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The Formation of Optimal Portfolio of Mutual Shares Funds using Multi-Objective Genetic Algorithm

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Abstrak

Investasi pada asset keuangan telah menjadi tren di era globalisasi, terutama investasi di reksadana saham. Investor yang ingin berinvestasi di reksadana saham dapat mengatur portofolio investasi untuk menghasilkan risiko minimal dan keuntungan yang maksimal. Dalam penelitian ini penulis menggunakan teknik Multi-Objective Genetic Algorithm Non-Dominated Sorting II (MOGA NSGA-II) dengan prinsip portofolio Markowitz untuk menentukan portofolio yang terbaik dari beberapa reksadana. Data yang digunakan adalah 10 perusahaan reksadana saham dengan periode waktu 12 bulan, 24 bulan dan 36 bulan. Parameter algoritma genetika yang digunakan adalah probabilitas crossover 0.65, probabilitas mutasi 0,05, Generasi 400 dan populasi yang berjumlah 20. Penelitian ini menghasilkan kombinasi portofolio terbaik untuk periode 24 bulan dengan waktu komputasi dari 63.289 detik.

Kata kunci: *Investasi, Reksa Dana Saham, AlgoritmaGenetika, Portofolio*

Abstract

Investments in financial assets have become a trend in the globalization era, especially the investment in mutual fund shares. Investors who want to invest in stock mutual funds can set up an investment portfolio in order to generate a minimal risk and maximum return. In this study the authors used the Multi-Objective Genetic Algorithm Non-dominated Sorting II (MOGA NSGA-II) technique with the Markowitz portfolio principle to find the best portfolio from several mutual funds. The data used are 10 company stock mutual funds with a period of 12 months, 24 months and 36 months. The genetic algorithm parameters used are crossover probability of 0.65, mutation probability of 0.05, Generation 400 and a population numbering 20 individuals. The study produced a combination of the best portfolios for the period of 24 months with a computing time of 63,289 seconds.

Keywords: *Investing, Mutual Fund Shares, Genetic Algorithms, Portfolio*

1. Introduction

Countries economic development in the era of globalization is affected by the components in the economic structure of the countries itself. One of them is the stock market. The stock market functions to bridge the funding from surplus units to the deficit units of funds. In developed countries like Japan, U.S. and UK, stock market is used as a measure to view the economic development of the country every year. The more developed a country's capital market is, the better the country's economy will be.

The development of the Indonesian stock market is still dominated by large investors and businesses. One of them is mutual funds. They grow very fast in Indonesia, and of course it certainly does have a positive influence on capital markets in Indonesia [1]

Mutual fund is an investment medium which main purpose is to assist and mobilize small and individual investors to invest in the stock market. Mutual funds give small investors the possibility to have a portion of the securities that may not be owned by the instruments of direct investment in marketable securities. Through mutual funds, investors are assisted by a management team or a representative of an investment manager to manage the investment. The investment manager's task is to analyze securities in the money market and the stock market as well as select the securities in accordance with the objectives to be achieved by the investor [2].

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In managing the investment, an investor should always do an analysis and form mutual funds of shares portfolio to get maximum returns with minimal risk. An efficient portfolio is defined as the portfolio that provides the greatest expected return under a certain risk or provides the smallest risk with a certain expected return. To determine the optimal portfolio, first we have to determine an efficient portfolio. An efficient portfolio is an optimal portfolio [3].

Over the past decade, a number of multi-objective evolutionary algorithms (MOEAs) have been suggested. The primasy reason for this is their ability to find multiple Pareto-optimal solutions in one single run. Since the principal reason why a problem has a multi –objective formulation is because it is not possible to have a single solution which simultaneously optimizes all objectives, an algorithm that gives a large number of alternative solutions lying on or near the Pareto-optimal front is of great practical value [4].

The problems that have several criteria or goals will become complex ones if must be fulfilled simultaneously. This will cause the objectives conflict with each other. That is why we need a way to overcome this problem by using a search solution that will best meet the goal of competing scenarios under different trade-offs. By considering a dual purpose (multi-objective) and the constraints that limit them, the optimization formulation can be determined, it is known as Multi-objective Optimization Problems (MOP). MOP is not possible to have one best solution (global minimum or maximum) for all objectives, but the solution is in the form of a set of superior solutions when the whole objectives are considered, but inferior to some other solutions in the search space on one or more objectives. These solutions are known as Pareto-optimal solutions or non-dominated solutions.

The objective of this research is to examine the optimal portfolio formatting multi-objective genetic algorithm using non-dominated sorting based on the calculation method of Markowitz portfolio on mutual funds of shares.

2. Research Method

2.1. Data Collection

In this study, the data used are data from the net asset value (NAV) of the mutual shares funds derived from Pusdok Business Magazine Indonesia (PMBI) which are secondary data. The shares mutual funds that will be the object of this research can be seen in Table 1.

Table 1. The List of Mutual Shares Fund

Code	Mutual Shares Funds
RDS01	GMT Equity Fund
RDS02	Makinta Growth Fund
RDS03	LautandhanaProgressive Equity
RDS04	MakintaMantap
RDS05	MNC Equity Funds
RDS06	BNI Developing Funds
RDS07	Panin Dana Maksima
RDS08	DanareksaMawar
RDS09	RencanaCerdas (Smart Plan)
RDS10	Trim Capital Plus

The data were taken based on the same monthly period, i.e January 2007 to December 2010.

2.1. Data Processing

The phase undertaken to determine the optimal portfolio in equity funds begins by calculating the expected NAV, return, and shares mutual funds risk, expected return and risk, calculating weights (allocations) of each mutual fund of shares, and calculating the return of expectations and risk of the portfolio formed using funds company as in Table 1.

2.1.1. Determining expected NAV per Unit

To calculate the expected NAV the researchers used exponential moving average (EMA) as in equation 1[5].

$$E(NAB) = \left[\frac{2}{N+1} x(NABCurrent - EMA(Prev))\right] + EMA(prev) \quad (1)$$

Whereas :
$E(NAB)$: Expected NAB
$PriceCurrent$: The value of the current NAB
$EMA(Prev)$:The value of the current NAB

2.1.2. Determining the expected return

To calculate the expected return of shares mutual funds the researchers subtracted the expected NAV of the relevant month (NABperunit$_n$) with the expected NAV of the previous month (NABperunit$_{n-1}$) and then divided by the expected NAV of the previous month (*NABperunit$_{n-1}$*).

$$E(R_n) = \frac{E(NABperunit_n) - E(NABperunit_{n-1})}{E(NABperunit_{n-1})} \quad (2)$$

Where:
E (Rn) = Return the month
NABperunit$_n$ = NAB perunitof the current month
NABperunit$_{n-1}$ = NAB per unit of the previous month[6].

And to calculate the risk, in this case the standard of deviation the researchers used equation 3.

$$\sigma_j = \frac{\sqrt{\sum_{t=1}^{n}\left(R_{jt} - E(R_j)\right)^2}}{(n-1)} \quad (3)$$

In which:
σ^2 = Variant of mutual shares funds
R_{jt} = Return of mutual sharesfund *j* in period *t*
$E(R_j)$ = Expected returnof the mutual sharesfunds *j*
n = Number of periods [7].

2.1.3. Determining the expected return and risk of the portfolio

The expected return portfoliocan be calculated by adding the expected return of each shares mutual fund that composes the portfolio based on their respective weights as in equation 4.

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) \quad (4)$$

In which:
$E(R_p)$= Expected returnof the portfolio
$E(R_i)$ = Return of the i-thmutual sharesfunds
w_i= Proportion of funds invested in the *i*mutual sharesfunds

$$\sum_{i=1}^{n} w_i = 1 \quad (5)$$

and a variety of portfolios that reflect the risk of a portfolio can be seen in equation (6).

$$\sigma^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} 2 w_i w_j \sigma_{ij} \quad (6)$$

In which:
σ^2 = Variant of the portfolio

σ_{ij}= Covariant of mutual sharesfunds*i* and *j*
w_i = Proportion of funds invested in mutual sharesfunds-*i*
σ_i^2 = Variant of *i*-th mutual shares funds [6].

2.2. Model Development

This model development uses an approach of multi-objective genetic algorithm, by determining the populationinitialization, the non-dominated sort, crowding distance, selection, crossover, mutation, elitism, and recombination and selection. Figure 1 shows the method employed for the model development.

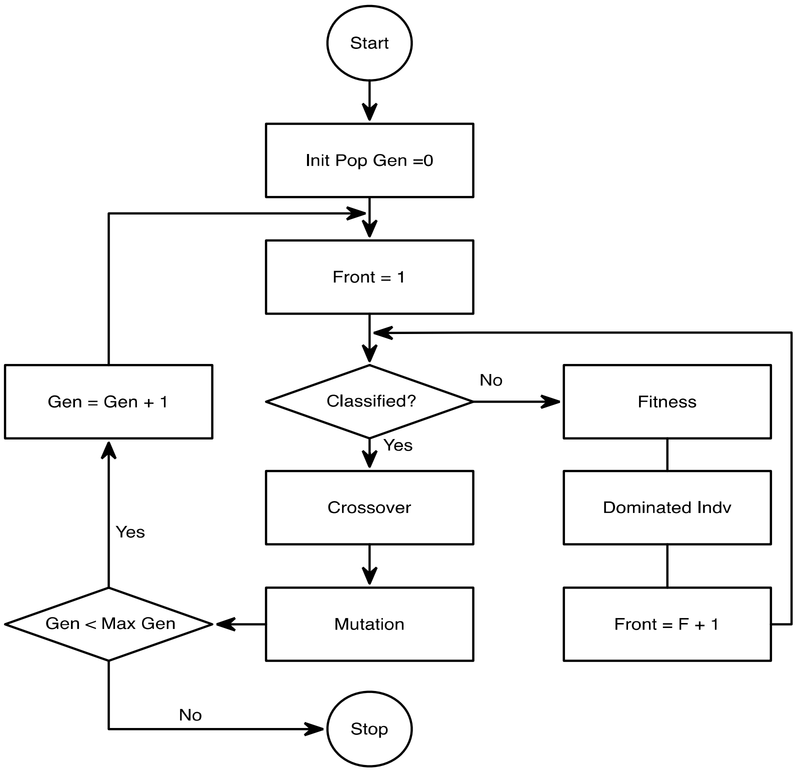


Figure 1.Model development of multi-objective genetic algorithm

2.2.1. Population Initialization

The type encoding scheme that is used to initialize the population is in the form of real number encoding. Each chromosome contains selected shares mutual funds information allocation weights in the shares mutual funds. The form of the chromosome is as follows:

W_1	W_2	W_3	W_4	…	W_i

In which:
w_i= weight (budget allocation)

2.2.2. Non-dominated Sort

After the initialization of the population, then the non-dominated sorting is done to classify the population into different fronts using the concept of dominance with the following algorithm.

```
t = 0;
Initialize (Pt);
```

```
Evaluate (Pt);
Qt =;
While t <T
Rt = PtQt;
F = Non_dominated_sort (Rt)
Pt +1 =, i = 1;
while | Pt +1 | + | Fi |> N
Crowding_distance_assignment (Fi)
Pt +1 = Pt +1 fi; i = i +1;
End while
sort (Fi,);
Pt +1 = Pt +1 Fi [1: (N - | Pt +1 |)];
Make_new_populationQt +1 = (Pt +1); t = t + 1;
End while
```

2.2.3. Crowding Distance

After non-dominated sorting is done, to maintain the population diversity, crowding distance with algorithm is undertaken:

```
Crowding-distance-assignment (L).
l = | L |
for each i L
L [i] distance = 0;
for each objective m
L = sort (L, m);
L [1] distance = L [l] = distance;
fori = 2 to (l-1);
```

2.2.4. Selection

To select new individuals in the population that will be formed, the tournament selection method with crowded-comparison-operator is conducted with the following algorithm:

1. non-domination rank p_{rank}, the individuals in front *Fi* will have a level of $p_{rank} = i$
2. crowding distance f_i (d_j)
   *p q, if
   - P_{rank}<q_{rank}
   - Or if p and q have the same front F_i then F_i (d_p)> F_i (d_q), which is selected from the bigger crowding distance value.

2.2.5. Genetic AlgorithmOperator

In this study, the genetic algorithms operator used is the Simulated Binary Crossover (SBX) using equation 7 and 8 [8].

$$c_{1,k} = 0.5(1 + \beta_k)p_{1,k} + (1 - \beta_k)p_{2,k} \quad (7)$$
$$c_{2,k} = 0.5(1 - \beta_k)p_{1,k} + (1 + \beta_k)p_{2,k} \quad (8)$$

Description:
$p_{1,k}$ = first parent with the element
$p_{2,k}$ = second parent with k element
$c_{1,k}$ = first child as the result of crossover
$c_{2,k}$ = second childas the result of crossover

and mutation uses a polynomial mutation as in equation 9, 10 and 11.

$$\delta_k = (2r_k)^{\frac{1}{mum+1}} - 1, \text{ If } r_k<0.5 \quad (9)$$
$$\delta_k = 1 - [2(1 - r_k)]^{\frac{1}{mum+1}}, \text{ If } r_k \geq 0.5 \quad (10)$$
$$c_k = c_k + \delta_k \quad (11)$$

Description:
r_k= random numbers at interval 0-1
Mum = Distribution of index for mutation

c_k= *k*-th childresulting from mutation

2.2.6. Recombination and selection

After non-dominated sort, crowding distance, selection, and application of genetic algorithm operators are done, recombination and selection are carried out to form new individuals in the next generation population.

3. Results and Analysis

The process of preparation for shares mutual fund portfolio produces a set of portfolios with maximum expected return valueand minimum risk value. The process to obtain the optimum portfolio is performed using Multi-Objective Genetic Algorithm (MOGA) NSGA-II so that the results obtained can be used to help investors to construct an optimal portfolio of shares mutual funds. The model used in the preparation of these mutual shares and fund portfolios is a model developed by Markowitz. This model aims to maximize profit and minimize risk or maximize profits with a certain level of risk, or a certain level of profit with minimum risk.

The data used as input to the model MOGA is the data of net asset value (NAV) per unit for each monthly mutual shares fund (the closing price at the end of each month) that were obtained from Pusdok Business Magazine Indonesia (PMBI) over a period of 4 years (2007-2010) or in 48 months.

3.1. Data Pre-processing

Shares mutual fund data used were obtained from PMBI for the period of January 2007 to December 2010 or 48 data for every mutual fund used. The data used are in the form of NAV data perunit each month with the number of shares mutual funds usedis10 out of the 85 mutual funds in Indonesia. The mutual funds used are as in Table 1.

3.2. Expected Net Asset Value (NAV)

Based on the NAV data obtained from PMBI with 10 shares mutual fund companies in Table 1, the NAV estimation is performed using exponential moving average (EMA) for the period of 12, 24 and 36 months using equation 1.1 to obtain expected NAV needed to perform the preparation of a portfolio.

3.3. EMAParameter

Table 2 is a parameter that is used to perform the expectation of the NAV.

Table 2. Expected Nav Parameter

Parameter	Amount
Mutual funds	10
Period (month)	12, 24 and 36

To make an estimation of NAV the researchers used a number of parameters, i.e 10 shares mutual funds that are used for the preparation of the portfolio and the period is based on Table 2. The result of the calculation using the EMA will provide the value of the estimated NAV using previous month's data. The data generated from the NAV estimation is used to calculate the expected return and risk.

3.4. Expected NAV

The graph below is a chart of the value of the expected NAV resulting from calculations using EMA. Figure 2(a) shows that in the period of 12 months RDS01, RDS03, RDS04, RDS05, RDS07, RDS08 and RDS09 increase, while RDS02 and RDS10 are stable and RDS06 decrease. Figure 2(b) shows that in the period of 24 months RDS01, RDS02, RDS03, RDS04, RDS05, RDS07, RDS08, RDS09 and RDS10 increase, whileRDS06 decreases. Figure 2(c) shows that in the period of 36 months RDS01, RDS04, RDS08 and RDS09 have increased growth, while RDS02 and RDS06 have decreased growth and RDS03, RDS04, RDS05, RDS07 and RDS10 have steady growth.

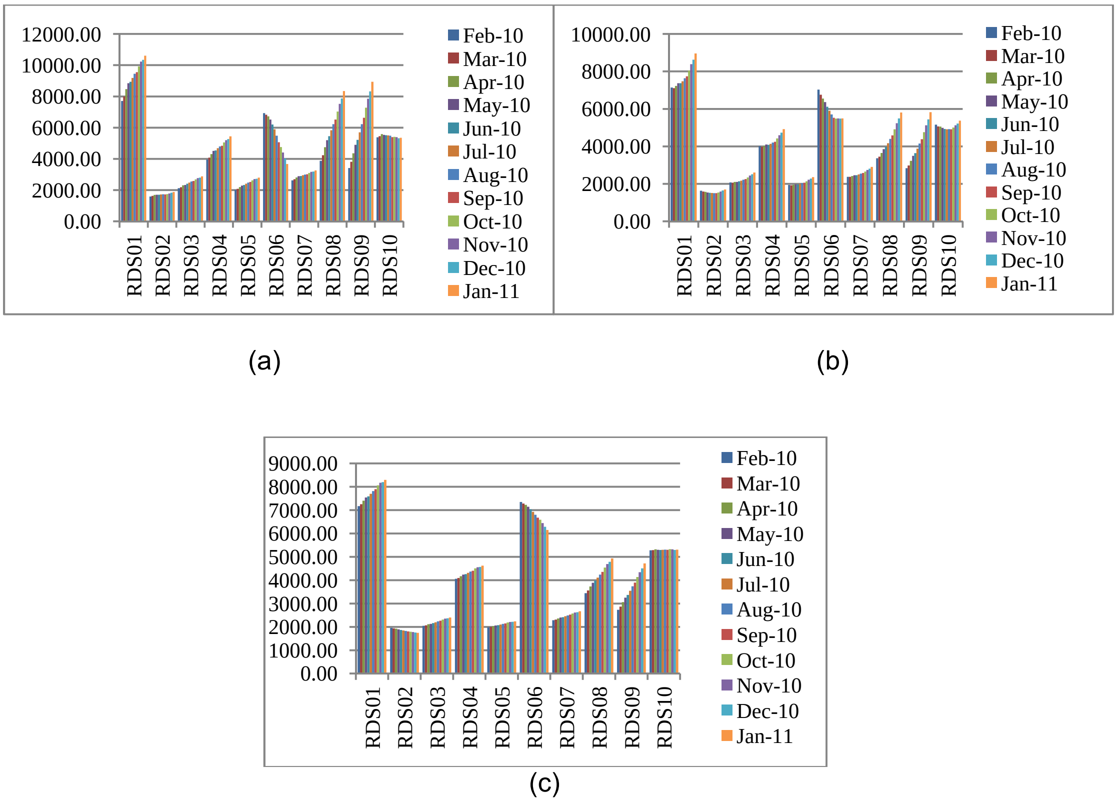


Fig. 2. (a) Expected NAV 12-month period, (b) Expected NAV 24-month period, (c) Expected NAV period of 36 months

3.5. Expected Return and Risk

Based on the expected NAV acquired in the periods of 12, 24 and 36 months, a calculationof expected return and risk is done in order to obtain the value of expected return and risk in Table 3.

Table 3. Expected Return and Risk in the Periods of 12, 24 And 36 Months

Shares Mutual Fund Code	12 Month Period Expected Return (%)	Risk (%)	24 MonthsPeriod Expected Return (%)	Risk (%)	36 Months Period Expected Return (%)	Risk (%)
RDS01	2.66	5.26	3.78	7.39	1.19	10.30
RDS02	2.06	3.85	3.10	10.34	0.00	12.42
RDS03	2.83	5.88	3.83	7.24	1.43	9.82
RDS04	3.18	5.80	3.94	7.21	1.19	9.72
RDS05	2.58	4.80	3.52	6.30	0.93	9.50
RDS06	0.00	19.73	0.16	15.99	0.00	15.25
RDS07	2.40	5.52	3.34	6.90	1.46	7.92
RDS08	5.96	31.92	5.80	24.93	2.95	22.44
RDS09	7.34	47.93	7.06	34.44	4.75	30.11
RDS10	0.70	11.18	2.92	10.07	0.28	10.83

From Table 3 above we can see that shares mutual fund that have the highest expected return for the period of 12 months, 24 months and 36 months in a row is a shares mutual fund at 7.34 % RDS09(12 months), 7.06% (24 months) and 4.75% (36 months), while mutual funds that provide the lowest expected return value in a row is RDS06 Mutual Funds at 0% (12 months), 0.16% (24 months) and 0% (36 months). From the above data it cannot be said that RDS09 shares mutual fund is directly better than other mutual funds because there are other factors that have not been taken into account, the risk factors. Below is the graph of the relationship between expected return and risk in the periods of 12 months, 24 months and a period of 36 months (Figure 5).

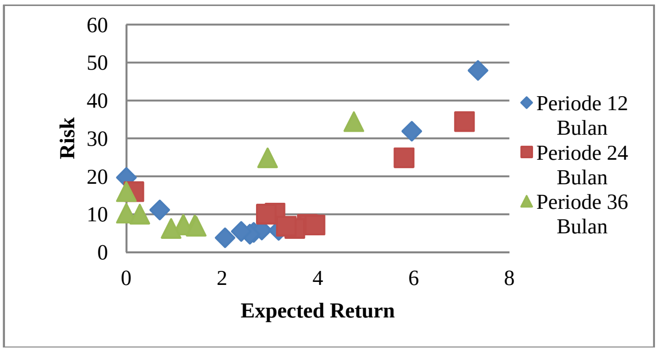


Figure 5 Graph showing the relationship between expected return and risk

3.6. Shares Mutual Fund Portfolios Using MOGA

The preparation of the portfolio of mutual funds is done based on the efficient method of Markowitz frontier. The formation of the efficient Markowitzfrontier is then optimized using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). In the Markowitz method, the formation of optimal portfolios is done by determining the weight of each shares mutual funds at random and multiplying it with the expected return of each shares mutual fund. The data used for the preparation of this portfolio are 10 shares mutual funds which expected monthly per unit NAV has been calculated using EMA and the expected return and risk method.

3.7. Parameter of Genetic Algorithm

The preparation of this portfolio used as many as 20 individuals in population size, the number of generations of 400 generations, probability for crossover on the genetic algorithm is 0.65 and the probability for mutations is 0.05. By applying the method of NSGA-II on the formation of this portfolio, theweights (allocations) of each shares mutual fund with expected return and risk of the portfolio are obtained; the parameters used are listed in Table 4:

Table 4. Parameter of Genetic Algorithm

Parameter	Value
Number of population	20
Number of generation	400
Probability of Crossover (Pc)	0.65
Probability ofMutation (Pm)	0.05
Periods (months)	12, 24 and 36

When the selection process begins, the population is sorted by using the concept of non-dominated sorting. Thus, the population is classified into a number of classes or fronts that does not dominate each other, after the non-dominated sorting is complete, the best solution in the population is on the first front, and the second best is the second front, and so on. Having formed the fronts, the crowding distance sorting is done to maintain the diversity of the population and to help the algorithm to explore the search space. Afterwards the crossover and mutation are done based on the probability that has been determined before.

3.8. Distribution of portfolios in Generation 1

Figure 6 illustrates the distribution of the portfolio of the 12, 24 and 36-month periods, and it can be seen that the spread of the distribution of the 24-month period dominates and has more optimum expected return over the other periods. From Figure 6 we can see the relationship between expected return and risk, and that the population distribution of the candidate portfolios varies. In the first generation (early plot) for the period of 12 months, individuals in the population are divided into 4 fronts, 24-month period divided into 5 frontsand 36-month period divided into 5 front s(Appendix). Table 5 shows the distribution of individuals formed inthe front.

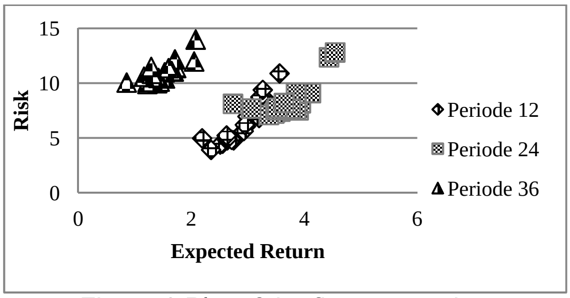


Figure 6 Plot of the first generation

Table 5. Distribution of the First-Generation Individuals

	12 month period	24 month period	36 month period
Front 1	10	9	8
Front 2	6	5	6
Front 3	2	3	3
Front 4	2	2	2
Front 5	0	1	1

3.8. Front Leader in Portfolio Formation

To view or change the movement of the front leading of the generation 1, 200, and 400 in the period of 12 months (Figure 7), 24 months (Figure 8), and 36 months (Figure 9)

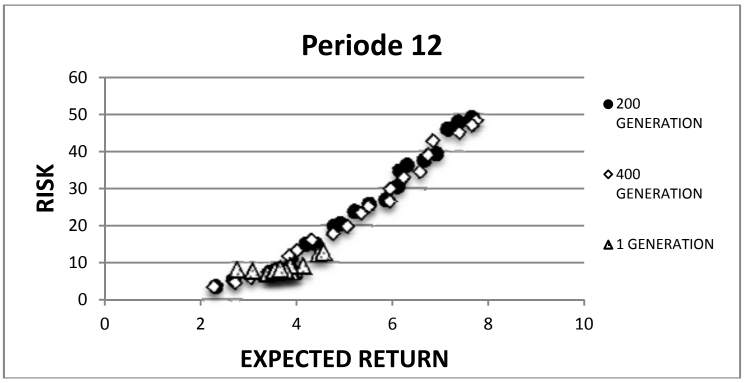


Figure 7 Front leading in 12 month period

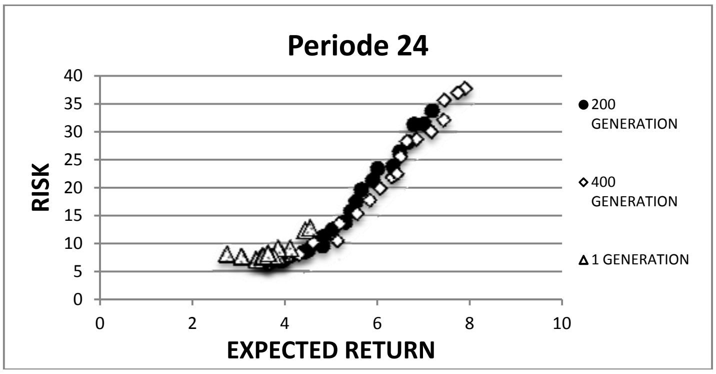


Figure 8 Front leading in 12 month period

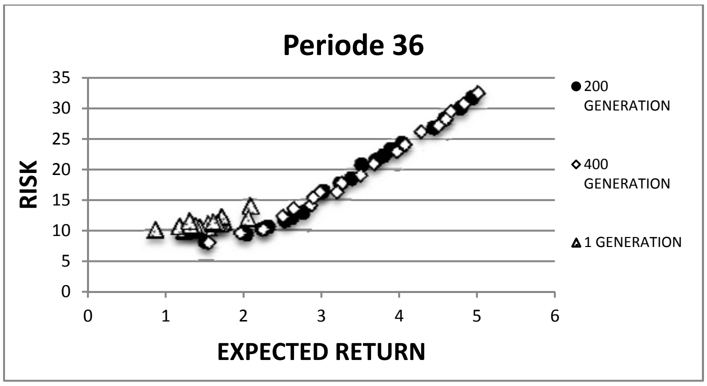
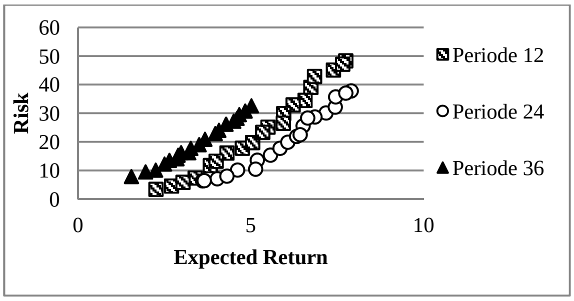


Figure 9 Front leading in 36 month period

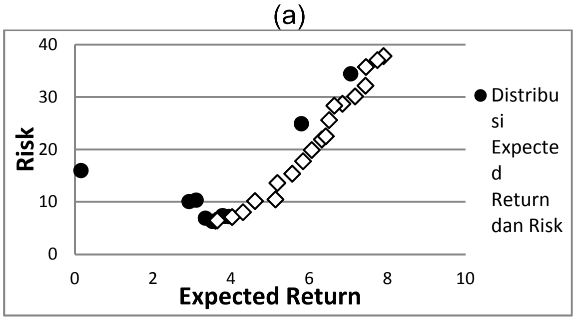
We can see that every front image resulted at generation 400 is better than the generation of the 200. Dominance result of generation 400 has a better value than the previous generation, so that it can be stated that it is an optimal result.

3.9. Optimal Portfolio

Below is a graph of the Pareto frontier in the period of 12 months, 24 months and 36 months with the parameters Pc = 0.65, Pm = 0.05, Generation 400 and the population 20.



(a)



(b)

Figure 10 (a) Graph of Pareto frontier (b) Graph of Expected return and risk on the Pareto frontier

Figure 10(a) is the ultimate graph in the process of preparing a portfolio of shares mutual fund change by using genetic algorithms on the 400thiterationand the process of non-dominated sorting, crowding distance, crossover, mutation, and elitism have been done. By using the concept of non-dominated, it is clearly visible from the charts that the optimum portfolio is found in the portfolio with a period of 24 months with Pc = 0.65 and Pm = 0.05. Individuals who are in the 12 and 36 months are dominated by individuals who are in a period of 24 months, so the 24-month period is the best composition of the portfolio. The computation time required during the process of genetic algorithms for the 24-month period is 63,289 seconds or 1.05 minutes.

Figure 10(b) is a plot between the distribution of expected return and risk before the portfolio is created with the expected return and risk after the portfolio formation (Pareto frontier). By using the concept of non-domination, it can be seen that the individuals before the formation of a portfolio are dominated by individuals after the formation of the portfolio, so the portfolio formed by using multi-objective genetic algorithm is an optimal portfolio. There are 20 of these portfolios and they are formed in accordance with the earlier initiation during the process of the genetic algorithm. The composition of the portfoliocan be seen in Table 6.

Table 6 is a table of shares mutual fund portfolio that is formed in the period of 24 months and has 20 portfolio compositions that have been established by using MOGA NSGA-II program. In individual 1 in the population there is a portfolio composition with the expected return 7.90% and 37.83% of risk and13% of allocation in RDS08 (DanareksaMawar) and 87% in RDS09 (RencanaCerdas/Smart Plan).

Table 6. Portfolio of Mutual Shares Fund

Population	Expected Return (%)	Risk (%)	RDS 01 (%)	RDS 02 (%)	RDS 03 (%)	RDS 04 (%)	RDS 05 (%)	RDS 06 (%)	RDS 07 (%)	RDS 08 (%)	RDS 09 (%)	RDS 10 (%)
1	7.90	37.83	0	0	0	0	0	0	0	13	87	0
2	3.60	6.41	0	0	1	0	54	0	0	0	8	37
3	5.56	15.38	0	0	22	40	0	0	0	0	38	0
4	5.84	17.77	0	0	0	57	0	0	0	0	43	0
5	5.18	13.60	18	0	0	50	0	0	0	0	33	0
6	7.17	30.12	0	0	0	0	0	0	20	0	80	0
7	7.44	32.18	0	0	0	0	0	0	15	0	85	0
8	6.07	19.90	0	0	1	47	0	0	0	0	52	0
9	5.13	10.48	0	0	4	74	0	0	5	0	18	0
10	6.51	25.61	0	13	0	0	0	0	16	0	71	0
11	7.45	35.74	0	0	0	0	0	0	0	14	86	0
12	4.02	7.12	0	0	10	0	51	0	0	0	6	33
13	6.85	28.73	0	0	7	0	0	0	8	26	59	0
14	6.64	28.36	0	0	0	0	0	0	20	0	81	0
15	7.74	37.07	0	0	0	0	0	0	0	14	86	0
16	6.32	21.92	0	0	0	43	4	0	0	0	59	0
17	6.42	22.52	0	0	0	45	0	0	0	3	54	0
18	4.61	10.17	9	0	0	52	0	0	16	0	23	0
19	4.30	8.04	4	0	12	69	0	4	0	0	11	0
20	3.65	6.47	0	0	1	3	48	0	0	0	9	36

3.10. Design and Optimization of AgroindustrySystem

Optimization by using Non-dominated Sorting Genetic Algorithm-II (NSGA-II) method is not only used in the shares field, but also be in the field of agro-industry. The field of agro-industry which is currently developed in the activities which are processing materials derived from plants or animals through processing, preservation, alteration of the physical, chemical conversion, packaging and marketing distribution [9]. One of activity is shop scheduling deals with the allocation of tasks (jobs) to resources (machines) into a pattern in such a way that con-straints are satisfied and certain goals are achieved [10][11]. Shop scheduling can be classified into flowshop, jobshop or openshop problems [12]. A flowshop is characterized by unidirectional flow of work with a variety of jobs all being processed sequentially in the same order, in a one-pass manner. The challenge in scheduling of flowshop is to determine the optimum sequence in which the jobs should be processed so that a particular performance measure such as makespan and total flowtime is minimized. In fact, many real-world scheduling problems are multiobjectivebynature, examples of such objectives are optimization of two or more of the following measures simultaneously, i.e. makespan and total flowtime as the multiple objectives for a flowshop scheduling problem.

4. Conclusion

From this research it can be concluded that: (i) MOGA NSGA-II can be used to determine the optimal weight (allocation) on the formation of shares mutual funds portfolio, (ii) the best portfolio is in the period of 24 months with Pc = 0.65, Pm = 0.05, Generation 400 and the population of 20 individuals with a computation time of 63,289 seconds or 1.05 minutes and (iii) the result obtained in this study in the form of 20 portfolio compositions and portfolios tables.

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