of 0.1670, outperforming the equal-weighted LQ45 portfolio in terms of return and Sharpe ratio. These findings confirm that incorporating practical investment constraints within a Genetic Algorithm framework provides a more effective portfolio construction strategy than passive equal-weight allocation. The optimized portfolio with genetic algorithm on LQ45 index stocks shows significantly superior performance compared to the portfolio that includes 45 stocks with equal weights. This indicates that selective and optimization-based approaches provide advantages in managing portfolios efficiently, even in the midst of declining market conditions.

From a theoretical perspective, this study contributes to the development of heuristic portfolio optimization by demonstrating that the simultaneous integration of cardinality and minimum return constraints within a Genetic Algorithm framework can effectively solve constrained portfolio optimization problems. The proposed framework extends the application of evolutionary optimization techniques to practical investment decision-making in the Indonesian capital market. From a practical perspective, the proposed optimization framework can assist investors. portfolio managers. and financial analysts in constructing portfolios that better align with specific investment objectives and risk preferences. By limiting the number of selected assets while maintaining a predefined minimum return. The resulting portfolios provide greater flexibility and are more applicable to real-world investment management than conventional passive allocation strategies. Despite these encouraging results. This study has several limitations. Portfolio performance was evaluated primarily using the Sharpe ratio and historical data from a single observation period. Future research may incorporate additional performance measures such as the Sortino ratio, Treynor ratio, or maximum drawdown, as well as explore hybrid optimization techniques. including Genetic Algorithm–Particle Swarm Optimization (GA–PSO) and Genetic Algorithm–Artificial Neural Networks (GA–ANN). Furthermore, extending the proposed framework to multi-objective optimization by simultaneously considering transaction costs. Liquidity or skewness may provide a more comprehensive portfolio optimization model under dynamic market conditions.

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