

Genetic Algorithm Approach in Forming the Optimal Portfolio of Issuer Companies with Dividend Distribution Criteria

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ABSTRACT

Investing in the capital market for some investors is a challenge in itself. Investors are required to be able to determine the right combination and proportion of shares when they want to place a number of funds in each share that make up the optimal portfolio. The solution to the optimal portfolio formation problem can be done (Place holder) by using a genetic algorithm method approach. The purpose of applying genetic algorithms is to form an optimal portfolio with a proportion of stocks that can generate optimal profits with a justifiable loss rate. A case study was conducted on the companies compiling the LQ-45 index with dividend distribution criteria as many as 35 shares traded on the Indonesia Stock Exchange. The results showed that by using the genetic algorithm method, an effective problem solving was obtained in the formation of an optimal portfolio in issuers with dividend distribution.

Keywords: *Optimal portfolio, Indeks Sharpe, Genetic algorithm, Dividend distribution.*

1. INTRODUCTION

The main objective of investing in the capital market is to make a profit. However, one thing that cannot be avoided when investing is investment risk if the price of the assets owned decreases. One of the ways that can reduce or control investment risk is by diversifying or diversifying assets. So that if the shares of a company suffer a loss, the effect can be neutralized by the profits from the shares of other companies [1].

The challenge when diversifying assets or diversifying in the formation of an optimal portfolio is determining candidate stocks and the proportion of the amount of funds placed in each stock that makes up the portfolio. The optimal portfolio is determined from an efficient portfolio which is a portfolio that provides the highest expected return with a certain risk or provides the smallest risk with a certain expected return [2]. There are several measures to assess portfolio performance based on the rate of return (return) and investment risk, one of which is the Sharpe index. The Sharpe index is a model that considers that the portfolio with the best performance is the one that has the highest rewards to variability ratio

(comparison between portfolio returns and portfolio risk).

Based on [3] and [4], it is known that the optimal portfolio problem solving by the genetic algorithm method is superior to other heuristic solving methods. In this study, the formation of an optimal portfolio of listed companies with the criteria for dividend distribution will be resolved using a genetic algorithm approach. The genetic algorithm approach is carried out to obtain the best chromosome that interprets the weight or proportion of each stock with the aim of obtaining a portfolio composition with an optimal rate of return / profit but with an accountable loss rate.

2. GENETIC ALGORITHM

Genetic algorithm is a heuristic method developed based on the principles of genetics and the scientific selection process of Darwin's theory of evolution [6]. Introduced by John Holland in 1960 and popularized by David Goldberg in 1980 [7]. Portfolio optimization using genetic algorithms gives better or superior results compared to other heuristic methods based on [8].

Following a natural process, a genetic algorithm begins by forming a population which is a number of individuals called chromosomes with the unique characteristics of an individual. So that in genetic algorithms, the chromosomes represent the optimized variable values. Each chromosome consists of a number of genes, the number of variables is involved in the optimization process. The genes in a chromosome can be of the type binary number (any number of 0 or 1) and real numbers (decimal numbers).

Furthermore, the fitness function is formed which is used to assess the quality of chromosomes in the population based on the objective function or optimization objective function. In general, the greater the value of the fitness function, the more likely it is to be retained into the next population. The fitness function can contain a penalty which is a constraint on optimization. Furthermore, based on Darwin's theory of evolution, the population in genetic algorithms undergoes an evolutionary process, including mutations (changes in genes in chromosomes), selection (selection of individuals with the highest fitness value), which is then cross-over which is the process of forming new individuals from results of parent crosses). The evolution process will form new individuals who represent the optimum solution candidates. Because the selection is done randomly, there is a possibility that the highest fitness value will not always be selected. Even if selected, it could be that the individual with the highest fitness value will be damaged (fitness value decreases) due to the crossing process (cross over). Thus, so that the individual with the highest fitness value is not lost during evolution, it is necessary to make one or more copies known as the elitism procedure. Furthermore, in [9] the evolution process can be stopped if it has met a certain number of generations or if there is no change in the highest fitness value after several generations.

3. Experimental Procedures

3.1. Materials

LQ-45 index is a reference index consisting of 45 of the most liquid stocks traded on the Indonesia Stock Exchange. Shares listed in the LQ-45 index for the period August 2020 to January 2021 will be formed by using dividend distribution criteria of companies. There are 35 companies compiling the LQ-45 Index that have criteria with the distribution of stock dividends.

3.2. Methods

3.2.1. Sharpe Index Model

In this study, the optimal portfolio calculation will be done first using Sharpe Index. The Sharpe index model, one of the most widely used models for portfolio

optimization, was introduced by William Sharpe in 1963 and it's a simplification of the Markowitz mean variance calculation. First, the stock return will be calculated;

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (1)$$

Expected return of a portfolio which is the weighted average of the rates of return of each share in the portfolio, i.e

$$P_r = \sum_{i=1}^N w_i r_t \quad (2)$$

The weights of each asset that make up a portfolio of M assets must have this form:

$$\sum_{i=1}^M w_i = 1, w_i \geq 1, 2, 3, \dots, M \quad (3)$$

Variance of return of portfolio stated the risk of a portfolio which can be expressed as;

$$\sigma_p = \sum_{i=1}^N \sum_{j=1}^M w_i w_j \sigma_{ij} \quad (4)$$

with σ_{ij} covariance of the i -th asset with the j -th asset.

Sharpe index model assumes that the portfolio that has the best performance is the one that has the highest rewards to variability ratio (comparison between portfolio returns and portfolio risk). Sharpe index can be calculated using the formula:

$$Sharpe = \frac{P_r}{\sigma_p} \quad (5)$$

3.2.2. Genetic Algorithm Method

The steps in selecting the optimal portfolio compiler stocks using the genetic algorithm approach are as follows: 1) Performing the initial initiation by forming a population consisting of a number of chromosomes, where each chromosome consists of stocks which are candidates for the optimum portfolio compiler. The chromosome length tells you the number of stocks that make up the portfolio. Each of these genes contains the weight / proportion of each share. The initialization process is carried out randomly. 2) Establish a fitness function to obtain a portfolio with the least risk. First, by calculating the Sharpe index value in equation (5).

$fitness = -Sharpe$

$$+ 100 \left[\left(\sum_{i=1}^N w_i - 1 \right)^2 + \sum_{i=1}^N (\max(0, w_i - 1))^2 + \sum_{i=1}^N (\max(0, -w_i))^2 \right]$$

Penalty function is

$$\left[\left(\sum_{i=1}^N w_i - 1 \right)^2 + \sum_{i=1}^N (\max(0, w_i - 1))^2 + \sum_{i=1}^N (\max(0, -w_i))^2 \right]$$

Penalty function added in order to ensure that the constraints in equation (3) are met. The constraint in equation (3) states that the share weight must be positive and short selling is not allowed. As a result, a portfolio with a global minimum variance (global minimum variance portfolio) will be obtained, that is, the portfolio with the smallest risk. The higher the value of the penalty function, the higher the global minimum variance portfolio. In order to achieve the global minimum, the penalty function is multiplied by 100 to increase the optimization process. Since the goal of the optimization is to maximize the Sharpe index value, but the penalty function works only for minimizing functions, the Sharpe index is multiplied by -1. 3) Evaluate the fitness value of each chromosomes. The chromosome with the highest fitness value illustrates that the stocks making up the portfolio have met all constraints with less risk. 4) Changing chromosomes with mutation and cross over operators. Chromosome crossing operators are carried out using the roulette wheel method, which is by providing a greater chance of selecting the chromosomes that have a higher fitness value. 5) Perform elitism to keep individuals with the highest fitness value maintained or not lost during the evolutionary process. 6) Carry out steps 4 and 5 continuously until a stable solution is obtained, where the fitness value has not changed over several generations. The best portfolio is expressed by the portfolio with the highest fitness value.

4. RESULTS AND DISCUSSION

Below is a list of shares of listed companies with dividend distribution criteria that compile the LQ-45 index list. Among 35 stocks with dividend distribution

criteria, 21 stocks have a positive mean return value and are included as candidates for the optimal portfolio composing assets.

Table 1. List of index LQ-45 stocks on August 2020 – January 2021

Stock Code	Mean Return	Standard Deviation
ADRO	0.10%	2.72%
ANTM	0.73%	4.39%
ASII	0.18%	2.33%
BBNI	0.15%	2.49%
BBRI	0.19%	2.45%
BBTN	0.24%	3.27%
BMRI	0.09%	2.50%
BTPS	0.20%	2.82%
CTRA	0.52%	2.87%
ICBP	0.09%	1.64%
INDF	0.16%	2.07%
INKP	0.34%	3.65%
INTP	0.06%	2.58%
ITMG	0.11%	2.22%
MIKA	0.20%	1.81%
PTPP	0.04%	2.40%
SMGR	0.09%	2.28%
SRIL	0.16%	2.67%
TBIG	0.33%	2.11%
UNTR	0.11%	2.49%
WIKA	0.16%	2.93%

4.1. Portfolio Optimization

Each optimal portfolio building / compiler asset using the Sharpe Index method will be obtained using the Portfolio analytics Package found in the R Studio software. Meanwhile, the genetic algorithm method was carried out with the help of Pustaka GA version 3.6.1 in R Studio statistical software which was done using macOS Mojave Version 10.14.3 with a 1.6 GHz Intel Core i5 processor. The results of portfolio optimization with the genetic algorithm method produce the highest fitness value -3.532575 with the number of generations 702, population size 50, crossover probability 0.8, mutation probability 0.1 and elitism 2.

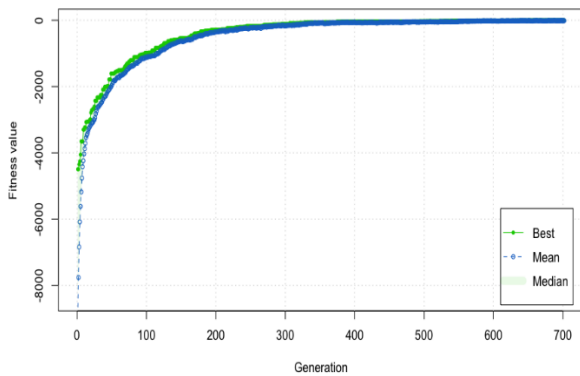


Figure 1. Optimal portfolio with the genetic algorithm approach

Figure 1 shows the population formed by a genetic algorithm with the average value and the highest fitness value from the initial (1st) generation to the 700th generation. It is clear that around the 200th generation, solutions have been found that tend to be stable, where the fitness value does not change in the next generation.

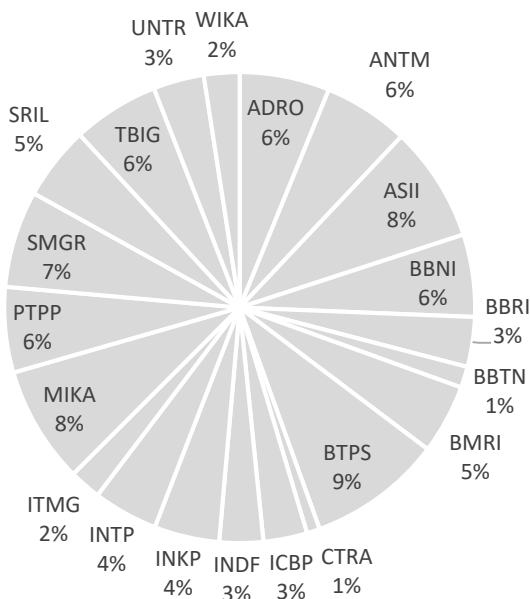


Figure 2. Optimal portfolio weight using genetic algorithm approach.

Figure 2 shows the composition of the optimal portfolio of genetic algorithms with the biggest weights, namely BTPS 9% and the smallest BBTN and CTRA each by 1%.

Table 2. Optimal portfolio weight composition

Stock Code	Optimal portfolio weight	
	Genetic Algorithms	Sharpe Index
ADRO	7.37%	9.05%

ANTM	6.99%	8.45%
ASII	9.45%	3.05%
BBNI	6.74%	9.27%
BBRI	4.08%	4.96%
BBTN	1.73%	6.20%
BMRI	5.68%	1.04%
BTPS	10.97%	2.66%
CTRA	1.07%	6.09%
ICBP	3.58%	2.47%
INDF	3.58%	3.13%
INKP	5.34%	0.05%
INTP	5.30%	8.03%
ITMG	2.60%	3.42%
MIKA	9.59%	3.38%
PTPP	6.99%	6.21%
SMGR	7.92%	0.50%
SRIL	6.02%	6.12%
TBIG	7.09%	2.85%
UNTR	4.16%	6.90%
WIKA	2.92%	6.18%

Table 2 shows the weight of shares in the formation of optimal portfolios with the genetic algorithm approach and the Sharpe index based on stocks listed on the LQ-45 index in table 1. From table 2 it can be seen that the portfolio formed using the genetic algorithm has met the constraints required in Table 2. equation (3) which results in the sum of all portfolio stock weights equal to 1. Based on the stock weights generated from the genetic algorithm method, that the largest proportion of the allocation of funds is consecutively placed on BTPS shares 10.97%, MIKA 9.59 % and ASII 9.45%. The smallest share weight was placed in CTRA shares, namely 1.07% and BBTN 1.73%. Sharpe index respectively allocates the largest share weight of 9.27% and 9.05%, respectively for BBNI and ADRO stocks and the smallest on INKP stocks 0.05% and SMGR 0.50%. It can be seen that using the genetic algorithm approach when Compared with the Sharpe index, the proportions or stock weights that make up the optimal portfolio are adjusted to the amount of return (mean return) of shares with the amount of stock risk (standard deviation) found in table 1. In addition, the proportions or weights of the assets that make up the optimal portfolio with the genetic algorithm approach, it can be said to be more stable because it is at the lowest weight interval of 1% to the highest of 10.97%. This means that when an optimal portfolio is formed by allocating funds based on the weights obtained using a genetic algorithm model, the

expected rate of return and the risk accounted for is in a stable condition. Sharpe index is at the lowest interval 0.05% to the highest 9.27%. Thus, this shows that the genetic algorithm method works effectively in solving the problem of optimal portfolio formation with the criteria of issuers with dividend distribution.

5. CONCLUSION

The problem solving the optimal portfolio formation of listed companies with the criteria for dividend distribution can be solved using the genetic algorithm method. The case study results show that the algorithm method works more effectively than the Sharpe index model. Further research is needed to compare the performance of the genetic algorithm with other portfolio optimization models in order to improve the performance of the portfolios formed.

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