Analysis of stock investment selection based on CAPM using covariance and genetic algorithm approach

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Abstract. Investment is one of the economic growth factors of countries, especially in Indonesia. Stocks is a form of investment, which is liquid. In determining the stock investment decisions which need to be considered by investors is to choose stocks that can generate maximum returns with a minimum risk level. Therefore, we need to know how to allocate the capital which may give the optimal benefit. This study discusses the issue of stock investment based on CAPM which is estimated using covariance and Genetic Algorithm approach. It is assumed that the stocks analyzed follow the CAPM model. To do the estimation of beta parameter on CAPM equation is done by two approach, first is to be represented by covariance approach, and second with genetic algorithm optimization. As a numerical illustration, in this paper analyzed ten stocks traded on the capital market in Indonesia. The results of the analysis show that estimation of beta parameters using covariance and genetic algorithm approach, give the same decision, that is, six underpriced stocks with buying decision, and four overpriced stocks with a sales decision. Based on the analysis, it can be concluded that the results can be used as a consideration for investors buying six under-priced stocks, and selling four over-priced stocks.

Keyword: CAPM, beta parameter, covariance, genetic algorithm, under-priced, over-priced.

1. Introduction
Financial investment, especially in stocks, is a liquid investment in a short term. Nevertheless, in Indonesia, real investment is a common investment done by society rather than financial investment [4]. This is assessed because there is still a lack of knowledge about stock investment instruments. In addition, the emergence of public concerns as potential investors toward risk and return in stocks as a means of investment [5; 17]. An investment, especially stock investment, certainly is not apart from the risk. Generally, investors avoid risk (risk averse), so for a risky investment, investors will see a large rate of return. In fact, the greater the benefits to be obtained, generally the greater the risk that must be faced by investors [14; 16]. Conversely, if you tend a lower risk, then the benefits will also be mild [13]. Therefore, thing that must be paid an attention to the investor is how the investment can...
generate an optimal return at a minimal level of risk. This can be done by predicting expected returns and investment risks, using the Capital Asset Pricing Model (CAPM) approach [9; 15].

There are several studies on stock investment decision analysis using the CAPM approach. Putra [13], examined the analysis of stock investment selection using CAPM and reward to variability ratio (RVAR), as a determinant of stock investment decision making. The study was conducted on corporations listed on the LQ45 index in Indonesia Stock Exchange, period February 2009 - July 2012. The results showed that from a sample of 25 stocks taken, with an analysis using the CAPM method, there are 13 stocks underpriced, with the decision to buy is above the security market line (SML). On the contrary, overpriced shares with the selling decision are below the SML line of 12 stocks. Fiarni [4], examined the investment portfolio recommendation system based on the genetic algorithm. The results showed that the optimal portfolio formed by using CAPM method and genetic algorithm, is able to give bigger profit that is equal to 32.28%, compared to stock average of individual forming of portfolio with value equal to 26.32%. The portfolio set up by the recommendation system also provides a lower risk of 1.05883, compared to the average risk of individual stocks of portfolio makers that is equal to 1.60095. Thus, the portfolio established using the recommendation system can be accepted by application users with a suitability rate of 67%. A similar study was also conducted by Zainashev [20], which is about using a genetic algorithm in the optimal investment portfolio decision-making process.

Based on the description above, in this research, the stock selection analysis using CAPM approach has been conducted. For the estimation of parameter of $\beta$ in CAPM is done by two ways that is by covariance method and genetic algorithm. This is what distinguishes this research from previous research conducted by Putra [13] and Fiarni [4]. According to Mukherjee and Kumar [11], genetic algorithm has been widely applied to solving optimization problems. Through this approach, it is expected to obtain parameter estimator value $\beta$ in CAPM as systematic risk. Thereafter, parameter estimator values $\beta$ are used for stock selection analysis based on assumptions in CAPM. The purpose of this study is to provide information for investors in considering the selection of stock investments. As a numerical illustration, some stocks are traded on the Indonesian capital market.

2. Methodology
This methodology discusses stock returns, Capital Asset Pricing Model (CAPM), genetic algorithms, and CAPM model significance tests, used in stock selection analysis for investment.

2.1. Stock returns
In this section, the objective is to determine the stock returns. Suppose that the stock price on a day-$t$ is $P_t$. To analyze financial data within horizon daily time, return $R_t$ often given in the form of continuously compound return or return in following formula:

$$R_t = \ln \left( \frac{P_t}{P_{t-1}} \right)$$

with $t = 1, 2, ..., T$ where $T$ is the number of observation data and it is assumed that $P_0 = 1$ [15]. Thus, we used this return for modeling in the following sections.

2.2. Capital asset pricing model
This section discusses about the Capital Asset Pricing Model (CAPM), which is used for stock selection analysis for investment. CAPM is a model that describes the expected risk and return relationship. In this model, the expected return is the risk-free return rate plus the premium that is based on systematic stock risk [1; 2]. In the equilibrium state, the required rate of return (required return) by the investor for a stock is affected by the risk of the stock. In this case, the only calculated risk is systematic risk or market risk as measured by the parameter coefficient. While the risk is not
systematic (unsystematic risk) is assumed as no effect, because the risk can be eliminated by diversification [3; 6].

Based on CAPM theory, expected return from a stock can be calculated by using equation as follows:

\[ E[R_t] = R_f + \beta (E[R_m] - R_f), \]

(2)

where \( E[R_t] \) is expected returns of stock, \( E[R_m] \) expected return of market, \( R_f \) return of risk-free assets, and \( \beta \) is a stock risk. In CAPM discussion, parameter \( \beta \) is interpreted as a systematic risk of the stock. Therefore the parameter \( \beta \) is considered to be representative for use in measuring systematic risk. Thus, the magnitude of a stock's risk is determined by its parameter value \( \beta \) [7].

Equation (2) empirically cannot be tested statistically, since equation (2) is an expectation equation, it is an unobserved value. Therefore, in order to be tested empirically, the CAPM regression equation must be changed as follows

\[ R_t - R_f = \beta (R_m - R_f) + \varepsilon_t. \]

(3)

Since the risk-free asset return has a constant rate, it can be written as \( \mu_f = E[R_f] \). Also because it is a risk-free asset, the variance is \( \sigma^2_f = Var[R_f] = 0 \) [15]. Thus, equation (3) can be expressed as

\[ R_t - \mu_f = \beta (R_m - \mu_f) + \varepsilon_t. \]

(4)

where \( \beta \) a slope, and \( \varepsilon_t \) residual of CAPM regression. Residual sequence \( \{\varepsilon_t\} \) is assumed as white noise, which is a normal distribution with zero and variance \( \sigma^2_\varepsilon \) [5].

In the covariance method approach, it is often assumed to be zero, and the magnitude of the parameter value can be estimated using the following equation:

\[ \beta = \frac{Cov[R_t, R_m]}{Var[R_m]} = \frac{\sigma_{tm}}{\sigma^2_m}, \]

(5)

where \( \sigma_{tm} = Cov[R_t, R_m] \) is a covariance of stock returns \( R_t \) and market return \( R_m \), and \( \sigma^2_m = Var[R_m] \) is variance of market returns \( R_m \). If \( \beta > 1 \), it means the increase in stock return is higher than the increase in market return, and usually the stocks are classified in aggressive stock. If \( \beta < 1 \) it means that the increase in stock return is lower than the increase in market return, and usually the stock is classified in defensive stock [5, 7].

2.3. Genetic algorithm

This section discusses the genetic algorithm of CAPM for parameter estimation of \( \beta \), in terms of stock selection for investment.

The genetic algorithm is a search method based on the mechanisms of artificial genetics and natural selection [8]. The mechanism of artificial genetics reflect the individual's ability to engage in marriage, and produce offspring that have similar characteristics to the parent. While the mechanism of natural selection illustrates that living things can survive, if it is able to adapt to the surrounding environment [15; 19]. Therefore, it is expected that the resulting offspring’s have the best combination of characteristics from the parent, and can sustain generations of offspring.

In general, the structure of the genetic algorithm can be given in the following steps [10; 18]:

a. Initial population generation, this initial population is generated randomly so as to obtain an initial solution;
b. The population is composed of a number of chromosomes representing desired solutions;
c. The formation of a new generation, in the formation of a new generation used three operators, namely reproduction / selection, cross over and mutation;
Evaluation of the solution, this process evaluates each population by calculating the fitness value of each chromosome, and evaluating it until the stop criteria are met. If the stop criterion has not been met, then the new generation will be re-established by repeating step b. Referring to the general structure of the genetic algorithm, the genetic algorithm for estimating the coefficients $\beta$ of CAPM as in equation (4), it can be arranged as follows [19]:

1) Generating the initial population. For each stock, the initial population generated $N$ amounts, which is generated randomly. This initial population random number is then converted into the form of decimal values $\beta$, where $\beta \in S$;

2) Evaluation of chromosomes. Referring to the CAPM form of equation (2), the fitness value of the chromosome is the objective function values in the form of:

$$
\text{Minimized } f(\beta) = \sum e_i^2 = \sum (R_i - \mu_f - \beta(R_m - \mu_f))^2.
$$

Based on the fitness values selected the smallest value, for the minimization program.

3) Calculation of population convergent percentage. The percentage convergent population $p_c$ is the percentage of the number of individuals who have the same fitness value and the most. This $p_c$ value is calculated using the following formula:

$$
p_c = \frac{n}{\text{pop}} \times 100\%,
$$

where $n$ the number of individuals who have the same fitness and the most, and $\text{pop}$ number of population.

4) Checking stop condition. The genetic algorithm process will stop when the generation counter has reached the specified number of generations, that is $g_c = 1000$, or the convergent percentage of the population reaches the defined threshold limit $\theta = 90\%$.

5) Chromosome selection. The selection process is done using roulette wheel selection. Due to the minimization program, it evaluates the fitness value $eval(v_i)$, $i = 1,...,N$, according to equation (4), with the function

$$
eval(v_i) = \frac{1}{1 + f(\beta)},
$$

where $f(\beta)$ is the fitness value due to equation (4).

6) Crosslinking. The new population of the selection results is cross-breded, using the Single-Point Crossover (SPC) method.

7) Mutasi. Mutations. Mutations of each generation are obtained by using $m \times \text{pop} \_ \text{size} \times p_m$, with $m$ are number of mutation, $\text{pop} \_ \text{size}$ size of population, and $p_m$ are probability of mutation (random value).

8) Decoding. It is the process of encoding the genes in a chromosome to get its value back as it was, changing the coding to decimal values.

Furthermore, this genetic algorithm is used to analyze the case of stock selection for investment as follows.

### 3. Result and discussion

This section discusses the results and discussion which include: data analyzed, parameter estimation using covariance method, parameter estimation using genetic algorithm method, determination of expected return, and comparison analysis.

#### 3.1. Data analysis

This sub-section discusses about the object data being analyzed. The object of this study is the closing price of the monthly stock in period of January 1, 2016 until December 31, 2016, obtained through the internet media https://finance.yahoo.com. The data used in this research is the monthly stock closing
price of AALI, ADRO, AALI, BBCA, INDF, JSMR, PGAS, SMGR, TLKM, UNTR, and Composite Stock Price Index (IHSG) in period of 2016. While the risk-free asset data used is the interest rate of Bank Indonesia. Furthermore, the price data of each stock, composite stock price index, and risk-free asset, determine the value of the return rate by using equation (1). The return data of each stock, stock price index, and risk-free asset are then used for analysis in the following sections.

3.2. Parameter estimation $\beta$ using covariance method

In this sub-section, parameter $\beta$ of each stock return is estimated. The parameter $\beta$ of each stock is a systematic risk that is usually called market risk, which needs to be estimated based on the return data of each stock. Here the estimation is done by the covariance method which refers to equation (5). Based on (5), the parameters $\beta$ of each individual stock are presented in Table 1.

| Stocks | Estimator $\beta$ |
|--------|-------------------|
| AALI   | 1.2808            |
| ADRO   | 0.8387            |
| ASII   | 1.6918            |
| BBCA   | 0.9460            |
| INDF   | 0.8941            |
| JSMR   | 1.3414            |
| PGAS   | 1.7293            |
| SMGR   | 1.1153            |
| TLKM   | 0.7185            |
| UNTR   | 0.6186            |

To ensure that the estimated parameter $\beta$ of each stock estimated using equation (5) is significant, a test is necessary. The significance test is done by referring equation (4), which is testing the significance of parameter estimator $\beta$ of each stock. To test the significance of parameter estimators, it is performed using Wald test statistic and test statistic $F$. Based on the result of significance test of parameter estimator $\beta$, it shows that parameter estimator $\beta$ of each stock has significant at significance level $\alpha = 5\%$. While testing the assumption of residual normality $\epsilon_t$ of each stock return, it is conducted by Kolmogorov-Smirnov test statistic. Based on the assumption of residual normality $\epsilon_t$ assumption of each stock return, it indicates that the respective residual stock return is normally distributed.

Therefore, based on the result of testing the significance of the estimator $\beta$ of each stock parameter estimated using equation (5) is significant, that it can then be used for analytical purposes. Taking into account to Table 1, it shows that 5 out of 10 stocks in the research object have parameter values $\beta > 1$, so it can be said that the stocks used as samples of this study have very high average risk. In the above calculation can be seen that PGAS shares have the highest beta value, that is equal to 1.7293.

In this sub-section, the calculation of expected return from CAPM is estimated using covariance method. Using the results of the calculation of market return, risk-free return, and parameter estimators (systematic risk) $\beta$ for each stock, and then we calculated the expected value of stock returns, using equation (2). The result of the calculation of expected return of 10 stock of research object is given in Table 2.
Table 2 shows that UNTR stocks have the highest expected return, which is 0.0221. Meanwhile, PGAS stock has the lowest expected return, which is equal to -0.0736. This shows that the size of the expected return rate is influenced by the size of the risk $\beta$ of the stock.

**Table 2. Expected return value $E[R_t]$ of CAPM using covariance method**

| Stocks | $E[R_t]$ |
|--------|----------|
| AALI   | -0.0350  |
| ADRO   | 0.0031   |
| ASII   | -0.0704  |
| BBCA   | -0.0061  |
| INDF   | -0.0020  |
| JSMR   | -0.0402  |
| PGAS   | -0.0736  |
| SMGR   | -0.0207  |
| TLKM   | 0.0135   |
| UNTR   | 0.0221   |

So that it is obtained by investment decision of stock based on CAPM method of covariance presented in Table 3.

**Table 3. Recommended decisions are based on CAPM with covariance method**

| Stocks | $R_t$ | $E[R_t]$ | Evaluation | Recommendation |
|--------|-------|----------|------------|----------------|
| AALI   | -0.0236 | -0.035    | Efficient  | Take or buy stock (under-priced) |
| ADRO   | -0.0481 | 0.0031    | Not efficient | Sell stock before stock price goes down (over-priced) |
| ASII   | -0.0152 | -0.0704   | Efficient  | Take or buy stock (under-priced) |
| BBCA   | 0.0017  | -0.0061   | Efficient  | Take or buy stock (under-priced) |
| INDF   | -0.0256 | -0.002    | Not efficient | Sell stock before stock price goes down (over-priced) |
| JSMR   | -0.0219 | -0.0402   | Efficient  | Take or buy stock (under-priced) |
| PGAS   | -0.0398 | -0.0736   | Efficient  | Take or buy stock (under-priced) |
| SMGR   | -0.0147 | -0.0207   | Efficient  | Take or buy stock (under-priced) |
| TLKM   | 0.0113  | 0.0135    | Not efficient | Sell stock before stock price goes down (over-priced) |
| UNTR   | 0.0009  | 0.0221    | Not efficient | Sell stock before stock price goes down (over-priced) |

The recommended investment options to investors based on Table 3, are stocks of AALI, ASII, BBCA, JSMR, PGAS, TLKM, and UNTR. Because the return value of realization $R_t$ is greater than the expected return $E[R_t]$.

### 3.3. Parameter estimation $\beta$ using genetic algorithm

In this sub-section, the parameter estimation $\beta$ of each stock is done by using genetic algorithm method. Parameter estimation using genetic algorithm method is done by referring to the general structure of genetic algorithm described in section 2.3. The estimation of each stock parameter is done with the intention of determining the parameter value that can minimize the objective function (6). The parameter estimation process is done with the help of Matlab 2010 application program. The parameter estimation $\beta$ results are given in Table 4.

As with the estimation of parameters $\beta$ using the covariance method, the estimator of each stock estimated using equation (6) is significant, it is necessary to test significance. Testing is done by referring equation (4), namely testing the significance of each stock parameter estimator $\hat{\beta}$. To test the significance of parameter estimators, it also performed using Wald test statistics and test statistic $F$. 
The result of significance test of parameter estimator $\beta$ for each stock has significant at significance level $\alpha = 5\%$. While testing the assumption of residual normality $\epsilon_t$ of each stock return, is conducted by Kolmogorov-Smirnov test statistic. The result of assumption of residual normality $\epsilon_t$ of each stock return shows normal distribution.

**Table 4. Parameter estimation $\beta$ of individual stock using genetic algorithm**

| Stocks | Estimator $\beta$ |
|--------|-------------------|
| AALI   | 1.3366            |
| ADRO   | 0.9999            |
| ASII   | 1.7366            |
| BBCA   | 0.8638            |
| INDF   | 0.8813            |
| JSMR   | 1.2366            |
| PGAS   | 1.6429            |
| SMGR   | 1.2068            |
| TLKM   | 0.7529            |
| UNTR   | 0.6907            |

Therefore, based on the result of testing the significance of estimator of each stock parameter estimated using equation (6) is significant, and then it can be used for further analysis purposes. Taking into account to Table 4. It appears that 5 out of 10 stocks of research object companies have parameter estimator values $\beta > 1$, so it can be said that the stocks used as samples of this study have very high average risk. In the above calculation, it can be seen that the stock PGAS has the highest beta value, that is equal to 1.7366.

In this sub-section, the expected return of each share has been calculated, based on CAPM using genetic algorithm method. Having obtained the parameter estimator value $\beta$ (systematic risk), together with the expected return of the composite stock price index, and the expected return of the risk-free asset, is used to determine the expected return of each stock.

**Table 5. Expected return value $E[R_t]$ of CAPM using genetic algorithm**

| Stocks | $E(R_t)$ |
|--------|----------|
| AALI   | -0.1769  |
| ADRO   | -0.0461  |
| ASII   | -0.0154  |
| BBCA   | 0.0016   |
| INDF   | -0.0249  |
| JSMR   | -0.0221  |
| PGAS   | -0.0401  |
| SMGR   | -0.0142  |
| TLKM   | 0.0111   |
| UNTR   | $-1 \times 10^{-5}$ |

The calculation of the expected value of stock returns $E[R_t]$ is done using equation (2). The result of the calculation of expected return of the 10 stocks used as the research object is presented in Table 5.
In Table 5, it shows that TLKM shares have the highest expected return $E[R_t]$, which is 0.0113. Meanwhile, ADRO stock has the lowest expected return, which is equal to -0.0475. Based on the results in Table 5, the efficiency classification is based on expected return using the CAPM method with parameter estimators $\beta$ by genetic algorithm method. The results of the efficiency classification of the stocks are presented in Table 6.

**Table 6.** Classification of stock's efficiency with CAPM based on parameter $\beta$ which is estimated by the genetic algorithm

| Stocks | $R_t$ | $E[R_t]$ | Evaluation | Recommendation          |
|--------|-------|----------|------------|--------------------------|
| AALI   | -0.0236 | -0.1769  | Efficient  | Take or buy stock (under-priced) |
| ADRO   | -0.0481 | -0.0461  | Not efficient | Sell stock before stock price goes down (over-priced) |
| ASII   | -0.0152 | -0.0154  | Efficient  | Take or buy stock (under-priced) |
| BBCA   | 0.0017  | 0.0016   | Efficient  | Take or buy stock (under-priced) |
| INDF   | -0.0256 | -0.0249  | Not efficient | Sell stock before stock price goes down (over-priced) |
| JSMR   | -0.0219 | -0.0221  | Efficient  | Take or buy stock (under-priced) |
| PGAS   | -0.0398 | -0.0401  | Efficient  | Take or buy stock (under-priced) |
| SMGR   | -0.0147 | -0.0142  | Not efficient | Sell stock before stock price goes down (over-priced) |
| TLKM   | 0.0113  | 0.0111   | Efficient  | Take or buy stock (under-priced) |
| UNTR   | 0.0009  | $1\times10^{-5}$ | Efficient  | Take or buy stock (under-priced) |

Investment options suggested to investors based on Table 6, are stocks of AALI, ASII, BBCA, JSMR, PGAS, TLKM, and UNTR. Because the return value of realization $R_t$ is greater than the expected return $E[R_t]$.

### 3.4. Comparison analysis

In this sub-section a comparative analysis of investment decisions is recommended, based on CAPM estimated using covariance method, and CAPM estimated using genetic algorithm (GA) method. To facilitate the comparative analysis, the classification of the stock efficiency given in Table 3, and the stock efficiency classification given in Table 6, is summarized as given in Table 7.

**Table 7.** Comparison of stock efficiency

| Saham | $R_t$ | $E[R_t]$ | Parameter $\beta$ covariance | Parameter $\beta$ GA | Evaluation | CAPM covariance | CAPM GA |
|-------|-------|----------|-----------------------------|---------------------|------------|-----------------|---------|
| AALI  | -0.0236 | 1.2808   | 1.3366                      | Efficient           | Efficient  |
| ADRO  | -0.0481 | 0.8387   | 0.9999                      | Not efficient       | Not efficient |
| ASII  | -0.0152 | 1.6918   | 1.7366                      | Efficient           | Efficient  |
| BBCA  | 0.0017  | 0.9460   | 0.8638                      | Efficient           | Efficient  |
| INDF  | -0.0256 | 0.8941   | 0.8813                      | Not efficient       | Not efficient |
| JSMR  | -0.0219 | 1.3414   | 1.2366                      | Efficient           | Efficient  |
| PGAS  | -0.0398 | 1.7293   | 1.6429                      | Efficient           | Efficient  |
| SMGR  | -0.0147 | 1.1153   | 1.2068                      | Efficient           | Efficient  |
| TLKM  | 0.0113  | 0.7185   | 0.7529                      | Not efficient       | Not efficient |
| UNTR  | 0.0009  | 0.6186   | 0.6907                      | Not efficient       | Not efficient |

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Taking into account Table 7, it appears that stock efficiency based on CAPM estimated using covariance method, and CAPM estimated using genetic algorithm method, has no significant difference. This can be seen from the parameter estimator $\beta$ value generated by both methods have no significant difference.

4. Conclusion
In this paper we have discussed the issues of stock investment selection based on CAPM using Genetic Algorithm. Here it is assumed that the stocks analyzed follow the CAPM model. Based on the analysis show that parameter estimator $\beta$ by using covariance method, for stocks: AALI, ASII, JSMR, PGAS, and SMGR, these are obtained parameter estimator value $\beta < 1$. As for stocks: ADRO, BBCA, INDF, TLKM, and UNTR, these are obtained parameter estimator value $\beta < 1$. Meanwhile, parameter estimator using genetic algorithm method also obtained parameter estimator value $\beta$ equal to those estimated using covariance method, that is for stocks: AALI, ASII, JSMR, PGAS, and SMGR, these are obtained parameter estimator value $\beta > 1$. As for stocks: ADRO, BBCA, INDF, TLKM, and UNTR, these are obtained parameter estimator value $\beta < 1$. Based on the evaluation of 10 stocks of research object, it can be concluded that there are 6 stocks underpriced i.e. AALI, ASII, BBCA, JSMR, PGAS and SMGR shares with the decision to buy the stock before the price rises, and there are 4 overpriced stocks which are ADRO, INDF, TLKM, UNTR shares with the decision to sell the shares before the price falls.

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