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IDX30 Stock Portfolio Optimization Using Genetic Algorithm Based on Capital Asset Pricing Model

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Abstract

The stock market plays a vital role in supporting economic growth by serving as a primary channel for companies to raise capital and for investors to gain profits through long-term investments. In practice, one of the biggest challenges for investors is identifying which stocks are worth purchasing and how to allocate their funds optimally. One commonly used approach to evaluate stock feasibility is the Capital Asset Pricing Model (CAPM), which helps identify undervalued and overvalued stocks based on the relationship between systematic risk and expected return. Additionally, it is necessary to determine the optimal investment weight allocation. Therefore, this study combines the CAPM method for stock selection and Genetic Algorithm, a metaheuristic approach capable of finding optimal solutions in complex problems, to determine the optimal portfolio weight composition. The object of this study includes stocks listed in the IDX30 index during the period from February 2021 to November 2023. The results show that five stocks—ADRO, BBCA, BBNI, KLBF, and TLKM—are classified as undervalued according to the CAPM method and are recommended for inclusion in the optimal portfolio. Portfolio optimization using the Genetic Algorithm results in the following stock weight composition: ADRO 26.55%, BBCA 36.20%, BBNI 9.09%, KLBF 12.20%, and TLKM 15.96%, with a Sharpe Ratio of 4.043906. The expected return and risk of the optimal portfolio are 0.00067373 and 0.00012407, respectively.

Keywords: Portfolio Optimization, IDX30, Genetic Algorithm, CAPM.

1. Introduction

Financial markets have an important role in supporting economic growth, one of which is through the stock market which is a means for companies to obtain capital and for investors to obtain returns on their investments. In Indonesia, the IDX30 index is often used as a reference because it contains stocks with large capitalization and high liquidity, and is considered to reflect the stability and fundamental strength of the company.

However, while the IDX30 offers attractive investment opportunities, the process of selecting the right stocks remains a challenge due to the differences in risk and return characteristics between stocks. For this reason, methods such as the Capital Asset Pricing Model (CAPM) are used to measure the expected return based on the systematic risk of a stock. With CAPM, investors can identify stocks that are undervalued or overvalued, which is an important basis for making investment decisions.

After stock selection is done, the next step is to determine the optimal allocation of funds so that the portfolio formed is in accordance with the risk profile and investment objectives. One effective method in solving portfolio optimization problems is Genetic Algorithm, which mimics the mechanism of natural selection to find the best portfolio combination. This method excels in handling complex constraints such as the maximum number of stocks in a portfolio (cardinality constraint) and searching for solutions in a wide space of possibilities.

Some previous studies have shown the effectiveness of the combination of CAPM and Genetic Algorithm in portfolio construction. Fiarni and Bastiyan (2013) developed an investment recommendation system based on CAPM and Genetic Algorithm in the form of Decision Support System to help investors form an optimal portfolio. Sukono et al. (2018) used Genetic Algorithm to estimate beta in CAPM and assess the investment feasibility of a stock, with results comparable to the covariance method. Meanwhile, Azim et al. (2021) used Genetic Algorithm to determine the investment weight that maximizes the sharpe ratio, and proved that this method produces a more optimal portfolio than random allocation.

Based on previous research, this study aims to not only identify potential stocks in IDX30, but also construct an optimal portfolio based on sharpe ratio. This research combines CAPM as a stock selection method and Genetic Algorithm as a portfolio optimization method.

2. Literature Review

2.1. Stock

Shares are one of the most popular investment instruments in the capital market. Shares represent a person's or legal entity's ownership of a company. According to Husnan and Pudjiastuti (2012), shares are a form of capital participation in a company with the hope of benefiting from rising share prices and dividends. By owning shares of a company, investors have rights to the company's income and assets after deducting the payment of all company obligations.

2.1.1. Stock Return

Returns can be in the form of realized returns that have occurred or expected returns that have not yet occurred but which are expected to occur in the future. Realized returns are returns that have occurred and are calculated based on historical data and can be calculated using the following formula (Widyaningrum et al., 2022):

$$R_{it} = \frac{P_{it} - P_{i(t-1)}}{P_{i(t-1)}} \tag{1}$$

Realized return is used to assess company performance and is the basis for calculating expected return which is used to estimate future risk. The equation for calculating the expected return of shares is as follows (Widyaningrum et al., 2022):

$$E(R_i) = \frac{\sum_{t=1}^{n} R_{it}}{n} \tag{2}$$

Market return refers to the level of return generated by a market index. In the context of the Indonesian stock market, the market return is represented by the return of the Composite Stock Price Index (JCI). To calculate the average, use the following equation (Ramdani and Nazar, 2021):

$$E(R_m) = \frac{\sum_{m=1}^{n} R_m}{n} \tag{3}$$

In addition, investors also need to consider the risk-free return (R_f), which represents the rate of return of a riskless investment. The risk-free return converted into daily form can be calculated using the following equation:

$$R_f daily = \left(1 + R_f annual\right)^{\frac{1}{n}} - 1 \tag{4}$$

2.1.2. Stock Risk

Stock risk relates to uncertainty about expected investment returns (Bodie et al., 2014). Risk measurement is essential in the investment decision-making process because it can provide an overview of the uncertainty that investors may face. To measure this risk, variance is used as a measure of the uncertainty of investment returns. Stock return variance describes how much the actual return deviates from the expected return. The greater the variance, the higher the return fluctuations that may occur, so the greater the risk faced by investors. Therefore, variance is considered the main indicator of stock risk and is calculated using equation (5). Meanwhile, standard deviation, which is the square root of variance, can be calculated using equation (6) (Hartono and Rohaeni, 2021).

$$\sigma_i^2 = \frac{\sum_{t=1}^{n} [R_{it} - E(R_i)]^2}{n-1} \tag{5}$$

$$|\sigma_i| = \sqrt{\sigma_i^2} \tag{6}$$

The variance of market returns, which represents market risk, reflects the degree to which market returns deviate from their expected values. The larger the variance value, the higher the volatility or uncertainty of market returns. The market return variance can be calculated using the following formula, which describes the level of volatility of market returns against their average value:

$$\sigma_m^2 = \frac{\sum_{t=1}^{n} [R_{mt} - E(R_m)]^2}{n-1} \tag{7}$$

Stock risk can be analyzed by looking at how a stock's return fluctuates relative to other stocks. One way to measure this relationship is by using covariance, which shows the direction and strength of the relationship between the movements of two assets. The equation for calculating covariance is as follows (Hartono and Rohaeni 2021):

$$\sigma_{i,j} = \frac{\sum_{t=1}^{n}[(R_{it} - E(R_i)) \cdot (R_{jt} - E(R_j))]}{n-1} \tag{8}$$

Ramdani and Nazar (2021) state that, a positive covariance value indicates that the values of the two variables move in the same direction. A negative covariance value indicates that the values of the two variables move in the opposite direction. The covariance value that shows zero reflects the two independent variables, meaning that the movement of one stock is not related to the movement of the other stock.

According to (Effendi, 2018), risk includes two main components, namely systematic risk that cannot be eliminated by diversification and non-systematic risk that can be reduced through diversification of assets in the portfolio.

1. Systematic Risk
   Systematic risk is the variation in investment returns that cannot be eliminated through diversification. The magnitude of a stock's systematic risk depends on its sensitivity to market changes, as measured by beta (β). Beta indicates the extent to which a stock's return moves relative to the market return and can be calculated using the following equation:
   $$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} = \frac{\sigma_{im}}{\sigma_m^2} \tag{9}$$
2. Non-systematic Risk
   Non-systematic risk is the portion of variation in investment returns that can be eliminated through diversification by investors and only affects a particular stock or sector.

2.2. Portfolio

A portfolio is a combination of various financial instruments, such as stocks, bonds, and other assets, formed by investors to achieve diversification and reduce risk. The main objective of portfolio formation is to diversify risk while optimizing return.

2.2.1. Portfolio Return

The portfolio return reflects the profit expected by investors from the overall investment they own (Bodie et al., 2014). Expected return portfolio is a weighted average of the expected return of each asset in the portfolio and can be calculated using the following equation:

$$E(R_p) = \mu_P = \sum_{i=1}^{n} w_i E(R_i) \tag{10}$$

2.2.2. Portfolio Risk

Portfolio risk is the degree of uncertainty or variability of portfolio returns. This risk includes two main components: systematic risk and non-systematic risk. The formula used to calculate portfolio risk is as follows (Hartono & Rohaeni, 2021):

$$\sigma_P^2 = w_i^2\sigma_i^2 + w_j^2\sigma_j^2 + 2w_iw_j\sigma_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{n} w_iw_j\sigma_{ij} \tag{11}$$

3. Materials and Methods

3.1. Materials

In this study, the objects used are stocks that are consistently listed in the IDX30 for three consecutive years, namely in the period February 1, 2021 to November 30, 2023. The data used is secondary data in the form of daily closing stock prices, obtained from the website www.investing.com and accessed on January 11, 2025. In addition, this study also uses BI 7-Day Reverse Repo Rate data for the same period as a risk-free asset.

3.2. Methods

3.2.1. Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is an equilibrium model used primarily in stock investment, where this model takes into account systematic risk (beta) to measure how much return is expected from an investment based on the level of risk (Chaudhary & Bakhshi, 2021) and can be calculated using the following equation:

$$E(R_i)_{CAPM} = R_f + (E(R_m) - R_f)\beta_i \tag{12}$$

3.2.2. Genetic Algorithm

Genetic Algorithm is a metaheuristic method used to solve an optimization problem. This method is based on the principles of natural selection and the principles of genetic science (Farid and Rosadi, 2022). The Genetic Algorithm works through several stages as follows:

a) Population initialization
   Create an initial population consisting of a number of individuals, where the gene value of each individual is determined randomly. The number of individuals in this population will depend on the type of problem to be solved.
b) Evaluation
   Each individual is evaluated using a fitness function that measures the quality of the resulting solution. This research aims to maximize the Sharpe Ratio. Sharpe Ratio measures how much additional return is earned for every unit of risk taken. Therefore, the higher the Sharpe Ratio value, the better the portfolio performance after adjusting for risk.
c) Selection
   Goldberg (1989) introduced a selection method known as roulette wheel selection in Genetic Algorithm. The higher the fitness value of an individual, the greater the portion it has in the roulette wheel, so the chances of being selected are also greater. The chromosomes selected through this process will become the parents used in the crossover stage to produce the next generation (Lim, 2020).
d) Crossover
   Crossover is the process of exchanging genes between two parents that aims to produce a new individual with the traits inherited from its parents. The method used in this research is arithmetic crossover. This technique produces new individuals by combining the values of the two parents based on arithmetic operations.
e) Mutation
   Mutation is an operator in genetic algorithms that serves to directly change the structure of a chromosome, resulting in a new chromosome that is genetically different from the previous chromosome. Mutation is necessary to restore genes lost from previous generations and introduce new genes that have not previously appeared.
f) Stopping criteria
   Stopping criteria in genetic algorithms are used to determine when the Genetic Algorithm will stop. Some stopping criteria that can be used are fitness function value limit, objective function value limit, computation time limit, many generations, and convergence.

4. Results and Discussion

4.1. Individual Stock Returns

The calculation of return for each stock is done using equation (1). Then, the calculation of expected returns for individual stocks and JCI in this study is carried out using equations (2) and (3). The results of the expected return calculation for the period February 1, 2021 to November 30, 2023 can be seen in the Table 1:

Table 1: Expected return of stocks and JCI

No.	Company Code	Expected Return
1	ADRO	0.001447
2	ANTM	-0.000244
3	ASII	-0.000004
4	BBCA	0.000485
5	BBNI	0.000265
6	BMRI	0.000222
7	CPIN	-0.000022
8	INDF	0.000133
9	KLBF	0.000290
10	PGAS	-0.000150
11	SMGR	-0.000594
12	TLKM	0.000342
13	TOWR	0.000225
14	UNTR	0.000127
	JCI	0.000251

Stocks of ANTM, ASII, CPIN, PGAS, and SMGR, which have negative expected return values, will not be included in the portfolio due to potential losses.

4.2. Risk-Free Rate of Return

The risk-free return calculation was carried out using the BI 7-Day Reverse Repo Rate in the period February 2021 to November 2023. The average risk-free rate for the three years is 4.43% per year. Furthermore, the average risk-free rate converted to a daily rate can be calculated using equation (4).

$$R_f daily = (1 + 0.044333)^{\frac{1}{252}} - 1 = 0.000172$$

4.3. Individual Stock Risk

The return variance for each stock in this study is calculated using equation (5), while the standard deviation is calculated using equation (6). Then, the calculation of variance for JCI is carried out using equations (7). The results of the calculation of variance and standard deviation for each stock and JCI are presented in Table 2.

Table 2: Individual stock risk

No.	Company Code	Variance	Standard Deviation
1	ADRO	0.000716	0.026760
2	BBCA	0.000177	0.013302
3	BBNI	0.000645	0.025404
4	BMRI	0.000640	0.025308
5	INDF	0.000186	0.013647
6	KLBF	0.000349	0.018684
7	TLKM	0.000245	0.015666
8	TOWR	0.000401	0.020031
9	UNTR	0.000503	0.022419
JCI		0.000055	0.007416

4.4. Individual Stock Beta

The individual stock beta (β_i) for each stock in this study is calculated using equation (9). The results of beta calculations for each stock are presented in Table 3.

Table 3: Beta of individual stocks

No.	Company Code	$\boldsymbol{\beta_i}$
1	ADRO	1.384711
2	BBCA	1.072139
3	BBNI	1.165836
4	BMRI	1.463222
5	INDF	0.354754
6	KLBF	0.621863
7	TLKM	0.795553
8	TOWR	0.834819
9	UNTR	1.109440

The beta value of each stock ranges from 0.354754 to 1.463222. Of the 9 stocks analyzed, there are 5 stocks with beta values greater than 1 ($\beta > 1$) and 4 stocks with beta values less than 1 ($\beta < 1$). This indicates that the 5 stocks with $\beta > 1$ are aggressive as they are more volatile compared to the market. Meanwhile, the other 4 stocks are defensive, with lower volatility than the market, so their movements are more stable and tend to be less affected by changes in the overall market.

4.5. Stock Classification Based on CAPM Method

The calculation of expected stock returns based on the CAPM method uses equation (12). The results of the expected return calculation using the CAPM method for each stock are presented in the following table:

Table 4: Stock classification based on CAPM method

Company Code	$E(R_i)$	$E(R_i)_{CAPM}$	$E(R_i) > E(R_i)_{CAPM}$	Conclusion
ADRO	0.001447	0.000281	Yes	*Undervalued*
BBCA	0.000485	0.000256	Yes	*Undervalued*
BBNI	0.000265	0.000264	Yes	*Undervalued*
BMRI	0.000222	0.000287	No	*Overvalued*
INDF	0.000133	0.000200	No	*Overvalued*
KLBF	0.000290	0.000221	Yes	*Undervalued*
TLKM	0.000342	0.000235	Yes	*Undervalued*
TOWR	0.000225	0.000238	No	*Overvalued*
UNTR	0.000127	0.000259	No	*Overvalued*

There are 5 stocks that have undervalued conditions, namely ADRO, BBCA, BBNI, KLBF, and TLKM. These stocks show better performance than predicted based on the CAPM method, so they can be included in the optimal portfolio candidate because they have the potential to provide higher returns.

4.6. Covariance between Selected Stocks

The covariance value between two stocks is calculated using equation (8). The results of the stock return covariance calculation using Microsoft Excel are presented in Table 5.

Table 5: Covariance value of stock returns

	ADRO	BBCA	BBNI	KLBF	TLKM
ADRO	0.000716	0.000034	0.000030	0.000013	0.000044
BBCA	0.000034	0.000177	0.000101	0.000044	0.000050
BBNI	0.000030	0.000101	0.000645	0.000057	0.000061
KLBF	0.000013	0.000044	0.000057	0.000349	0.000043
TLKM	0.000044	0.000050	0.000061	0.000043	0.000245

Based on Table 5, a positive covariance indicates that the returns of two stocks tend to move in the same direction, meaning that if the price of a stock increases, then there is a possibility that the price of another stock also increases.

4.7. Portfolio Optimization Using Genetic Algorithm

Genetic Algorithm calculations using Python are carried out through several trials, with the criteria stopping when the best fitness value reaches 60% convergence or the iteration has reached 300 generations. The Genetic Algorithm optimization results are shown in Table 6, which shows the stock weights and Sharpe Ratio values for various combinations of probability of crossover (P_c) and probability of mutation (P_m).

Table 6: Experimental results of Genetic Algorithm with variations of P_c and P_m

No.	P_c	P_m	Stock Weight					Sharpe Ratio
			ADRO	BBCA	BBNI	KLBF	TLKM	
1	0.6	0.001	0.285299	0.323209	0.092024	0.092024	0.207443	4.002370
2		0.05	0.277474	0.318049	0.090909	0.136341	0.177226	4.025314
3		0.1	0.283695	0.343756	0.090909	0.143368	0.138273	4.028762
4		0.15	0.265463	0.362040	0.090909	0.122016	0.159571	4.043906
5	0.7	0.001	0.279120	0.232106	0.093337	0.187103	0.208334	3.893655
6		0.05	0.274376	0.313432	0.090536	0.090536	0.231120	3.988477

7		0.1	0.268402	0.381161	0.090909	0.107608	0.151920	4.043110
8		0.15	0.266718	0.345044	0.091173	0.130798	0.166267	4.038625
9	0.8	0.001	0.257209	0.386124	0.119359	0.096794	0.140514	3.926780
10		0.05	0.284719	0.339804	0.090909	0.142285	0.142284	4.028445
11		0.1	0.289276	0.320492	0.091412	0.138347	0.160473	4.019719
12		0.15	0.269972	0.352834	0.086017	0.086017	0.205160	4.032917

Based on Table 6, the largest Sharpe Ratio value is obtained in the experiment when $P_c = 0{,}6$ and $P_m = 0{,}15$. With the combination of $P_c = 0{,}6$ and $P_m = 0{,}15$ convergence occurred after 175 generations, while the best fitness value was achieved in the 115th generation. The portfolio with the largest fitness value, which is 4.043110, has the following portfolio-forming stock weights: ADRO 26.55%, BBCA 36.20%, BBNI 9.09%, KLBF 12.20%, and TLKM 15.96%. Expected return of the portfolio is calculated using equation (10) and obtained a value of 0.00067373. Meanwhile, portfolio risk is calculated using equation (11) and a value of 0.00012407 is obtained. The fitness value calculated using the sharpe ratio produces a positive value, which indicates that the optimal portfolio is able to provide a higher investment return compared to investment in risk-free assets.

5. Conclussion

Based on the results and discussion, the following conclusions were obtained: 1) Based on the CAPM method, stocks recommended for investment are stocks that are classified as undervalued. Of the 14 stocks in the IDX30 index, there are 5 stocks that meet these criteria, namely ADRO, BBCA, BBNI, KLBF, and TLKM.; 2) The composition of the optimal stock portfolio weight using Genetic Algorithm on IDX30 stocks is ADRO 26.55%, BBCA 36.20%, BBNI 9.09%, KLBF 12.20%, and TLKM 15.96%. The expected return and risk values of the optimal portfolio generated by the Genetic Algorithm are 0.00067373 and 0.00012407, respectively. With an expected return that is greater than the risk, this portfolio shows higher profit potential than the level of risk.; 3) The sharpe ratio value of the optimal portfolio generated by the Genetic Algorithm is 4.043906, indicating that this portfolio is able to provide high returns compared to the risks faced. That is, for every one unit of risk borne, this portfolio generates a return of 4.043906 units, which reflects the efficiency of portfolio performance in managing risk and return.

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