Forecasting Portfolio Optimization using Artificial Neural Network and Genetic Algorithm

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***Abstract* — Investment has an important role in the economic growth of a country. The higher investment value obtained by a country, the faster the country is able to develop their prosperity. However, the investor faces some obstacle in investment activity to have a reasonable return and acceptable risk. In stock investments area, investors could increase chance of getting higher returns by making predictions and diversifying by forming a stock portfolio. Previous studies have stated that Artificial Neural Network (ANN), which are one of the machine learning models inspired by the activity of human brain cells have more advantages to predict the stock future value in terms of speed, accuracy, and the amount of data that can be processed compared to other stock prediction models. Diversification is a method of dividing investment funds into different index stocks, with the aim of reducing the investment risk. With thousands of stocks in the market, deciding which portfolio should be chosen is difficult. This study extends the scope of several previous studies, which are only limited to perform predictions using ANN or GA without forming an optimal stock portfolio. The objective of this study is to predict future stock values using ANN, then form those optimal stock portfolios using GA with aims to get the best optimization of maximal return and minimal risk value. The results of this study show, the implementation of GA as an alternative to the Single Index Model (SIM) method show better optimization index.**

Keywords— Investment, Stock Portfolio, Prediction, Machine Learning, Single Index Model, Artificial Neural Network, Genetic Algorithm

I. Introduction

Investment is an activity to place funds in a certain period with the intention to generate profits and increase the value of the investment [3]. Investment has an important role in improving the country's economy, the higher investment value obtained by a country, the greater country's ability to develop faster [4]. However, there are several obstacles faced by the investors, uncertain returns and high risks of investment. It is a certainty that every investor wants to get the maximum profit with the lowest risk. In investment principle, various ways to get it are by making predictions and diversifying.

One form of investment is the stock investment. In a stock investment, investors are highly expected to analyze the current stock's value and predict the future stock's value. There are 2 analysis techniques that aim to predict the future stock's value, namely Fundamental Analysis and Technical Analysis [5]. Fundamental analysis is an analysis that studies the fundamental conditions of a company, while a Technical Analysis is an analysis technique that analyses price fluctuations within a certain time span by observing patterns of stock price movements.

Normally, both analysis techniques are carried out by humans.The investment decisions are based on assumptions about market trends, indicators in the form of graphs, and the intuition of investors itself. This approach certainly cannot be justified, because humans tend to do things that are inconsistent.

The most superior machine learning algorithm in making predictions now is Artificial Neural Networks (ANN). ANN is an algorithm inspired by the activity of human brain cells that able to study data patterns and generalize their knowledge to see patterns formed in the future [4]. Previous studies state that ANN is the most accurate prediction method compared to other prediction methods such as logistic regression, vector autoregressive, and autoregressive integrated moving average (ARIMA) [6, 7, 8].

In some previous studies, ANN and GA have been widely used in terms of prediction and optimization. Kai and Wenhua [12] make stock price predictions by utilizing GA to train the weight in the ANN process, this is done in order to get the highest weight with predictive accuracy. Kim and Han [13] predict stock prices by utilizing GA to perform discretization features on the connection weight and attributes on ANN. Kim and Shin [14] predict stock prices by utilizing GA to perform time delay optimization and network architecture on Ann. Handavandi et al [15] predicts stock prices with genetic fuzzy systems and artificial neural networks. Mahasagara et al [5] making stock price predictions using time series with ANN, this research succeeded in predicting stocks with historical data today and data the previous day. In this study also utilize a backpropagation algorithm, this is done to get a good level of accuracy. Wahyuni et al [11] make optimization of stock portfolios by utilizing SIM results optimized with GA. The purpose of this study is to predict stock future value using Artificial Neural Networks then form an optimal stock portfolio using genetic algorithm on the stock value predicted by ANN. This study extends the scope several previous studies, which are only limited to making predictions using ANN or GA without forming an optimal portfolio, or the opposite. By optimizing portfolio proportions on predicted stock values, Investor shall to determine the optimal portfolio of the future and determine the best profitable shares to be purchased, along with the proportional value of each share. With this method, investors are expected to get maximum profit, with minimum risk. In this study, we use index stock data which continues to be on the LQ45 index list in the period 2008-2018 to forming optimal forecast portfolio. LQ45 is a list of stock index that has high liquidity.

II. Literature Review

A. Investment, Diversification, and Portfolio

The returns and risks have an important role in making investment decisions. This decision includes the decision to

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make an investment or not, and which stock decision must be included in the portfolio [16]. One solution for investors to minimize risk is One solution for investors to minimize risk is to diversify. An example of the application of diversification is to make a portfolio [10]. Portfolios help investors determine stock combinations.

Investors have difficulties in determining the stocks that include the portfolio. Single Index Model (SIM) is able to construct the portfolio with optimization rules [17]. SIM can form an optimal portfolio by valuing stocks based on the excess value of returns to the beta of each stock. Excess returns to beta (ERB) show the relationship between returns and the risks [10]. There are several studies on portfolio optimization with the SIM [16, 17, 18]. Singh and Gautam [17] utilize the SIM in the formation of a portfolio of 10 companies listed on the Indian national stock exchange (NSE) and CNX bank price index. The data in this study is the monthly closing price of the selected stocks, and in the period of Jan 2009 to Dec 2013. The aims of this study to analyze the opportunities available for investors based on their returns and the risks. From this study, 2 stocks were chosen as investment destinations from 10 companies. Pratiwi and Yunita [18] formed a portfolio by comparing the SIM and the constant correlation model. In this study, the SIM has a better performance than the constant correlation model based on 3 portfolio performance measurements, namely: Sharpe, Treynor, and Jensen. The formation of a portfolio with time series data or historical data cannot describe the condition of future portfolios [4]. Therefore, the idea in this study is to establish a portfolio with predictive data to help investors know the condition of the optimal portfolio of the future.

B. *Artificial Neural Network*

Artificial Neural Network is a computational system inspired by the activity of human brain cells that are able to study data patterns and generalize their knowledge to see patterns formed in the future [19]. ANN are also commonly referred to as interrelated links that have related weights. Neural networks open new avenues to the field of making a prediction that is efficient and useful for profit. ANN are utilized in many fields because they are very effective in predicting tools to help the scientific community [20]. ANN usually consists of three layers: an input layer, a hidden layer, and output layer. In the three layers, there is a process of multiplying the input signal flow with synaptic weights (W_{1j}, W_{2j}, W_{nj}), then summing all the inputs that have been given the previous weight. The sum of results is able to call linear output (net_j) [21]. Fig. 1 shows a mathematical non-linear model of a neuron.

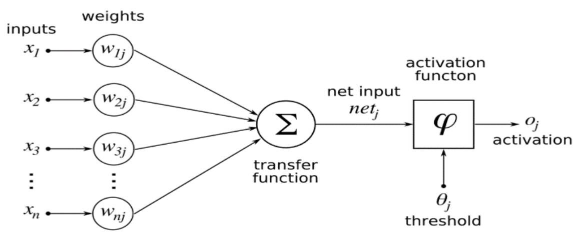

Fig. 1. Mathematical non-linear Model of Neurons

In recent years a lot of research has been done on the neural network to predict stock prices. One of the first studies was carried out by Kimoto and colleagues [22] who predicted ANN on the Tokyo Stock Exchange Index. The research that predicted stock prices with ANN had also been conducted in one of the stock industry sectors in Indonesia. This study found that in making stock price predictions using time series data or historical data, this research succeeded in predicting stocks with historical data today and data the previous day. In this study also utilize a backpropagation algorithm, this is done to get a good level of accuracy [5].

One of the supervised learning algorithms utilized in making predictions is backpropagation. ANN backpropagation is the gradient descent method to minimize the total square error in the output of the network calculation results [23]. In this process training is conducted to find a set of weights and bias values (trial and error) to get the results closest to the target value, this process is repeated until the most optimal set of weights and bias values is obtained [24].

C. *Genetic Algorithm*

The concept of Genetic Algorithms (GA) is inspired by the process of evolution in nature [24], where better individuals are able to survive so that the individual be the optimal solution to a problem. GA's have been widely utilized to solve complex problems. The process in GA begins with the initialization stage, which is to create random individuals who have a certain arrangement of genes chromosomes. This chromosome represents the solution to the problem. The next stage is reproduction to produce offspring from individuals in the population. This step of calculating fitness is called the evaluation stage. The final stage is selection, namely choosing individuals from the population set and offspring. Individuals who are selected are kept alive in the next generation [25].

There are several studies that have applied GA's to the recommendation system for stock portfolio selection [10, 11, 25, 26]. Shrivastava and Singh [25] formed a portfolio with GA's by utilizing historical data from the Bombay Stock Exchange (India). Historical data from these stocks is utilized to determine the rate of return of these stocks. This rate of return becomes input to the fitness function of the GA. Research on the formation of portfolios with GA's has also been conducted with data on Indonesian stocks. Wahyuni *et al.* [11] constructing a portfolio with 4 shares listed on the Indonesia stock exchange. In this study, the calculation of a Single Index Model (SIM) was utilized as input from the fitness function of the GA. The results of the proportion of each share produced by the SIM are utilized to become chromosomes in the process of GA's. In this study, the results of the proportion of GA's were able to produce higher rates of return and lower risk of the SIM.

III. METHODOLOGY

In this research, we use a sample of 38 stocks from 45 stocks listed in LQ45 Indonesian Stock Exchange. These 38 selected stocks are stock indexes that have listed for the past 10 years. LQ45 index consists of the company with high liquidity. Historical stock data collected from Yahoo Finance with a total data of 2464 days of stock data from 6th October 2008, to 21st September 2018. The Historical stock data consist of opening prices, highest prices, lowest prices, closing prices, and stock trading volume. We conducted this research based on the research framework shown in Figure 2.

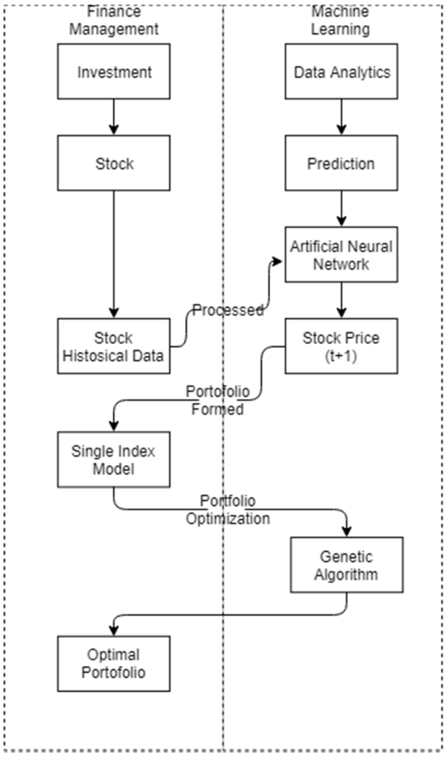

Fig. 2. Research Framework

A. Stock Prediction with Artificial Neural Network

The stock price prediction uses ANN using multi-layer perceptron model with single hidden-layer. The input variable utilized are 10: opening price (t-1 & t), daily highest price (t-1 & t), daily lowest price (t-1 & t), closing price (t-1 & t), and transaction volume of the day (t-1 & t). while the output layer is the closing price the next day (t+1). Figure 3 show network architecture in this study.

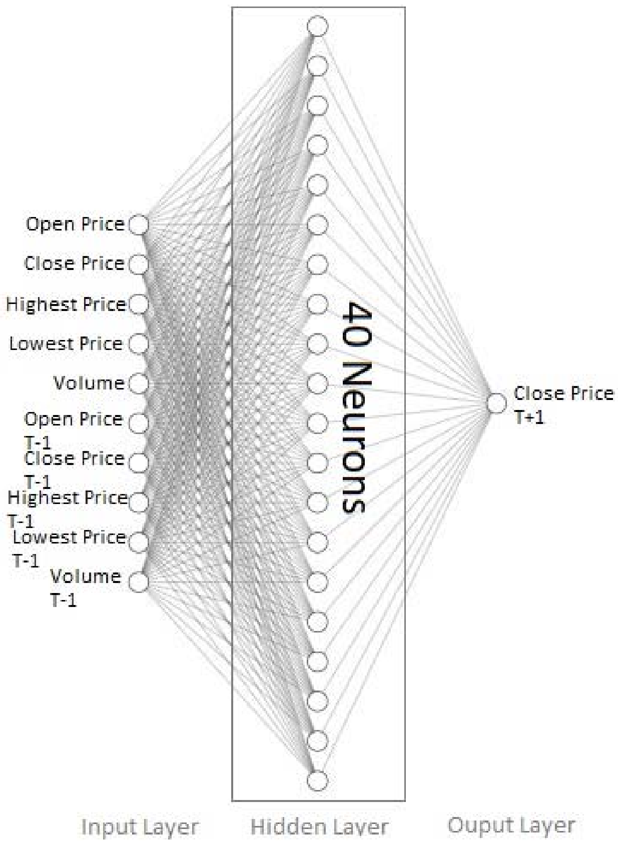

Fig. 3. Neural Network Architecture

We utilize historical data of the day and historical data of the previous day to get higher accuracy in making predictions with time series data. We also normalize the input and target patterns at certain intervals that aims to make the training process more efficient because synaptic weights on neurons are usually made in small intervals, for example [-1, +1].

Along with the principle of machine learning. The dataset was divided into a training dataset and testing dataset with the proportion 80 for training and 20 for testing. in our study a training dataset containing 7 years and 12 days of stock data, and 1-year testing datasets and 128 days of stock data ANN prediction results are validated by calculating the error ratio. calculation of the error ratio used Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). MAE is the absolute difference between predicted prices and actual prices, while MAPE is a MAE calculation in the form of a percentage.

B. Portfolio Formation using Single Index Model

In making a portfolio with a SIM, the results of the stock price prediction with ANN are carried out several calculations such as the expected return, variance, and standard deviation. From the results of the calculation, 7 stocks have a negative expected return. Then the sample utilized to make a portfolio based on a Single Index Model (SIM) becomes 31 stocks. The first step that must be done in SIM is measuring the Excess Return to Beta (ERB) for each stock. ERB shows the relationship between the return and the risk.

The optimal portfolio contains stocks with an ERB value that is still higher than the cut-off rate. The last ERB, whose value is still higher than the cut-off level, is the last limit of shares entering the portfolio. Each stock in the portfolio has its own proportion. each proportion is a factor in calculating the expected portfolio return and portfolio risk. Fig. 4 shows workflows performed by the SIM.

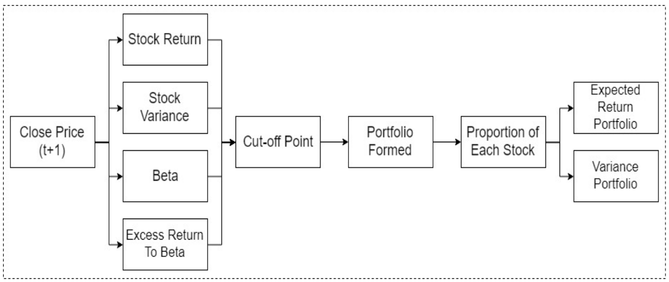

Fig. 4. Single Index Model Workflow

C. Portfolio Optimization using Genetic Algorithm

In optimizing the stock portfolio with GA, the proportion of shares formed on SIM is represented as a chromosome representation. after the chromosome representation is formed, the parent selection process is done by calculating the fitness value of each individual. the reproductive process is done by crossover and mutation. The reproductive process was also carried out in several population trials to get the best individuals. The best individuals are individuals with a generation that has the highest average fitness value. Figure. 5 shows the GA process workflow, which is done repeatedly until it reaches the stopping criteria in the generation with the highest fitness value.

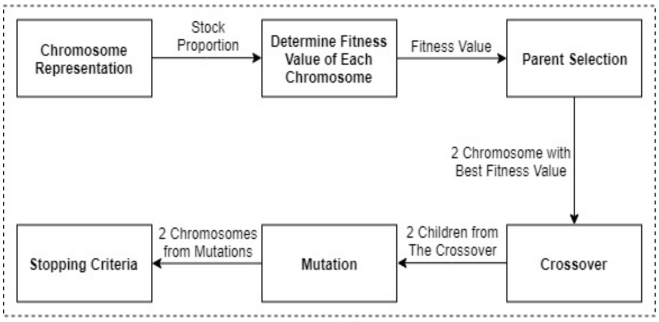

Fig. 5. Genetic Algorithm Process Workflow

The GA process can be elaborated using the following steps:

1. *Chromosome Representation*. Chromosomes are filled with original values, namely the proportion of each stock in the portfolio. Each chromosome must have a proportion equal to 1. The example of chromosome representation is able to be seen in Table I.

TABLE I. THE SAMPLE OF CHROMOSOME REPRESENTATION.

SMGR	GGRM	INKP	UNVR
0.35	0.15	0.27	0.23

2. *Fitness Value.* The aim of making a portfolio is to get an optimal level of return and a low level of risk. Therefore, the formula of the risk and the return is utilized as a fitness function, where higher fitness values are better. The expected return portfolio and the risk portfolio obtain from the SIM calculation.

$$Fitness\ Value = \frac{Expected\ Return\ Portfolio}{Risk\ Portfolio} \quad (1)$$

The purpose of optimization in equation (1) is to produce the best return with the lowest risk. Therefore, in equation (1) the return becomes a numerator and the risk becomes the denominator.

3. *Parent Selection.* The objective of parent selection is to get chromosomes with the highest fitness value in the population, to become parents in the next generation process. From the selection results, selected parents undergo the next generation process and the rest die or are eliminated. The parents formed are carried out in the process of crossover and mutation.

4. *Crossover.* This process is utilized to produce new individuals (offspring) with genes that are different from previous individuals, namely parents. We use an extended intermediate crossover. In this crossover, the crossover produces two new children. The number of offspring generated in the crossover process is the crossover rate (cr) x population size (n). Suppose that P1 and P2 are two parent chromosomes, then offspring C1 and C2 is able to be generated as follows:

$$C1 = P1 + \alpha(P2 - P1) \quad (2)$$

$$C2 = P2 + \alpha(P1 - P2) \quad (3)$$

The value of α is arranged randomly at predetermined intervals [0, 1].

5. *Mutation*. This process genetically modifies the child's chromosome as a result of the crossover operation. Mutations are based on probability. To do this process, reciprocal exchange mutations are utilized. This mutation randomly selects two positions (exchange point / XP) on the parent chromosome and then exchanges values in each position.

6. *Stopping Criteria*. The stopping criteria are performed on the number of generations that have the highest average fitness value.

IV. RESULTS

A. Stock Prediction using Artificial Neural Network

After conducting several experiments with different network architectures, Table II shows training errors from several network architectures.

TABLE II. TRAINING RESULTS

Number of Neurons in the Hidden Layer	Error Training	Accuracy
20	0.035	0.98279
30	0.025	0.98304
40	0.017	0.98414

The network architecture that produces the prediction model with the smallest training error is 10 input neuron - 40 hidden neuron - 1 output neuron, as the result we use the 10-40-1 architecture to predict stock prices. The table shows a comparison between the actual stock price and the predicted stock price.

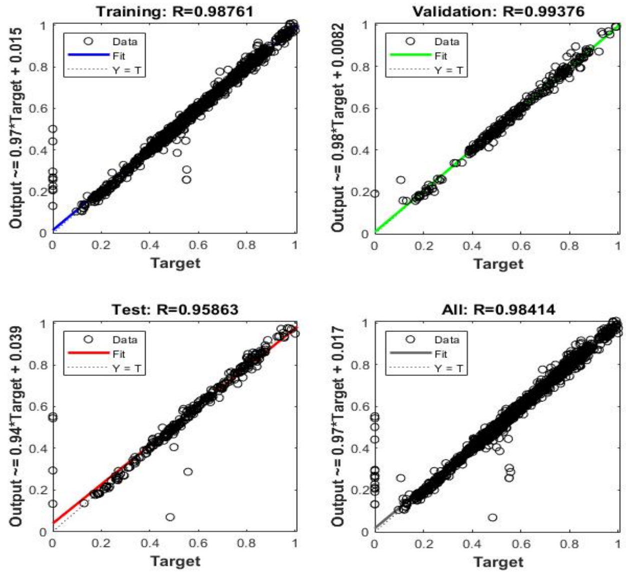

Fig. 6. Plot Regression with 1 hidden layer (40 hidden neuron)

Figure 6 shows that most results are in the fit line, although there are still a number of outliers. It also shows predictions made by ann according to the actual data.

TABLE III. SAMPLE OF EMPIRICAL RESULTS USING 10-40-1 NEURAL NETWORK PREDICTIVE MODEL

Sample Period	SMGR Stock	
	Actual Price	Predicted Price
21/10/2016	9975	9988.78
24/10/2016	10150	9922.67
25/10/2016	10075	10099.62
26/10/2016	10075	10053.7
27/10/2016	9975	10061.94
28/10/2016	9850	9902.99
31/10/2016	9500	9813.49
1/11/2016	9450	9431.39
2/11/2016	9275	9632.4
3/11/2016	9275	9337.17

Table III shows the difference between the ANN prediction results and the actual stock price. It implies that the ANN prediction results are similar to the actual price of the stock.

TABLE IV. AVERAGE ERROR RATIO FROM PREDICTION OF ARTIFICIAL NEURAL NETWORK

Average 38 Stock Error Ratio	
MAE (Rupiah)	**MAPE**
485.96	5.60%

Table IV shows the mean of Mean Absolute Error and Mean Absolute Percentage Error from each sample stock. the average error of the MAE shows only IDR 485.96. -, this shows a small error rate. Reinforced with The Mean of MAPE value does not exceed 6%, which mean the prediction of ANN 10-40-1 has low error value.

B. Portfolio Construction based on the Single Index Model

Table V shows the results formed in a stock portfolio with the SIM is a combination of 20 selected shares from 31 initial shares. 20 shares are chosen based on the ERB value, whose value is greater than the cut-off point value. The cutoff point is the value used as the stock limit included in the portfolio. With a SIM, generate a portfolio with expected returns of 0.28% and a risk of 1.86%.

TABLE V. PROPORTION OF FUNDS, RETURNS, RISKS OF PORTFOLIO BASED ON THE SINGLE INDEX MODEL

Stock	Proportion	Stock	Proportion
ADRO	0.88%	ITMG	0.24%
AKRA	3.84%	JSMR	3.50%
ANTM	31.50%	KLBF	2.16%
BBNI	0.54%	MEDC	0.34%
BRPT	0.14%	MNCN	0.39%
BSDE	0.13%	PTBA	0.50%
ELSA	3.64%	SCMA	0.15%
GGRM	1.63%	SMGR	31.76%
INDF	2.41%	UNTR	1.16%
INTP	8.88%	UNVR	6.20%
Expected Return Portfolio		**0.28%**	
Risk Portfolio		**1.86%**	

C. Portfolio Optimization using Genetic Algorithm

Genetic algorithms are stochastic methods that produce different results each time it is run. Therefore, each experiment is carried out 5 times and calculates the average fitness value in each process be. In the first experiment, a number of population sizes were tested. Population size is arranged in the range of 100 to 2000 chromosomes, with a step of 100 each.

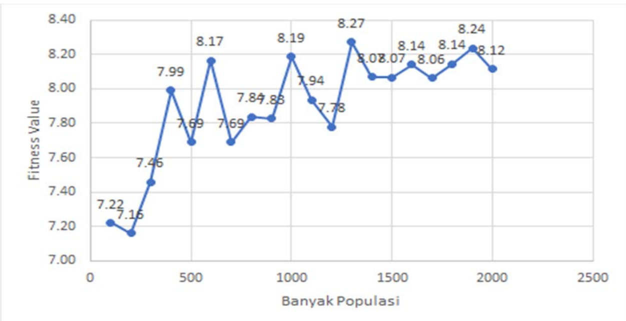

Fig. 7 Comparison of Average Fitness Value from Several Population Sizes

Fig. 7 shows that the highest average fitness value is when the population reaches 1300 chromosomes. The population size obtained in this experiment is the optimal population utilized to determine the proportion of the optimal stock portfolio. This population size is utilized in the next experiment. This experiment was conducted to get the generation with the highest fitness value. The size of the generation utilized in this experiment is from the range of 100 to 2000.

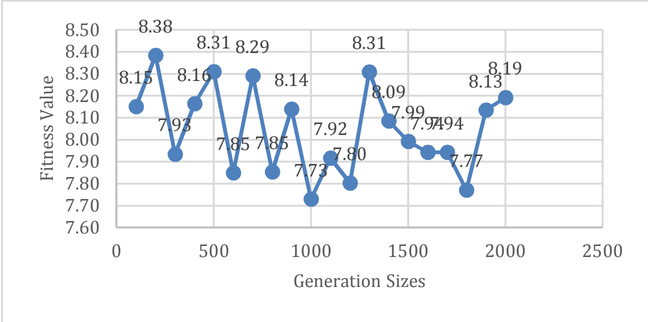

Fig. 8 Comparison of Average Fitness Values in A Number of Generations

Fig. 8 shows that the average fitness value is highest obtained when it reaches the 200th generation. This makes the next experiment use stopping criteria in the 200th generation because when it reaches the 200th generation it has achieved the most optimal fitness value.

The last experiment is to test the crossover rate (cr) and mutation rate (mr), and in this experiment using 1300 populations with stopping criteria in the 200th generation. The combination of cr and mr is equal to 1.

TABLE VI. RESULTS IN COMBINATION OF CROSSOVER AND MUTATION PROBABILITY

Crossover Rate	Mutation Rate	Fitness Value
0.1	0.9	8.33
0.2	0.8	8.30
0.3	0.7	8.02
0.4	0.6	8.35
0.5	0.5	7.87
0.6	0.4	8.00
0.7	0.3	8.24
0.8	0.2	7.95
0.9	0.1	7.92

Table VI shows that the combination of cr and mr with the highest fitness value is in the combination of crossover rate 0.4 and mutation rate 0.6. It is able to be concluded that the best combination of crossover rate and mutation rate is 0.4:0.6. With all the experiments above, the most optimal combination of proportions for an optimal portfolio with the GA is obtained.

TABLE VII. PROPORTION FUNDS, RETURNS, RISKS OF PORTFOLIOS OPTIMIZATION FROM GENETIC ALGORITHM

Stock	Proportion	Stock	Proportion
ADRO	2.2%	ITMG	2.68%
AKRA	1.8%	JSMR	2.2%
ANTM	2.12%	KLBF	1.84%
BBNI	2.56%	MEDC	4.64%
BRPT	15.64%	MNCN	17.2%
BSDE	10.08%	PTBA	6.44%
ELSA	6.36%	SCMA	9.36%
GGRM	3.16%	SMGR	3.84%
INDF	2.44%	UNTR	2.68%
INTP	1.36%	UNVR	1.4%
Expected Return Portfolio		**1.42%**	
Risk Portfolio		**0.15%**	

Table VII shows that from all the above experiments a portfolio with a proportion of stocks is generated as above and produces a portfolio return of 1.42% and the portfolio risk of 0.15%.

Figure 9 shows the comparative results of SIM and GA based on the portfolio expected return and portfolio risk generated. Fig. 9 also shows that GA is able to optimize the portfolio from the SIM. The optimal result of GA optimization portfolio can be seen from the value of a larger portfolio expected return and the risk of a smaller portfolio than that generated by a SIM.

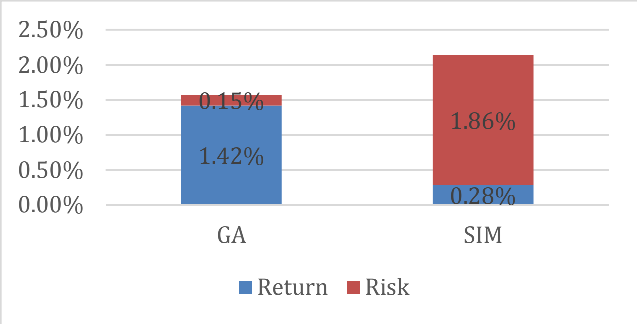

Fig. 9 Comparative Results of SIM and GA

V. CONCLUSION

Building accurate stock price predictions is important in helping investor decision making. Accurate predictions help investors build good optimal portfolio predictions. This research optimizes stock portfolios with prediction data. This aims to determine the condition of the optimal portfolio of the future.

Based on the research we conducted, ANN successfully predicts daily closing prices quite accurately. This is evident from the results of 2 low erosion ratios. MAE results were 485.96 and MAPE results were 5.60%.

This study proves that genetic algorithms have succeeded in optimizing index of stocks made by the previous SIM. GA's are able to find the most optimization index of stocks in a portfolio formed by the financial methodology. The portfolio returns and risks generated by our methodology using GA are better than what is practiced by SIM. This is evidenced by higher returns and lower risks generated by GA. GA optimization results have a portfolio return of 1.42% and portfolio risk of 0.15%, while SIM only has a portfolio return of 0.28% and portfolio risk of 1.86%.

Therefore, the prediction of stock portfolios has the potential to support investors in making investment decisions by offering a condition of a portfolio of stock combinations in the future compared to predictions consisting of only one stock. As future research, we propose to expand the time horizon and the number of shares built by the portfolio.

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