DECISION SUPPORT SYSTEM FOR STOCK TRADING USING FUZZY LOGIC AND GENETIC ALGORITHM

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***Abstract*— Investors use technical analysis to make buy/sell decisions on stock trading. The funds allocated to the stock may be diversified to minimize risk. This paper discusses on the design and implementation of a decision support system for stock trading that uses fuzzy logic to generate buy/sell recommendation and genetic algorithm to allocate portfolio. The system is then tested using data from the Indonesia Stock Exchange.**

Keywords—fuzzy logic; technical analysis; genetic algorithm; stock portfolio;

I. INTRODUCTION

The development of information technology has given a lot of positive effects on the financial sector such as stock trading. In the stock market, millions of stocks are being traded daily, this process is made efficient using computers and software.

Trading in stock is highly profitable compared to other investment instruments, but it is also highly risky due to the volatility of stock prices. To gain as much profits as possible while reducing as much risk as possible, stock traders make an analysis of the stock first. Analysis can help predict price movements in the future. Analysis can be done in two ways, using technical analysis or fundamental analysis. Technical analysis uses historical stock prices to predict future price trends while fundamental analysis uses companies' financial reports to make an estimate of the companies' value and determine whether the current prices are overvalued or undervalued. This paper discusses the usage of technical analysis in a recommendation system for stock trading.

Technical analysis assumes that prices move according to current trends or patterns for a limited amount of period. Changes in these trends can be observed using technical indicators or chart patterns, which can be calculated from historical price and volume data. The success of this analysis depends on how one interprets the signals. Because technical analysis uses probabilities, most of the time the solution isn't a clear cut answer of whether to buy or sell. Also, different traders can interpret the technical signals differently. In this instance, fuzzy logic can be useful to model the process of evaluating technical indicators to analyze current price trends. Based on the results, a recommendation on whether to buy or sell a stock can then be generated. In this paper we propose a fuzzy inference system to give recommendation on buy/sell decisions in trading stocks.

Besides making buy/sell decisions, traders also usually encounters a problem on how to diversify his investments. Diversification is the practice of allocating funds on a variety of investments to reduce the exposure of any one particular asset. A trader would want to invest in more than one stock to reduce risk. Given a set of assets or stocks in a portfolio, diversification is the problem of optimizing how much funds goes into which stock so that we can gain the maximum profits and the minimum risk. Each stock is given a weight to determine how much fund goes into that stock. We then try to find the optimal combination of weights of all the stocks in one portfolio. Genetic algorithm is particularly useful for optimization problems like this. This paper will also discuss the usage of genetic algorithm to optimize stock portfolio allocation.

By using fuzzy logic to make recommendation on buy/sell decisions and genetic algorithm to optimize portfolio, we can make a decision support system for stock trading. This paper discusses on designing and building such system. The system will then be tested using data from the Indonesia Stock Exchange. In the following chapters we discuss the theory behind the system followed by the design and implementation of said system and we finish with an analysis of the results and conclusions.

II. FUZZY LOGIC

Fuzzy logic is a generalization from classical logic based on fuzzy set theory. In a classical set, every entity is categorized into either a member of that set or not, but in a fuzzy set there is no clear definition on what separates entities into member or not member. Instead the membership of an entity is determined using a membership function. This models the thought process of humans better.

The definition of fuzzy set according to Zadeh is explained in the following. Let us assume that X is a set with generic element x so that X = {x}. A fuzzy subset A of X is characterized by the membership function $fA(x) \rightarrow [0,1]$. The value of fA(x) represents membership degree. The closer the value of fA(x) is to 1 the higher the membership degree. In a classical set, the only allowed value of fA(x) is 0 if x isn't a member of A or 1 if x is a member of A.

Membership function can take different forms such as triangular, gaussian, sigmoid, etc. The membership function used is chosen specifically to suit the needs based on the problem encountered.

Operation on fuzzy set is based on operation on classical set. There are three main operations, union, intersection, and complement. Union operator corresponds to OR operator, intersection operator corresponds to AND operator, and complement operator corresponds to NOT operator. The result of these operation is a new membership degree.

In classical logic, a proposition can only be either true or false. This paradigm creates a problem when the truth value of a proposition is not known for sure. That is why the concept of two-valued classical logic is expanded into n-valued logic or multivalued logic. Fuzzy logic is an infinite-valued logic where the degree of truth is represented by all real numbers in the range [0,1]. This logic is also called Lukawiecz logic [1].

A simple proposition in fuzzy logic has the form:

$$p:V \text{ is } F \tag{1}$$

where V is a variable that has the value v and F is a fuzzy set on V that represents a fuzzy predicate such as high, expensive, etc. Let us assume that v is included in the set F with a membership degree F(v), this membership degree is interpreted as a truth degree T(p) from proposition p, so that we have

$$T(p) = F(v) \tag{2}$$

For every v from variable V on proposition p. In other words, T is a fuzzy set that determines membership degree F(v) for every v of variable V.

Linguistic variable is one of the components in fuzzy logic which is a variable that has linguistic value and associates with a fuzzy set. This linguistic variable can be words from natural language that explains the corresponding variable. A linguistic variable in fuzzy logic has the components:

1. The name of linguistic variable
2. The domain of quantitative value
3. Semantic rule

A fuzzy inference system is a system that process data and creates conclusion from that data in a condition of ambiguity and uncertainty using fuzzy logic. In the inference process, a fuzzy rule is specified in a proposition which has the scheme

IF antecedent THEN consequent

Each antecedent and consequent in a proposition can have one or more variables with connectives AND, OR, or NOT. The phases of fuzzy inference system is explained below:

1. Fuzzification, the process of converting crisp input into fuzzy input using membership function.
2. Determining the truth value of antecedent with fuzzy logic operations AND, OR, or NOT. The result is called rule strength.
3. Calculating the consequent from fuzzy rule by combining rule strength of the antecedents from the previous phase with membership function of the output.
4. Combining all outputs from fuzzy rules into one fuzzy output distribution. This is done using the OR operator on all outputs.
5. Defuzzification, the process that converts the fuzzy output distribution into a crisp value based on membership function of the output. This can be done using the centroid method.

III. Genetic Algorithm

Local search algorithm is an algorithm that operates using a current node and traverse the neighboring nodes without storing the path taken into memory. Local search algorithm is very useful in a search where the path to the solution is not important such as in the case of optimization problems. The benefit of local search is that not much memory is needed and the solution can be found from a large state space. Genetic algorithm is one of local search algorithms.

Genetic algorithm operates by combining two parent states into one successor state. This process begins with a number of states that is generated randomly, the set of these states is called population. Each state is represented by an alphabet string that usually takes the form of binary string. Each state is then evaluated using a fitness function. The fitness function must return a better value for more a desirable state. The probability of a state to be included in the next phase depends on the fitness value. In the selection phase, two pairs of state is selected based on fitness value. In the crossover phase, a crossover point is selected randomly from a position in the string. The successor state is produced by doing a crossover on the parent states. The last phase is mutation where every digit has a small probability to mutate randomly.

Selection process is the process of choosing individuals from population for the next phase, which is crossover. There are a variety of selection types that can be used, that is:

a. Elitism Selection

In an elitism selection, the best individuals are retained for the next generation without modification.

b. Roulette-Wheel Selection

In a roulette wheel selection, each individual is given a fitness value. The probability of that individual to be chosen is calculated using the following formula:

$$p_i = \frac{f_i}{\sum_{j=0}^{N} f_i} \tag{3}$$

c. Tournament Selection

In a tournament selection, a number of individuals are selected from the population. A tournament is executed on these individuals by selecting the best individuals using fitness value. This tournament is done a few times to choose the individuals that is going to be used in the crossover phase.

The crossover phase is a process that produces new individuals by recombining the genes or bits in a pair of parent individuals. There are a variety of crossover types that can be used, that is:

1. Single Point Crossover

In a single point crossover, a point in the parent chromosome is selected randomly. Every bit after this point is switched between the two parents to create two children individuals.

2. Double Point Crossover

In a double point crossover, two points instead of one is selected.

3. Cut and Splice

In a cut and splice, the points selected on the parents is on different positions resulting on children individuals with different lengths.

4. Uniform Crossover

In a uniform crossover, the chromosome bits from parents are switched according to a mixing ratio. Mixing ratio controls how much bits are being switched between the two parents.

The mutation phase converts one or more bits on the chromosomes. This process is used for diversifying the individuals in a population. The variety of mutation types that can be used are:

1. Bit String Mutation

In a bit string mutation, bits on the chromosomes are inverted randomly.

2. Flip Bit

In a flip bit mutation, all bits on the chromosomes are inverted.

3. Boundary

In a boundary mutation, the genes are converted to an upper bound or lower bound value. His can only be done on chromosomes that has integer or float genes.

IV. STOCK ANALYSIS

Stock is a type of security that signifies ownership in a corporation and represents a claim on part of the corporation's assets and earnings. The Profits of the corporation is shared with the stock holders in the form of dividend the more stocks owned the more dividend received. Stock has the form of a certificate paper, but nowadays these certificates are no longer held physically by the investor because all transactions are recorded digitally.

The prices of stocks change daily through the effects of supply and demands. The more the demands the higher the price becomes. The more the supply the lower the price becomes. The basic principle is that the movement of price indicates how much is the corporation valued by investors.

There are two methods of analyzing stocks, technical and fundamental. Fundamental analysis observes the effects of economic factors to prices. While technical analysis observes historical price data to predict price movements in the future. This paper will only include technical analysis. The benefits of technical analysis is that it can be done quickly, but on the other hand it can only be used when there are no extreme external factors affecting the market.

An important tool in technical analysis is the technical indicators. Indicators are the statistics that are used to measure the current economic and financial condition and predict future trends. Technical indicators are calculated mathematically based on historical prices and volume data.

Moving average is one of the most popular technical indicators. Moving average is the average of a number of data in a certain time period. This average moves because only the latest data are used in the calculation, so that with each time unit the data used are renewed and the average is recalculated [2].

Moving average can smoothen the price movements by filtering noise from random price fluctuations. Moving average is a lagging indicator because it is based on past data. There are a variety of moving indicators that are going to be explained in the following:

a. Simple moving average (SMA)

SMA is calculated from the average of closing prices from recent data. The formula used is:

$$SMA = \frac{p_i + p_{i-1} + \cdots + p_{i-(n-1)}}{n} \quad (4)$$

b. Linear Weighted Moving average

Linear weighted moving average gives bigger weight on more recent data. The formula used is:

$$LWMA = \frac{wp_i + (w-1)p_{i-1} + \cdots + 2p_{(i-w+2)} + p_{(i-n+1)}}{w + (w-1) + \cdots + 2 + 1} \quad (5)$$

c. Exponential Moving average (EMA)

Exponential moving average (EMA) is a type of moving average that gives bigger weight on more recent prices to make it more responsive to changes and reduce lag. The formula used is:

$$EMA = (P * \alpha) + (Previous\ EMA * (1 - \alpha)) \quad (6)$$

Where P is Current Price, α is smoothing factor = 2/(1+N), and N is the time period. The value of previous EMA in the first calculation can use SMA value.

The longer the time period used in moving average the bigger the lag. A 10-day moving average will follow price movements more quickly than a 100-day moving average. Therefore the time period used should be evaluated according to the needs of the analyst

The movement direction of moving average can be used to identify the movement of trends. A rising moving average represents a rising price trend and a falling moving average represents a falling price trend. Two moving averages used in the same time can produce a crossover signal. This crossover involves one shorter and one longer moving average. A bullish (rising) Crossover happens when the shorter moving average cross above the longer moving average. This signifies a change in price trend to bullish (rising prices). A bearish (falling) Crossover happens when the shorter moving average cross below the longer moving average. This signifies a change in price trends towards bearish (falling prices).

Moving Average can also be used as an oscillator called the Moving Average Convergence Divergence (MACD). MACD has two lines, that is MACD line and signal line. MACD line is calculated from the difference between two EMA on closing price. Usually the period used are 12-day and 26-day EMA. The signal line is calculated from the 9-day EMA of the MACD.

Relative strength index (RSI) is a technical indicator that compares the amount of profit and loss to determine if a stock is overbought or oversold. The formula used is:

$$RSI = 100 - 100/(1 + RS) \tag{7}$$

Where RS = Average gain/Average loss.

Stochastic oscillator (SO) is based on the observation that with rising prices, the closing price is closer to the highest high of the day. Inversely on a falling trend, the closing price is closer to the lowest low of the day. There are two lines used in this indicator, the %K line and the %D line. The formula used for %K line is:

$$\%K = 100[C - L(N)/H(N) - L(N)] \tag{8}$$

Where C is last close price, L(N) is lowest low of period N, and H(N) is highest high of period N. The %D line is a moving average of the last 3 days of %K.

On balance volume (OBV) is a momentum indicator that uses volume to predict price changes. The formulas used is:

$$OBV = OBV_{prev} + \begin{cases} volume; jika\ close > close_{prev} \\ 0; jika\ close = close_{prev} \\ -volume; jika\ close < close_{prev} \end{cases} \tag{9}$$

Portfolio is a set of financial assets held by an individual or corporation. The process of selecting portfolio is based on evaluating expected return as something desirable and variance of return as something undesirable. This is called the "mean-variance" rule [5].

V. Decision Support System

The definition of decision support system according to Scott Morton is an interactive system based on computers that makes decisions using data and model to solve unstructured problems [6].

According to Turban, Aronson, and Liang, decision making is the process of choosing between a few alternatives of action to achieve one or more goals [7]. There are four phases to decision making, intelligence, design, choice, and implementation.

1. Intelligence

This phase begins with identifying the goal and objective of the problem that needs to be solved. In this phase the problem is identified and defined by monitoring and analyzing data.

2. Design

This phase includes finding or developing and analyzing the possible actions to take, this includes understanding the problem and testing alternate solution. A model of the problem is created, tested, and validated.

3. Choice

This is a critical phase where a decision is taken and commitment to follow through a certain action is made. This includes finding, evaluating, and recommending a possible solution.

4. Implementation

In this phase the solution that was chosen is implemented and changes to the organization are executed.

Because there is no consensus on the definition of decision support system there is no agreement on the characteristics and standard abilities of a decision support system. Below are a set of ideal characteristics of DSS.

1. Supports decision making in solving semi-structured or unstructured problems by combining human judgement and computer information.
2. Supports all level of managerial.
3. Supports individuals or group.
4. Supports interdependent or sequential decisions.
5. Support all phases of decision making.
6. Supports a variety of decision making process and style.
7. Adaptive to time
8. User friendly
9. Raises the effectivity of decision making as opposed to its efficiency.
10. Gives control fully to the user.
11. Lets the user develops and modify the system.
12. Uses model to analyze decision making situation.
13. Gives access to a variety of data sources, format, and types.
14. Can be used as standalone tool or by the whole organization.

VI. System Design

The system that is going to be built is used to help a stock trader to make decisions on buying or selling stocks. There are four main function to this system:

1. Stock data monitoring

The system needs to be able to download the latest stock price data and show it as a chart.

2. Buy/Sell Recommendation

Fuzzy inference system is used to give a recommendation on what action to take on a stock. The trader chooses a stock to analyze and the system generates buy/sell signals using fuzzy inference system.

3. Portfolio allocation

The user can choose a number of stocks to include in a portfolio. The system can then give a recommendation on how much funds to invest on each stock using genetic algorithm.

4. Evaluating the recommendation result

The top recommended stocks from fuzzy system can be used as input for the genetic algorithm. The portfolio will consist of only the top recommended stocks from fuzzy system. The result is then tested on market data.

The data used is data downloaded from Yahoo! Finance site. Only stocks listed in LQ45 from Indonesia Stock Exchange are used. This is because The LQ45 list consists of the most liquid stocks in the market. The data downloaded are in the form of csv file.

The fuzzy inference system uses four technical indicators as input. The technical indicators are MACD (Moving Average Convergence Divergence), RSI (Relative Strength Index), SO (Stochastic Oscillator), and OBV (On Balance Volume). Mamdani inference system is used. First, the four indicators are calculated based on historical price data. Then the four indicators are transformed into fuzzy input using defined membership function. The system then uses inference rule to process the input into output that is then defuzzified into crisp real value that represents the recommendation of action to take.

Each technical indicator has rules that determines the buy/sell signals The rules are:

1. IF MACD is HIGH THEN BUY
2. IF MACD is LOW THEN SELL
3. IF RSI is HIGH THEN SELL
4. IF RSI is MEDIUM THEN HOLD
5. IF RSI is LOW THEN BUY
6. IF SO is HIGH THEN SELL
7. IF SO is MEDIUM THEN HOLD
8. IF SO is LOW THEN BUY
9. IF OBV is HIGH THEN BUY
10. IF OBV is LOW THEN SELL

Based on these ten rules we create inference rules. The inference rules used are as follows:

1. IF MACD is HIGH and RSI is HIGH and SO is HIGH and OBV is HIGH THEN BUY

2. IF MACD is HIGH and RSI is HIGH and SO is HIGH and OBV is LOW THEN BUY

3. IF MACD is HIGH and RSI is HIGH and SO is LOW and OBV is HIGH THEN BUY

4. IF MACD is HIGH and RSI is LOW and SO is HIGH and OBV is HIGH THEN BUY

5. IF MACD is LOW and RSI is HIGH and SO is HIGH and OBV is HIGH THEN BUY

6. IF MACD is LOW and RSI is LOW and SO is HIGH and OBV is HIGH THEN HOLD

7. IF MACD is LOW and RSI is HIGH and SO is LOW and OBV is HIGH THEN HOLD

8. IF MACD is LOW and RSI is HIGH and SO is HIGH and OBV is LOW THEN HOLD

9. IF MACD is HIGH and RSI is LOW and SO is LOW and OBV is HIGH THEN HOLD

10. IF MACD is HIGH and RSI is LOW and SO is HIGH and OBV is LOW THEN HOLD

11. IF MACD is HIGH and RSI is HIGH and SO is LOW and OBV is LOW THEN HOLD

12. IF MACD is LOW and RSI is LOW and SO is LOW and OBV is LOW THEN SELL

13. IF MACD is HIGH and RSI is LOW and SO is LOW and OBV is LOW THEN SELL

14. IF MACD is LOW and RSI is HIGH and SO is LOW and OBV is LOW THEN SELL

15. IF MACD is LOW and RSI is LOW and SO is HIGH and OBV is LOW THEN SELL

16. IF MACD is HIGH and RSI is LOW and SO is LOW and OBV is HIGH THEN SELL

The chromosome design is as follows, each stock has weight w that is represented as 8-bit binary string so that it has value ranging from 0 to 255. The shape of the chromosome is illustrated on the figure below.

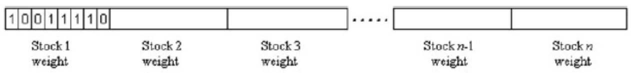

Figure 1 – Chromosome Design

The process of the genetic algorithm is as follows:

1. Initialize population randomly. The number of individuals used is 100.
2. Evaluate fitness function on each individuals.
3. Choose individuals with the best fitness value. The selection uses elitism selection, where the best individuals are retained for the next generation without modification.
4. Do crossover on the chosen individuals using single point crossover.
5. Do mutation on the resulting individuals.

6. Repeat process until termination condition is achieved.

There are two aspects on the basis of the fitness function. The first is to maximize return, the second is to minimize risk. Maximizing return can be done by calculating the expected return. Minimizing risk can be done by calculating variance.

From those two aspects, the fitness function is designed as follows:

$$f = \left[\sum_{i=1}^{n} w_i R_i\right] - \left[\sum_{i}\sum_{j} w_i w_j \sigma_{ij}\right] \qquad (10)$$

In the above formula, the first operand is used to maximize return while the second operand is used to minimize risk. The genetic algorithm is run to find the maximum fitness value.

VII. Implementation

The system is built as an application with the following limitations:

1. Stock price data is downloaded from finance.yahoo.com daily. The data is then stored in local offline database. The data used isn't real-time.

2. The portfolio allocation assumes that the user only needs to create new portfolio. The system doesn't process old portfolio which is currently held by the user.

The environment in which the application is implemented is as follows:

1. Operating system: Windows 10
2. Implementation tool: Microsoft Visual Studio 2015 and Notepad++
3. Programming language: C#
4. Framework: .NET Framework 4.5

The hardware specification used on testing is as follows:

1. Processor: Intel Core i7
2. Memory: 4 GB
3. Bit type: 64 bit

The main interface of the application is illustrated in the figure below. The main interface includes stock prices chart and recommendation of stock from the fuzzy inference system.

Figure 2 – Main Interface

The interface to the genetic algorithm is used to allocate funds into a maximum of 10 stocks. The genetic algorithm interface is illustrated in the figure below.

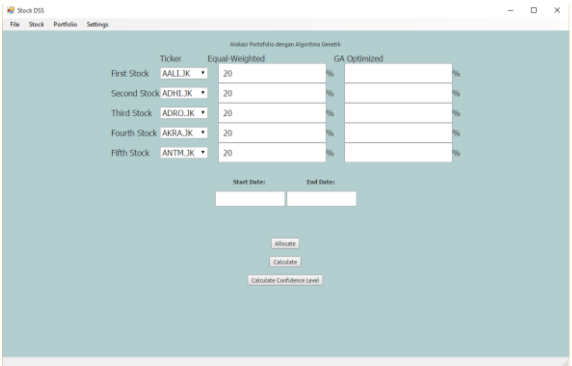

Figure 3 – Genetic Algorithm Interface

VIII. Testing And Analysis

There are two testing that needs to be done. The first is testing the accuracy of the recommendation from fuzzy system. The second is testing whether or not the genetic algorithm optimized portfolio can outperform an equally-weighted portfolio. The accuracy of fuzzy system is tested by counting the number of correct recommendation and calculating the percentage of correct recommendation out of all recommendations. The genetic algorithm portfolio is tested by comparing its returns with the returns of an equally-weighted portfolio.

The system is tested on the Indonesia Stock Exchange. The data used for testing is data of LQ45 stocks from 1 February 2012 to 13 November 2015.

The accuracy of fuzzy system is tested from counting the number of correct recommendations. Each correct recommendations is called a hit, while each wrong recommendation is called a miss. The percentage of hit is then calculated. Below are the results of testing.

Table 1 – Fuzzy Inference System Testing Results

Ticker	Hit	Miss	Hit Percentage
AALI	8	3	72.73%

ADHI	4	4	50%
ADRO	3	4	42.86%
AKRA	5	4	55.56%
ANTM	1	4	20%
ASII	2	1	66.67%
ASRI	6	3	66.67%
BBCA	8	2	80%
BBNI	7	4	63.64%
BBRI	8	1	88.89%
BBTN	6	4	60%
BMRI	4	2	66.67%
BMTR	4	1	80%
BSDE	7	4	63.64%
CPIN	6	3	66.67%
CTRA	5	4	55.56%
EXCL	6	3	66.67%
GGRM	9	2	81.82%
ICBP	7	1	87.5%
INCO	6	3	66.67%
INDF	4	1	80%
INTP	4	5	44.44%
ITMG	3	4	42.86%
JSMR	4	3	57.14%
KLBF	5	1	83.34%
LPKR	4	4	50%
LPPF	3	0	100%
LSIP	3	5	37.5%
MNCN	8	3	72.73%
MPPA	6	1	85.71%
PGAS	3	0	100%
PTBA	3	3	50%
PTPP	7	2	77.78%
PWON	8	2	80%
SCMA	5	2	71.43%
SILO	3	0	100%
SMGR	5	2	71.43%
SMRA	7	1	87.5%
SSMS	6	1	85.71%
TBIG	2	0	100%
TLKM	6	2	75%
UNTR	5	7	41.67%
UNVR	6	2	75%
WIKA	7	1	87.5%
WSKT	3	1	75%
TOTAL	232	110	69.64%

The genetic algorithm is tested by comparing the returns of genetic algorithm optimized portfolio with the returns of an equally-weighted portfolio. If the optimized portfolio is able to outperform the equally-weighted one, we consider it to be valid or accurate. Below are the results.

Table 2 – Genetic Algorithm Testing Results

Ticker	Optimized weight	Optimized Return	Unoptimized Return	Validity
AALI ADHI ADRO AKRA ANTM	AALI: 32.94% ADHI: 28.51% ADRO: 20.53% AKRA: 12.41% ANTM: 5.61%	15.72%	37.22%	Valid
ASII ASRI BBCA BBNI BBRI	ASII: 6.32% ASRI: 27.35% BBCA: 7.35% BBNI: 22.21% BBRI: 36.76%	22.82%	35.29%	Valid
BBTN BMRI BMTR BSDE CPIN	BBTN: 21.53% BMRI: 18.31% BMTR: 34.92% BSDE: 7.12% CPIN: 18.14%	43.84%	50.05%	Valid
CTRA EXCL GGRM ICBP INCO	CTRA: 33.33% EXCL: 4.87% GGRM: 24.06%	47.93%	51.46%	Valid

	ICBP: 18.87% INCO: 18.87%			
INDF INTP ITMG JSMR KLBF	INDF: 31.70% INTP: 4.07% ITMG: 5.05% JSMR: 24.68% KLBF: 34.50%	5.31%	9.85%	Valid
LPKR LPPF LSIP MNCN MPPA	LPKR: 13.17% LPPF: 25.89% LSIP: 21.30% MNCN: 2.96% MPPA: 36.69%	61.26%	84.93%	Valid
PGAS PTBA PTPP PWON SCMA	PGAS: 19.12% PTBA: 25.00% PTPP: 26.18% PWON: 20.88% SCMA: 8.82%	56.89%	71.21%	Valid
SILO SMGR SMRA SSMS TBIG	SILO: 16.60% SMGR: 2.39% SMRA: 24.83% SSMS: 25.90% TBIG: 30.28%	53.63%	56.95%	Valid
TLKM UNTR UNVR WIKA WSKT	TLKM: 11.55% UNTR: 26.79% UNVR: 12.02% WIKA: 25.48% WSKT: 24.17%	18.16%	24.20%	Valid

When the system is given input data on stock prices between 2012 to 2015, the result is that the recommendation from fuzzy system managed to be accurate 69.64% of the time. This shows that the fuzzy inference system can give quite good recommendation although far from perfect. There are a few factors that can contribute to this, among them are the fuzzy rule, the fuzzy set membership functions, or the technical indicators.

The result of genetic algorithm testing is that the optimized portfolio is able to outperform the equally-weighted portfolio for every case tested. The recommendation for portfolio allocation can then be used by the user as a guide on allocating funds to invest.

IX. Conclusion

The conclusions are as follows:

1. A recommendation system for buying and selling stocks can be built using fuzzy logic that receives technical indicators as input.

2. Optimizing stock portfolio allocation can be done using genetic algorithm that uses expected return and variance as criteria for fitness function. The chromosome is encoded from the weight of each stock.

3. The result from fuzzy inference system is that the system is able to give recommendation to the accuracy of 69.64% for the given test case.

4. The result from genetic algorithm is that the optimized portfolio is able to outperform equally-weighted portfolio for the given test case.

In the case that this system is going to be developed further in the future, some suggestions are made:

1. Testing for other technical indicators should be done to try to improve accuracy.
2. The criteria for genetic algorithm fitness function can be modified to include other things like liquidity to suit the needs of the investors.
3. Portfolio allocation should be improved to process currently held portfolio by the investors.
4. The application can be remade on web or mobile platform for easier usage.
5. The application can be improved to handle real-time data.

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