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Determination of Optimal Portfolio by Calculating Transaction Costs using Genetic Algorithms on the Jakarta Islamic Index

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ABSTRACT

The optimal portfolio is a portfolio that can provide maximum returns at the same level of risk. In investing, the term "high return, high risk" is known, meaning that the higher the return, the higher the risk. Therefore, investors need to develop an optimal portfolio to obtain the maximum return on investment at the same level of risk. This study aims to determine the optimal formation of a stock portfolio by calculating transaction costs using the genetic algorithm method on stocks that are members of the Jakarta Islamic Index. This research uses data of daily return on stocks included in Jakarta Islamic Index from 1 August 2020-1 August 2022. The dataset consists of two variables: the date of observation and daily stock returns. The method used in this study is the minimum variance method and the genetic algorithm. Data analysis was divided into two stages: model formulation and model testing through case studies. The analysis of optimal portfolio formation using genetic algorithms shows that in terms of performance, the minimum variance portfolio is superior to the genetic algorithm portfolio, as indicated by the Sharpe ratio value. Meanwhile, the genetic algorithm portfolio is superior to the minimum variance portfolio regarding transaction costs. The genetic algorithm portfolio can provide a fairly high total return, small transaction costs, and good performance compared to the minimum portfolio. Hence, the genetic algorithm portfolio is worthy of recommendation to investors.

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A. INTRODUCTION

Stocks are securities showing proof of company ownership, and shareholders are entitled to a share of the company's operating results (Financial Services Authority, 2015). In investment, the term "high return, high risk" is known, meaning that the higher the return rate, the investment profit, the higher the risk. Portfolio return is the level of profit investors obtain as a return on their investments. On the other hand, risk is defined as the large possibility of deviation from the return obtained with the expected return. An optimal portfolio means that the portfolio can provide a combination of shares to obtain the best-expected return and risk (Mahayani & Suarjaya, 2019).

The problem that an investor often faces is the difficulty of allocating funds owned to several stock options to get maximum profit at the same level of risk. Allocating funds into several stock options is called a portfolio. The optimal portfolio involves arranging a combination of stocks to get the best-expected return and risk (Mahayani & Suarjaya, 2019). Modern Portfolio Theory (MPT) is based on the idea that a combination of assets can yield better returns with less risk than individual assets (Grover & Lavin, 2007). Parker (2016) noted that according to the MPT paradigm, investors should seek to minimize variance while maximizing returns and optimizing risk-reward tradeoffs with investor returns.

Following the above problems, investors need to determine the weight of each stock on their portfolio so that the maximum profit is obtained at the same level of risk. One strategy that can be done is to diversify stocks, placing investment funds into several stocks with different characteristics. By diversifying stocks, investors will still benefit from other stocks in the portfolio when stocks experience a decrease in return. This diversification later became the basis for developing Markowitz's modern portfolio theory (Markowitz, 1952).

In practice, buying and selling shares on the exchange has several provisions, including provisions on the minimum transaction amount and transaction costs. According to Darmadji & Fakhruddin (2012), the stock exchange has a minimum limit in buying and selling shares in the regular and cash market known as lots. One lot of shares on the Indonesia Stock Exchange amounts to 100 shares, so investors must buy shares in lots or multiples of 100 shares (Setiawan & Rosadi, 2019). According to Arnott & Wagner (1990), the transaction costs in buying and selling shares are not too high, but if ignored, they will affect long-term investment results. If a portfolio can provide high returns with large costs, then the total investors get will also not be optimal. The non-optimal condition certainly has an effect if left for a long period. Therefore, investors need to consider transaction costs in the process of forming their portfolio in order to obtain optimal investment results.

Genetic Algorithms (GA) is a heuristic optimization technique inspired by the Darwinian evolution principle. Through selection, crossover, and mutation, populations coalesce into single chromosomes with high fitness (Cheong et al., 2017). One of the advantages of using GA for multi-objective optimization is that it works on a population of individuals, so it can find multiple non-dominant solutions in a single pass. Due to the lack of restrictive assumptions about the solution space, GA is a powerful technique for solving optimization problems. GA also less sensitive to the non-convexity of the search space than other techniques. However, GA is time-consuming, and if the optimal solution is not known, the algorithm stops if the efficiency frontier does not improve significantly (Baixauli-Soler et al., 2012). Chang et al. (2009) used GA for portfolio optimization problems in different risk measures. Chang et al. (2009) argue that GA can be a good alternative in complex cases where there is no analytic solution. Woodside-Oriakhi *et al.* (2011) show that portfolio optimization using GA provides better results than other heuristic methods. In Indonesian stock market, GA was applied by Azim et al. (2021) as well as Fahria & Kustiawan (2020) to optimize portfolios on LQ45 stocks.

GA also used to solve portfolio optimization problems with various constraints such as minimum number of transactions, cardinality constraints, and transaction costs. Liagkouras & Metaxiotis (2018), Yoshimoto (1996), Fang et al. (2005), Ruiz-Torrubiano & Su´arez (2015), and DeMiguel et al. (2016) provides examples of portfolio optimization studies that consider various constraints. Lin & Liu (2008) used genetic algorithm for portfolio selection problems with minimum transaction lots. Suksonghong et al. (2014) used muti-objective GA for solving portfolio optimization problems in the electricity market. In particular, Wang et al. (2022) and

Vazhayil & Balasubramanian (2014) are some well-known examples of studies that consider the optimization portfolio using GA.

A study by Sofariah et al. (2016) used a genetic algorithm to optimize portfolios with transaction costs on LQ45 stocks. However, this study has limitations since the amount of transaction costs considered equal, and the determination of better performance is calculated based on the return only. Realizing these limitations, this study examine mean-variance optimal portfolio with assumption that there are different costs of buy and sell stock. In addition, we examine the process of portfolio rebalancing since the transaction to rebalance the portfolio will cause a cost to sell and buy some assets. Therefore, this study aims to provide portfolio optimization methods that has lower transaction cost with similar level of return.

These methods than applied in determining optimal portfolio in stocks that comprise the Jakarta Islamic Index (JII). In general, JII are selected stocks that have undergone a rigorous review process by liquidity and sharia' principles (Rudiawarni et al., 2022). This index is important in practice since the majority of Indonesia's population is Muslim, so the growth potential of the Islamic market is large.

B. METHODS

This research is quantitative with an experimental approach based on case studies using secondary data in the form of daily returns on Jakarta Islamic Index (JII) shares from 1 August 2020-1 August 2022. Data was collected from Yahoo Finance website (Yahoo Finance, 2022). The data analysis techniques used to optimize the portfolio are the minimum variance method and the multi-objective genetic algorithm. Data analysis was carried out with the help of R studio software R Core Team (2021) using the Performance Analytics package Peterson & Carl (2020) to calculate the Sharpe Ratio and the GA package Scrucca (2017) for optimization with genetic algorithms. The stages of data analysis are divided into two stages, namely model formulation and model testing.

The model formulation stage includes formulating a minimum variance optimization model with no transaction costs and minimum variance with transaction costs. The minimum variance model without transaction costs aims to minimize variance (risk) or is mathematically written as follows (Peterson, 2012):

$$\min \sigma_p^2 = \min \boldsymbol{w}^T \boldsymbol{\Sigma} \boldsymbol{w} = \min \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{1}$$

where σ_p^2 is portfolio variance, w_i denoted the portion of funds invested in the i^{th} stocks, w_j denoted the portion of funds invested in the j^{th} stocks, and σ_{ij} denoted covariance between stocks i^{th} and j^{th}. Assuming short selling is not allowed, minimum variance portfolio optimization can be expressed in matrix form as follows:

$$\min_{w} \sigma_p^2 = \min_{w} \boldsymbol{w}^T \boldsymbol{\Sigma} \boldsymbol{w} \tag{2}$$

with constraints:

1. $\boldsymbol{w}^{\boldsymbol{T}}\mathbf{1}_p = 1$
2. $w_i \geq 0$ to $i = 1,2, \dots, n$

Transaction costs arise from the sale and purchase of shares. Transaction costs represent the total cost of selling and buying stocks. Selling costs are obtained from a percentage of the costs of selling shares applied on the stock exchange (a_1) multiplied by the value of the shares to be sold $(max(0, w_i^0 - w_i))$. Meanwhile, purchasing costs are obtained from a percentage of costs buy shares applied on the exchange (a_2) multiplied by the share value to be purchased $(max(0, w_i - w_i^0))$. Mathematically it can be written as follows:

$$\begin{aligned} TC &= selling\ cost\ +\ buying\ cost \qquad (3) \\ &= (a_1 \times value\ of\ shares\ sold) + (a_2 \times value\ of\ shares\ purchased) \\ &= a_1 \times \textstyle\sum_{i=1}^{n} \max(0, w_i^0 - w_i) + a_2 \times \sum_{i=1}^{n} \max(0, w_i - w_i^0) \end{aligned}$$

where TC is transaction costs, a_1 denoted percentage of cost of selling shares, a_2 is percentage of cost of buying shares, w_i^0 denoted the initial weight of stocks in the portfolio, and w_i denoted new weight of stocks in the portfolio.

In establishing the minimum variance optimization model with transaction costs, it is assumed that there are no provisions on the number of lots in share buying and selling transactions on the stock exchange so that the resulting share weight is in the form of a percentage rather than in lot units. The alpha value (α) is used to determine which is more prioritized by investors, in this case minimizing portfolio variance (risk) or minimize transaction costs, the value of α were tested in this study is 0.90, 0.80, 0.70 and 0.50. Mathematically, the minimum variance optimization model with transaction costs can be written as follows:

$$\begin{aligned} \min \alpha(\sigma_p^2) + (1-\alpha)TC &= \alpha \textstyle\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} + (1-\alpha)TC \\ &= \alpha \boldsymbol{w}^T \textstyle\sum \boldsymbol{w} + (1-\alpha)TC \end{aligned} \qquad (4)$$

with constraints:

1. $\sum_{i=1}^{n} w_i = 1$
2. $w_i \geq 0$

The model testing phase was carried out based on case studies on four JII index stocks selected based on criteria set by researchers. To implement these model we used genetic algorithm as follows. Let w_i be the chromosome with the fitness function based on the model formed above. A case study using stock in JII is provided. The fitness function is stock returns, transaction cost percentages, stock weights, and alpha values. The genetic algorithm process begins by determining the type of gene coding, namely by real valued encoding. Next, generate the initial population, calculate individual fitness values, determine parents with roulette wheel selection, perform crossovers with one-point crossovers, perform mutations (mutations) with gene mutations, and perform iterations until optimal individuals are obtained.

Case study illustration: An investor wants to invest his money into four stocks that make up the JII index with great profit opportunities in the future. The transaction costs provisions applied on the exchange are 0.4% for selling transactions and 0.3% for buying transactions. Investors want to have a portfolio that can provide maximum return at the same level of risk. On the other hand, investors do not want the cost of selling and buying their shares to swell. Therefore, it is necessary to form an optimal portfolio that can provide maximum profit with risks and transaction costs that can be tolerated by these investors.

C. RESULT AND DISCUSSION

First of all, it is necessary to select the stock to be used in the case study. The stocks selected as candidates for portfolio building are stocks that are consistently in the JII index during the observation period and have positive returns. Based on these criteria, 10 stocks were obtained as portfolio candidates. The list of stocks can be seen in Table 1.

Table 1. List of portfolio candidate stocks

Company	Stock code	Mean *return*	Standard deviation of *return*	*Expected return*
Adaro Energy Indonesia Tbk.	ADRO	0.002261	0.028487	0.010504
Aneka Tambang Tbk.	ANTM	0.002011	0.037860	0.009341
Bukit Asam Tbk.	PTBA	0.001553	0.023326	0.007217
Vale Indonesia Tbk.	INCO	0.001198	0.030392	0.005563
United Tractors Tbk.	UNTR	0.000842	0.025115	0.003913
Telkom Indonesia Tbk.	TLKM	0.000670	0.019215	0.003113
Perusahaan Gas Negara Tbk.	PGAS	0.000587	0.027367	0.002728
Chandra Asri Petrochemical Tbk.	TPIA	0.000538	0.020012	0.002499
Indofood CBP Sukses Makmur Tbk.	INDF	0.000101	0.015673	0.000470
Kalbe Farma Tbk.	KLBF	0.000058	0.019944	0.000270

Mean return shows the average daily return during the observation period. Standard deviation of return shows the stock risk and expected return shows the return that is expected to be obtained during the observation period. In this study, the stocks selected for the optimal portfolio formation case study are shares of Adaro Energy Indonesia Tbk. (ADRO), Vale Indonesia Tbk. (INCO), Indofood CBP Sukses Makmur Tbk. (INDF), and Chandra Asri Petrochemical Tbk. (TPIA). These stocks are the most popular stocks among investors and have good prospects along with rising stock prices on the stock exchange. The daily stock return graph is shown by Figure 1.

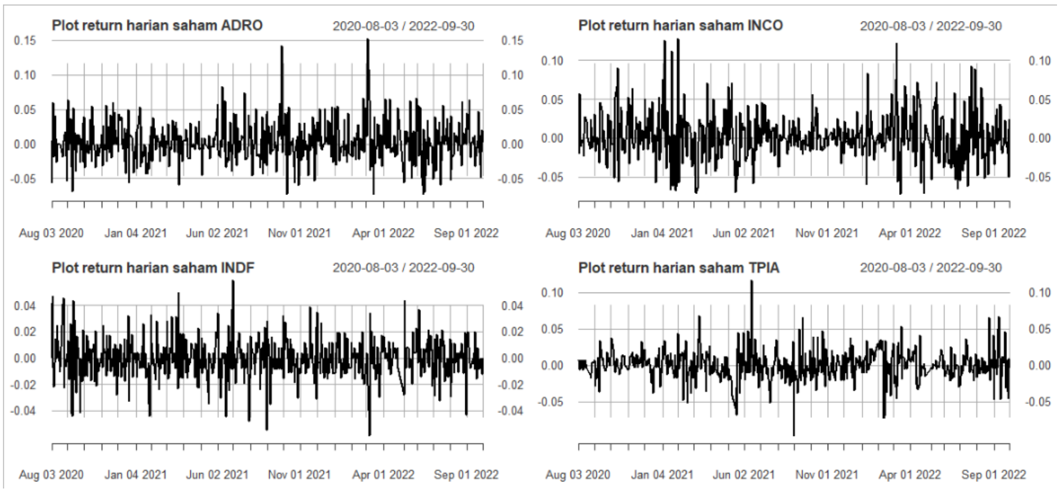

Figure 1. Daily returns of ADRO, INCO, INDF and TPIA shares

Based on Figure 1, most stocks produce daily returns ranging from -5% to 10%. However, there are shares whose daily returns reach >10%, namely ADRO and INCO shares. This indicates that this stock is worth considering for investors who want a high return on investment. However, you need to remember that the higher the return, the higher the investment risk. Returns are said to be profitable if they are positive and they are said to be losses if they are negative. This shows that stocks can produce large daily returns, sometimes they can produce negative daily returns that are just as large. The next stage is the formation of an optimal portfolio of stock. At this stage, several test scenarios are carried out using the minimum variance method and genetic algorithms. The test scenario of determining the optimal portfolio of JII index stocks is shown in Figure 2.

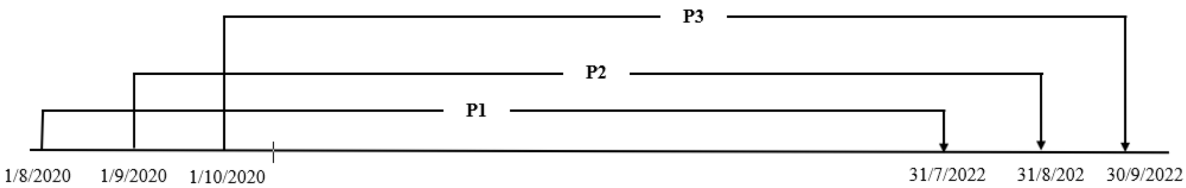

Figure 2. Timeline of optimal portfolio formation scenarios of JII index stocks

Based on Figure 2, three optimal portfolios of stocks are formed using the minimum variance method without transaction costs namely P1, P2, and P3. Portfolio I (P1) was formed on August 1, 2022 using daily return data on JII index stocks from August 1, 2020 to July 31, 2022. Portfolio II (P2) was formed on September 1, 2022 using daily return data on JII index stocks in the period September 1, 2020-August 31, 2022. Portfolio III (P3) was formed on October 1, 2022 using daily return data on JII index stocks in the period of October 1, 2020-September 30, 2022. The optimal portfolio of JII index stocks to be formed is described in Table 2.

Table 2. Optimal portfolio formation testing scenarios

Portfolio name	Date formed	Test scenarios
P1 MV	1-08-2022	Portfolio I *minimum variance* without transaction costs
P2 MV	1-09-2022	Portfolio II *minimum variance* with no transaction costs
P2A	1-09-2022	Portfolio II GA transaction cost with P1MV as initial weight and α = 0.90
P2B	1-09-2022	Portfolio II GA transaction cost with P1MV as initial weight and α = 0.70
P2C	1-09-2022	Portfolio II GA transaction fee with P1MV as initial weighting and α = 0.50
P2D	1-09-2022	Portfolio II GA transaction cost with P1MV as initial weight and α = 0.30
P3 MV	1-10-2022	Portfolio III *minimum variance* with no transaction costs
P3A	1-10-2022	Portfolio III GA transaction fee with P1MV as initial weighting and α = 0.90
P3B	1-09-2022	Portfolio III GA transaction cost with P1MV as initial weight and α = 0.70
P3C	1-09-2022	Portfolio III GA transaction cost with P1MV as initial weight and α = a 0.50
P3D	1-09-2022	Portfolio III GA transaction cost with P1MV as initial weight and α = a 0.30
P3AA	1-09-2022	Portfolio III GA transaction fee with P2MV as initial weight and α = 0.90
P3BB	1-09-2022	Portfolio III GA transaction fee with P2MV as initial weight and α = a 0.70
P3CC	1-09-2022	Portfolio III GA transaction fee with P2MV as initial weight and α = a 0.50
P3DD	1-09-2022	Portfolio III GA transaction costs with P2MV as initial weight and α = 0.30

Portfolio I is formed using minimum variance method without transaction costs named the P1 MV portfolio. The P1 MV portfolio acts as an initial weight in the optimization process with a genetic algorithm. Minimum variance analysis is done manually using Rstudio software refers to Equation 1. The weights of stocks in the P1 MV portfolio are shown in Table 3.

Table 3. Portfolio I (P1MV)

Stock code	Stock weighting	Stock weight percentage (%)
ADRO	0.09458575	9.46%
INCO	0.08751188	8.75%
INDF	0.51428945	51.43%
TPIA	0.30361293	30.36%

Based on Table 3, INDF shares make up the portfolio with the largest percentage while ADRO shares make up the portfolio with the smallest percentage, namely of the total shares owned by investors. Portfolio II (P2) is formed using two methods, minimum variance without transaction costs and minimum variance with transaction costs. First, a minimum variance portfolio without transaction costs will be formed using the same procedure as P1MV, the only difference between the two is the data used to form the portfolio which is explained in Figure 2. Portfolio II (P2) minimum variance without transaction costs is named P2 MV. The weights of shares in the P2 MV portfolio are shown in Table 4. The P2MV portfolio shows results that are in line with P1MV where INDF shares make up the portfolio with the largest percentage and ADRO shares make up the portfolio with the smallest percentage.

Table 4. Portfolio II (P2MV)

Stock code	Stock weighting	Stock weight percentage (%)
ADRO	0.08612482	8.61%
INCO	0.09010988	9.01%
INDF	0.54190570	54.19%
TPIA	0.28185959	28.19%

The minimum variance portfolio model with transaction costs formed in Equation 4 is solved with a genetic algorithm using Rstudio software. In the process of optimizing the weights of portfolio constituent shares, several test scenarios are carried out with different alpha values according to the investor's wishes or until the most optimal results are found. Analysis was carried out using the ga() function which is available in the GA package in Rstudio. The genetic algorithm parameters used are, P_c=0.8, P_m=0.1, population size (popSize) 100 and maximum number of iterations (maxiter) 1000. Using Portfolio P1MV as initial weighting, optimization of stock weights with transaction costs using a genetic algorithm produces Portfolio II (P2) as shown in Table 5.

Table 5. Portfolio II (P2) genetic algorithm with P1MV as initial weighting

Portfolio name	Alpha value	Stock code	Stock weighting	Stock weight percentage (%)
P2A	0.90	ADRO	0.0945340	9.45%
		INCO	0.0876570	8.77%
		INDF	0.5142800	51.43%
		TPIA	0.3035270	30.35%
P2B	0.70	ADRO	0.0947765	9.48%
		INCO	0.0875374	8.76%
		INDF	0.5140493	51.40%
		TPIA	0.3036367	30.36%
P2C	0.50	ADRO	0.0953253	9.53%
		INCO	0.0868040	8.69%
		INDF	0.5142593	51.42%
		TPIA	0.3036112	30.36%
P2D	0.30	ADRO	0.0947937	9.48%
		INCO	0.0874255	8.74%
		INDF	0.5141903	51.42%
		TPIA	0.3035904	30.36%

Based on the share weights listed in Table 5, a greater proportion of share weights are placed on shares with the smallest portfolio risk as shown in Table 1. INDF and TPIA shares have a smaller risk compared to ADRO and INCO shares so that the allocation proportion funds to INDF and TPIA shares are greater than the proportion of funds allocated to ADRO and INCO shares. The same thing was done to form Portfolio III (P3) using two methods, namely minimum variance without transaction costs and minimum variance with transaction costs. A minimum variance portfolio without transaction costs will be formed using the same procedure as P1MV and P2MV, the only difference between the two is the data used to form the portfolio which is explained in Figure 2. Portfolio III (P3) minimum variance without transaction costs is named P3 MV. The weights of shares in the P3 MV portfolio are shown in Table 6.

Table 6. Portfolio III (P3MV)

Stock code	Stock weighting	Stock weight percentage (%)
ADRO	0.09596978	9.60%
INCO	0.09125807	9.13%
INDF	0.56382570	56.13%
TPIA	0.24894645	24.89%

The P3MV portfolio shows results that are in line with P1MV and P2MV where INDF shares make up the portfolio with the largest percentage and ADRO shares make up the portfolio with the smallest percentage. The minimum variance portfolio model with transaction costs in Portfolio III is formed using the same procedures as P2A, P2B, P2C, and P2D as previously described. The only difference is in the initial weight, where Portfolio III will use P1MV and P2MV as its initial weight while Portfolio II will only use P1MV as explained in Table 2. The genetic algorithm operator used to form Portfolio III (P3) is the same as the operator used to form Portfolio II (P2). The results of stock portfolio optimization by considering transaction costs using a genetic algorithm are presented in Table 7.

Table 7. Portfolio III (P3) genetic algorithm with P1MV as initial weighting

Portfolio name	Alpha value	Stock code	Stock weighting	Stock weight percentage (%)
P3A	0.90	ADRO	0.0947526	9.48%
		INCO	0.0874998	8.75%
		INDF	0.5141372	51.41%
		TPIA	0.3036104	30.36%
P3B	0.70	ADRO	0.0947132	9.47%
		INCO	0.0870325	8.70%
		INDF	0.5144443	51.44%
		TPIA	0.3038099	30.38%
P3C	0.50	ADRO	0.0945195	9.45%
		INCO	0.0876086	8.76%
		INDF	0.5142925	51.43%
		TPIA	0.3035793	30.36%
P2D	0.30	ADRO	0.0942988	9.43%
		INCO	0.0886921	8.87%
		INDF	0.5143373	51.43%
		TPIA	0.3026717	30.27%

Table 7 shows the share weights formed using several combinations of alpha values with P1MV as the initial weight. Based on the share weights listed in Table 7, a greater proportion of share weights are placed on shares with the smallest portfolio risk as shown in Table 1. INDF and TPIA shares have a smaller risk compared to ADRO and INCO shares so that the allocation proportion funds to INDF and TPIA shares are greater than the proportion of funds allocated to ADRO and INCO shares, as shown in Figure 3.

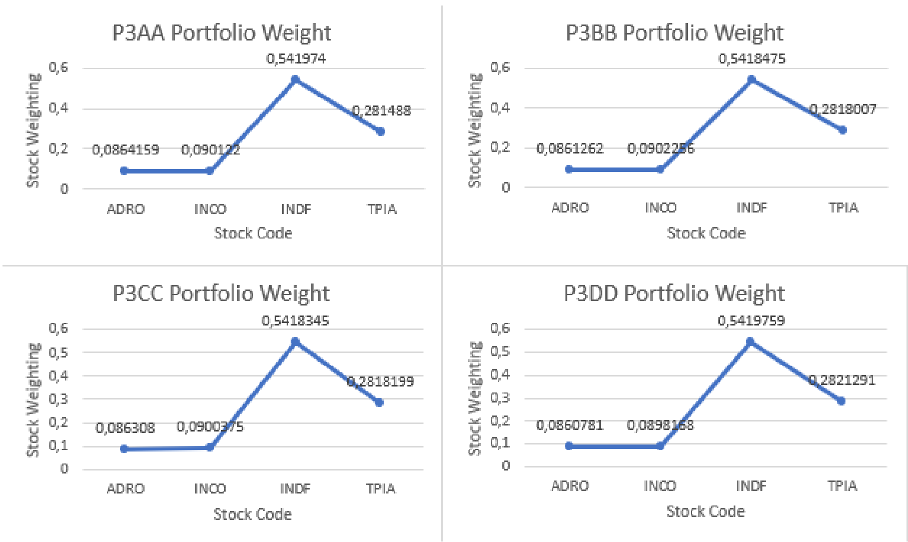

Figure 3. Portfolio III (P3) genetic algorithm with P2MV as initial weighting

Next, Portfolio III was formed using P2MV as the initial weight. Still using the same genetic algorithm procedure as before, the share weights that make up Portfolio III using a genetic algorithm with transaction costs are presented in Figure 3. Based on the share weights presented in Figure 3, a greater proportion of share weights are placed on shares with the smallest portfolio risk as shown in Table 8. INDF and TPIA shares have a smaller risk compared to ADRO and INCO shares so that the allocation proportion funds to INDF and TPIA shares are greater than the proportion of funds allocated to ADRO and INCO shares. Next, evaluate the results and performance of the portfolio formed. The portfolio that has been formed needs to be calculated in total and average return to find out how much return will be obtained by investors if they apply the portfolio. Standard deviation is calculated to determine the risk. Performance measurement of each portfolio is carried out using the Sharpe Ratio measure. The portfolio formed was tested for performance using daily return data on ADRO, INCO, INDF, and TPIA stocks three months later, namely September 2022-December 2022. The total return, average return, standard deviation, and sharpe ratio values are shown in Table 8.

Table 8. Total return, average return, standard deviation, and sharpe ratio of the portfolio

Portfolio name	Total return	Average return	Standard deviation	Sharpe Ratio
P1 MV	0.08425981	0.00096850	0.008381722	0.1155
P2 MV	0.08492809	0.000976185	0.008237673	0.1185
P3 MV	0.08498367	0.000976823	0.008088699	0.1208
P2A	0.08427029	0.00096862	0.008380969	0.1156
P2B	0.08425398	0.00096843	0.00838214	0.1155
P2C	0.08419394	0.00096774	0.008383303	0.1154
P2D	0.08424766	0.00096836	0.008381938	0.1155
P3A	0.08425306	0.00096842	0.008381958	0.1155
P3B	0.08422700	0.00096812	0.008383543	0.1155
P3C	0.08426784	0.00096859	0.008381337	0.1156
P3D	0.08434394	0.00096947	0.008374348	0.1158
P3AA	0.0849218	0.000976112	0.008235846	0.1185
P3BB	0.08493498	0.000976264	0.008237242	0.1185
P3CC	0.08491776	0.000976066	0.008237674	0.1185
P3DD	0.08491106	0.000975989	0.008239403	0.1185

Based on Table 9, reviewed from the sharpe ratio value, the minimum variance portfolio has superior performance compared to the genetic algorithm portfolio. The highest sharpe ratio for portfolio minimum variance is 0.1208 while the highest sharpe ratio for portfolio genetic algorithms is 0.1185. The highest average return of the genetic algorithm portfolio is 0.000976264 while the highest average return of the minimum variance portfolio is 0.000976823. The average return doesn't look much different, but genetic algorithm portfolios have a higher standard deviation (risk) than minimum variance portfolios. This causes the minimum variance portfolio to be superior compared to the genetic algorithm portfolio.

Based on the results above, the performance of the minimum variance portfolio is superior to the performance of the genetic algorithm portfolio, so the total transaction costs for each portfolio formed will be calculated to see which side of the portfolio costs is more profitable for investors. The aim is to provide insight to investors when they want to compile a portfolio with small transaction costs, which portfolio they should choose. In this case study, to make calculations easier, let's say an investor will invest IDR 100,000,000. Referring to Table 8 and Equation 3, the total return and total transaction costs for each portfolio are shown in Table 9.

Table 9. The total transaction cost in each portfolio when invested is IDR 100,000,000

Portfolio	Total Return (IDR)	Transaction Costs (IDR)
P1MV-P2MV	8,425,981	2,114,998
P1MV-P3MV	8,492,809	3,826,653
P2MV-P3MV	8,498,367	2,303,920
P1MV-P2A	8,427,029	10,219
P1MV-P2B	8,425,398	16,806
P1MV-P2C	8,419,394	51,775
P1MV-P2D	8,424,766	14,562
P1MV-P3A	8,425,306	11,683
P1MV-P3B	8,422,700	33,553
P1MV-P3C	8,426,784	6,986
P1MV-P3D	8,434,394	85,969
P2MV-P3AA	8,492,180	26,012
P2MV-P3BB	8,493,498	8,198
P2MV-P3CC	8,491,776	12,825
P2MV-P3DD	8,491,106	23,781

Based on Table 9, genetic algorithm portfolios have a fairly high total return and smaller total transaction costs than minimum portfolio variance. The minimum variance portfolio has a total return that is not much different from the genetic algorithm portfolio but has more expensive transaction costs than the genetic algorithm portfolio. So, in terms of transaction costs and total return, the genetic algorithm portfolio is superior to the minimum variance portfolio. In the genetic algorithm portfolio, the weight of the adjusted results shows results that are not much different from the initial weight, so several shares traded are also not much. This condition causes the costs that investors must incur for buying and selling transactions to be minimal. Genetic algorithm portfolios emphasize minimizing transaction costs rather than minimizing variance (risk), making them more suitable for investors who want a portfolio with low transaction costs. In contrast, the minimum variance portfolio emphasizes minimizing variance (risk) so that transaction costs increase. This portfolio is more suitable for investors who want a portfolio with a small level of risk.

The data analysis results show that the genetic algorithm portfolio with transaction costs performs no less well than the usual minimum variance portfolio. Even this portfolio can generate high returns and small transaction costs. This result aligns with the research results by Sofariah et al. (2016). Some papers focus more on improving portfolio efficiency; Yang (2006) presents a decision-making process that combines a genetic algorithm with a state-dependent dynamic portfolio optimization system. Yang (2006) said that a genetic algorithm can improve the accuracy of the expected return estimation and improve the overall efficiency of the portfolio compared to the classic mean-variance method. However, this paper focuses on developing a minimum variance portfolio model with transaction costs and then optimizing it using a genetic algorithm. In previous research, the percentage of transaction costs for buying and selling shares on the stock exchange was considered the same; in reality, the transaction costs for buying and selling shares on the stock exchange were not the same. Therefore, this research uses the percentage of share buying and selling transaction costs adjusted to the fees imposed on the Indonesian Stock Exchange.

D. CONCLUSION AND SUGGESTIONS

The minimum variance portfolio exhibit higher Sharpe Ratio compared to the portfolio obtained by genetic algorithm. The highest Sharpe ratio value for the minimum variance portfolio is 0.1208, while the highest Sharpe ratio for the genetic algorithm portfolio is 0.1185. On the other hand, when viewed in terms of transaction costs, the genetic algorithm portfolio is superior to the minimum variance portfolio in minimizing transaction costs. Therefore, the genetic algorithm portfolio is more suitable for investors who want a portfolio with low transaction costs. In further research, other obstacles can be added, such as the provision of lots or the minimum number of transactions in determining the optimal portfolio so that the results obtained can be more optimal.

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REFERENCES

Arnott, R. D., & Wagner, W. H. (1990). The measurement and control of trading costs. *Financial Analysts Journal*, *46*(6), 73–80. https://doi.org/10.2469/faj.v46.n6.73

Azim, M. F., Azizah, & Anggraeni, D. (2021). Optimasi portofolio saham dengan pembobot menggunakan algoritma genetika. *Jurnal Sains Matematika Dan Statistika*, *7*(1), 58. https://doi.org/10.24014/jsms.v7i1.12190

Baixauli-Soler, J. S., Alfaro-Cid, E., & Fernandez-Blanco, M. O. (2012). A naïve approach to speed up portfolio optimization problem using a multiobjective genetic algorithm. *Investigaciones Europeas de Dirección y Economía de La Empresa*, *18*, 126–131. https://doi.org/10.1016/S1135-2523(12)70002-3

Chang, T.-J., Yang, S.-C., & Chang, K.-J. (2009). Portfolio optimization problems in different risk measures using genetic algorithm. *Expert Systems with Applications*, *36*(7), 10529–10537. https://doi.org/10.1016/j.eswa.2009.02.062

Cheong, D., Kim, Y. M., Byun, H. W., Oh, K. J., & Kim, T. Y. (2017). Using genetic algorithm to support clustering-based portfolio optimization by investor information. *Applied Soft Computing*, *61*, 593–602. https://doi.org/10.1016/j.asoc.2017.08.042

Darmadji, T., & Fakhruddin, H. M. (2012). *Pasar modal di Indonesia: Pendekatan tanya jawab* (3rd ed.). Salemba Empat. https://digilib.ukwk.ac.id/index.php?p=show_detail&id=5086

DeMiguel, V., Mei, X., & Nogales, F. J. (2016). Multiperiod portfolio optimization with multiple risky assets and general transaction costs. *Journal of Banking & Finance*. https://doi.org/10.1016/j.jbankfin.2016.04.002

Fahria, I., & Kustiawan, E. (2020). Algoritma genetika dalam pembentukan portofolio optimum perusahaan emiten. *Jurnal Matematika Dan Statistika Serta Aplikasinya*, *8*(2), 70. https://doi.org/10.24252/msa.v8i2.16030

Fang, Y., Lai, K. K., & Wang, S. Y. (2005). Portfolio rebalancing model with transaction costs based on fuzzy decision theory. *European Journal of Operational Research*, *175*(2), 879–893. https://doi.org/10.1016/j.ejor. 2005.05.020

Financial Services Authority. (2015). *Buku saku Otoritas Jasa Keuangan* (2nd ed.). Otoritas Jasa Keuangan. www.ojk.go.id

Grover, J., & Lavin, A. M. (2007). Modern portfolio optimization: A practical approach using an excel solver single-index model. *The Journal of Wealth Management*, *10*(1), 60–72. www.iijournals.com

Liagkouras, K., & Metaxiotis, K. (2018). Multi-period mean–variance fuzzy portfolio optimization model with transaction costs. *Engineering Applications of Artificial Intelligence*, *67*, 260–269. https://doi.org/10.1016/j.engappai.2017.10.010

Lin, C.-C., & Liu, Y.-T. (2008). Genetic algorithms for portfolio selection problems with minimum transaction lots. *European Journal of Operational Research 185 (1)*, 393–404. https://doi.org/10.1016/j.ejor.2006.12.024

Mahayani, N. P. M., & Suarjaya, A. A. G. (2019). Penentuan portofolio optimal berdasarkan model markowitz pada perusahaan infrastruktur di Bursa Efek Indonesia. *E-Jurnal Manajemen Universitas Udayana*, *8*(5), 3057. https://doi.org/10.24843/ejmunud.2019.v08.i05.p17

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1). https://doi.org/10.1111/j.1540-6261.1952.tb01525

Parker, F. J. (2016). Goal-based portfolio optimization. *The Journal of Wealth Management*, *19*(3), 22–30. https://doi.org/10.3905/jwm.2016.19.3.022

Peterson, B. G., & Carl, P. (2020). *PerformanceAnalytics: Econometric Tools for Performance and Risk Analysis* (R package version 2.0.4). https://doi.org/10.1016/j.heliyon.2022.e092921

Peterson, S. (2012). *Investment theory and risk management*. John Wiley & Sons. https://books.google.co.id/books?hl=id&lr=&id=yrA9Wj3A8d4C&oi=fnd&pg=PP15&dq=Peterson,+S.+(2012).+Investment+theory+and+risk+management.+John+Wiley+%26+Sons.&ots=1kjEtMK_Og&sig=5SExUxyeOJYELb0dVUB35LuCXas&redir_esc=y#v=onepage&q=Peterson%2C%20S.%20(2012).%20Investment%20theory%20and%20risk%20management.%20John%20Wiley%20%26%20Sons.&f=false

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://cir.nii.ac.jp/crid/1370294721063650048

Rudiawarni, F. A., Sulistiawan, D., & Sergi, B. S. (2022). Is conservatism good news? The case of stocks of Jakarta Islamic index. *Heliyon*, *8*(4). https://www.cell.com/heliyon/pdf/S2405-8440(22)00580-1.pdf

Ruiz-Torrubiano, R., & Su´arez, A. (2015). A memetic algorithm for cardinality-constrained portfolio optimization with transaction costs. *Applied Soft Computing*, *36*, 125–142. https://doi.org/10.1016/j.asoc.2015.06.053

Scrucca, L. (2017). On some extensions to GA package: hybrid optimisation, parallelisation and islands evolution. *The R Journal*, *9*(1), 187–206. https://doi.org/10.32614/RJ-2017-008

Setiawan, E. P., & Rosadi, D. (2019). Model pengoptimuman portofolio mean-variance dan perkembangan praktisnya. *Jurnal Optimasi Sistem Industri*, *18*(1), 25–36. https://doi.org/10.25077/josi.v18.n1.p25-36.2019

Sofariah, A., Saepudin, D., & Umbara, R. F. (2016). *Optimasi portofolio saham dengan memperhitungkan biaya transaksi menggunakan algoritma genetika multi-objective*.

https://openlibrarypublications.telkomuniversity.ac.id/index.php/engineering/article/view/3730

Suksonghong, K., Boonlong, K., & Goh, K.-L. (2014). Multi-objective genetic algorithms for solving portfolio optimization problems in the electricity market. *Electrical Power and Energy Systems*, *58*, 150–159. https://doi.org/10.1016/j.ijepes.2014.01.014

Vazhayil, J. P., & Balasubramanian, R. (2014). Optimization of India's electricity generation portfolio using intelligent Pareto-search genetic algorithm. *Electrical Power and Energy Systems*, *55*, 13–20. https://doi.org/10.1016/j.ijepes.2013.08.024

Wang, Z., Zhang, X., Zhang, Z., & Sheng, D. (2022). Credit portfolio optimization: A multi-objective genetic algorithm approach. *Borsa Istanbul Review*, *22*(1), 69–76. https://doi.org/10.1016/j.bir.2021.01.004

Woodside-Oriakhi, M. (2011). *Portfolio optimisation with transaction cost*. School of Information Systems, Computing and Mathematics, Brunel University. http://bura.brunel.ac.uk/handle/2438/5839

Yahoo Finance. (2022). *Yahoo Finance*. Https://Finance.Yahoo.Com/Quote/ADRO.JK/History?Ltr=1&guccounter=1.

Yang, X. (2006). Improving portfolio efficiency: A genetic algorithm approach. *Computational Economics*, *28*(1), 1–14. https://doi.org/10.1007/s10614-006-9021-y

Yoshimoto, A. (1996). The mean-variance approach to portfolio optimization subject to transaction costs. *Journal of the Operations Research Society of Japan*, *39*(1), 99-117. https://doi.org/10.15807/jorsj.39.99