

Stock Price Prediction Model through Hybrid Approach with Fuzzy Logic Approach

Dhaha Praviandi Kuantan

Doctorate in Management, Bogor Agricultural University, Indonesia
Email : dhahagreat@gmail.com

Abstract: Decision making in financial investment especially the stock market is complex. It needs the expertise to understand information that affects the development of the financial sector. Stock investment also requires speed and accuracy of momentum. In addition, disciplinary factors to the investment rules that have been prepared are determinants of success in investing in the stock market. This is in line with BarberdanOdean (2001, 2002), Kahneman and Riepe (1998), Raghunathan and Corfman (2006) which showed that investors experience behavioral and cognitive bias to determine asset prices, so they tend to be mis-valuation. Therefore, a mechanism is needed that can help the process of making investment decisions in stocks as well as investment guidelines so that investors can increase the investment discipline. Currently, many trading algorithms have been developed to answer those needs. However, the algorithm is more technical in nature and has not included the fundamental aspects of the issuers or asset diversification as contained in Ijegwa, Rebecca, Olusegun and Isaac (2014). Besides, the lack of algorithm in the model of Ijegwa, Rebecca, Olusegun and Isaac (2014) has not separated the bubble and normal markets. This is important because in a market with bubble condition, the ability of technical indicators are decline. So the investment decisions are not right. In practice, investors also not only depend on one technical aspect, but hybrid by including macro-micro fundamental aspects and asset diversification. This study will build a more comprehensive algorithm by considering the fundamental aspects of macro finance, micro issuers, and diversification to complement the technical aspect (hybrid model) with fuzzy logic approach. In term of investor, this is expected to increase the reliability of the algorithm in predicting return. From a macro perspective, algorithms based on macroeconomic and micro-fundamentals are expected to contribute to financial system stability.

Keywords: *Fuzzy Logic, Stock Prediction, Hybrid Model*

I. INTRODUCTION

I.1 Background

Decision making in financial investment, especially in stock market is complex. This complexity is increasing in line with the development of financial instrument, economic innovation, digital finance and financial system integration. The previous economic system was built with the flow of data and information more structured and more direct because exclusive was issued by the authority institution. The implication is that the role of authorities tends to more easily influence the perception and behavior of economic actors.

Nowadays, we are dealing with a situation that is the opposite of the condition in the past. Today, we live in a world where data and information are no longer exclusively owned by official institution, but also made and disseminated by the society through various communication tools, in real time and no longer in the same direction.

These environmental changes make the perception and respond of economic actors easily change due to the large amount of data and information available. Behavior action of the economic actors change rapidly which result the rise of uncertainty. Based on economics prespective, this type of uncertainty comes from something unknown ("unknown uncertainty / unknown"). The response of economic actors becomes unpredictable.

In term of investors, this complexity arises from investor behavior that sometimes no longer rational. In financial science, real individuals are assumed to be rational in seeking information that is unbiased and formulates information to form an investment strategy to produce optimal investment performance. However, several studies show the opposite where stock prices are determined by

psychological factors which is irrational compared to fundamental rational factors.

Various literature from BarberdanOdean (2001, 2002), Kahneman and Riepe (1998), Raghunathan and Corfman (2006), show that investors experience the behavioral and cognitive bias to determine asset prices. Some of these psychological biases distort decision making. Cognitive bias is the human tendency to make systematic mistakes in certain circumstances based on cognitive factors. This kind of bias result is from processing information associated with psychology. Cognitive bias causes investors not to interpret information correctly and tend to overreact or react to new information. Individuals tend to rely too much on specific information and rely on one piece of information when making decision.

Responding to the complexity requires expertise in understanding financial information, the success of investment in stock market also requires speed, accuracy of momentum and discipline factors for the investment rules arranged to determine the success in investing to the stock market.

Therefore, a mechanism is needed to help the process of making investment decision in stock as well as investment guidelines so that investors can increase the discipline of investment. Currently, many trading algorithms have been developed to answer those needs. However, the algorithm is more technical in nature and has not included the fundamental aspects of the issuer or asset diversification as contained in Ijegwa, Rebecca, Olusegun and Isaac (2014).

I.2 Scope of the Research

The discussion in this paper is limited to fuzzy logic application in a more comprehensive stock prediction model. The choice of variables will be based on a fairly strong theoretical foundation. In this paper, the modeling solution is solved by the software namely matlab with the Fuzzy Logic toolbox.

I.3 Purpose of the Research

This research will build a more comprehensive algorithm by considering the fundamental aspects of macro finance, micro issuers, and diversification to complement technical aspect as found in Ijegwa, Rebecca, Olusegun and Isaac (2014). Therefore, the approach used hybrid term with fuzzy logic approach. In term of investor, this is expected to increase the reliability of the algorithm in predicting return. From a macro perspective, algorithms based on macroeconomic and micro-fundamentals are expected to contribute to financial system stability.

I.4 Research Gap and Research Novelty

The novelty of research designed to compare the preliminary research about stock price prediction, including Ijegwa, Rebecca, Olusegun and Isaac (2014) are as follows:

Table 1. Research Novelty

Aspect	Ijegwa, Rebecca, Olusegun dan Isaac (2014)	Research Design
Technical	MACD, Stochastic Oscillator, RSI and On Balance Volume	Replacing RSI becomes a more robust RMI
Fundamental	Not yet considered	<ul style="list-style-type: none"> Incorporating macro financial aspects (PER ICI) Incorporating micro aspects of the issuer (Z-Score)
Asset Diversification	Not yet considered	Incorporating with variable correlation with the market index

I.5 Systematic Discussion

After the introduction in Chapter I, the author will include the theoretical basis in Chapter II which will be the basis for discussing the problem in Chapter IV. Meanwhile, the problem will be defined in Chapter III. In Chapter V, the author will give conclusion and suggestions for the problems that exist.

II. THEORITICAL FRAMEWORK

II.1 Irrational Investor

Daniel, et al. (1998) argue that investors who are overconfident tend to overestimate the information they have and overreact after receiving good news and reacting limited after getting bad news information. Mullainathan, (2001) assumes that individuals do not fit Bayesian because they think based on categories discrete and thus assume the most representative scenario.

Rhodes-Kropf, et al., (2005) developed a decomposition of the Marketto Book ratio to three components, namely: (1) the difference between the observed price and the size of the valuation that reflects t-time fundamental (firm-specific error), (2) the difference between valuation depends on t-time fundamental and company-specific assessments that reflect long-term value (time-series sector error), and (3) the differences between valuation based on long-term value and book value (long-run value to book). Research is intended for merger analysis. It was found that there could be a mis-valuation that might be a result of behavioral anomalies or asymmetric information so that it affects the party that acquiring.

II.2 Macro Financial Condition Variable - Price Earning Ratio (PER) ICI

The financial crisis has provided valuable lesson about the importance of understanding the

financial cycle in which Alamsyah et al (2014) stated that there is a possibility of financial and macroeconomic pressures during the boom and bust in financial cycle. Even Borio (2012) states that it is very difficult to understand the fluctuation in business cycle (real sector) and future policy challenge without understanding the financial cycle.

In Boom condition, the stock market experienced over-valuation. One simple indicator used to measure over-valuation is the PER ratio. PER is high if it is above fair PER, which is around 50x. The fair PER value can be approached with the function $PER = 1 / (Rf + (Market Risk Premium - Rf) - GDP growth)$.

II.3 Micro finance Condition Variable - Z-Score

The Z-score is a linear combination of four or five financial ratios weighted with certain coefficients from Altman's estimation result. The financial indicators used were included:

1. The working Capital indicator per Total Asset is used to measure liquid asset in relation to the total size of the company.
2. Retained Earning per Total Asses is used to measure company profitability.
3. EarningBefore Interest and Tax per Total Assets is intended to measure operating efficiency.
4. Market indicator is used Market Value of Equity per Book Value of Total Liabilities.
5. The last indicator is turnover, Sales per Total Asset.

To produce coefficient, Altman separates samples between companies that have declared bankruptcy and survived. Then, the company is classified again based on size and financial ratio. After the sample is classified, the coefficient is determined by discriminant analysis method. Measurements by modifying z-score is better than traditional ratio analysis. Beaver (1967) who found that some of these indicators can separate between failed and non-failed companies through univariate analysis and determining the degree of importance of profitability, liquidity and solvency ratios. While weighting between ratios also shows a high level of subjectivity. Furthermore, the company is divided into 3 zones, namely "safe", "gray" and "distress" according to the size of the z-score.

This study used the bankruptcy model, Altman z-score, which has been adjusted for developing countries. The testing population included all companies that have been established from 2005 to 2008. Companies that were established or joined the stock exchange in 2006, 2007 and 2008 were excluded. This limitation is intended to find out the differences of the company's resilience in a intact period. The data used is an annual end of period data obtained from Bloomberg.

Table 2. Global Z-Score Model and Emerging Market Model

Z-Score Bankruptcy Model:	Z-Score Bankruptcy Model for developing country:	Information
$Z = 1.2T1 + 1.4T2 + 3.3T3 + .6T4 + .999T5.$	$Z = 6.56T1 + 3.26T2 + 6.72T3 + 1.05T4$	<ul style="list-style-type: none"> • T1 :Working Capital per Total Asset, • T2: Retained Earning per Total Asset, • T3: Earning Before Interest and Tax per Total Asset, • T4: Market Value of Equity per Book Value of Total Liabilities, • T5: Sales per Total Asset.
<p>Zones of Discrimination:</p> <ul style="list-style-type: none"> • $Z > 2.99$ - "Safe" Zone • $1.8 < Z < 2.99$ - "Grey" Zone • $Z < 1.80$ - "Distress" Zone 	<p>Zones of Discrimination:</p> <ul style="list-style-type: none"> • $Z > 2.6$ - "Safe" Zone • $< Z < 2.6$ - "Grey" Zone • $Z < 1.1$ - "Distress" Zone 	

II.4 Technical Variable - Relative Strength Index Development becomes Relative Momentum Index

The Relative Strength Index (RSI) is the most popular oscillator technical approach. The RSI was introduced by Wilder (1978) considering whether an asset is overbought or oversold. Where is the average RS of closing n-day / n-day average closing; n is the number of days, most analysts use 9-15 RSI days. The RSI ranges from 0 to 100. The RSI is explained in the equation, as follows:

$$RSI = 100 - \frac{100}{(1 + RS)}$$

In its development the Relative Strength Index (RSI) is enhanced by adding momentum variable to consider whether an asset is overbought or oversold. The difference is that the ratio is not between the closing price (t) compared (t-1), but compared to (t-n). If High: $RMI > 70$, sell recommendation, If Medium: $30 \leq RMI \leq 70$ then hold. If Low: $RMI < 30$ then buy recommendation.

II.5 Asset Diversification Variable - Correlation ρ

Return and Risk follows the Modern Portfolio Theory where return is defined as return with weight based on allocation. The amount of the allocation used in the model is the same. The expected return and risk formula is as follows:

$$E(R_p) = w_A E(R_A) + w_B E(R_B) = w_A E(R_A) + (1 - w_A) E(R_B).$$

$$\sigma_p^2 = w_A^2 \sigma_A^2 + w_B^2 \sigma_B^2 + 2w_A w_B \sigma_A \sigma_B \rho_{AB}$$

There are more than two assets, therefore a more general formula is used, namely as follows:

$$E(R_p) = \sum_i w_i E(R_i)$$

$$\sigma_p^2 = \sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij},$$

$$= [w_1 \sigma_1 \dots w_n \sigma_n] \times \begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{1n} \\ \rho_{21} & 1 & \dots & \rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1} & \dots & \dots & 1 \end{bmatrix} \times \begin{bmatrix} w_1 \sigma_1 \\ \vdots \\ w_n \sigma_n \end{bmatrix}$$

An asset will have a value in reducing unsystematic risk if the correlation (ρ) of the asset is < 0 .

II.6 Fuzzy Logic

Fuzzy logic was introduced by Dr. Lotfi Zadeh from the University of California, Berkeley in 1965. Fuzzy logic is an increase of Boolean logic that introduces the concept of truth in part. Where classical logic states that all things can be expressed in binary term (0 or 1, black or white, yes or no), fuzzy logic replaces the boolean truth with the level of truth. (Marimin 2005).

It is important for computer to understand human language, but the obstacles are that there is a lot of ambiguity in everyday language that cannot be solved by ordinary logic processing, so a logic device is needed in order to be able to express ambiguity.

Fuzzy logic allows membership values between 0 and 1, gray, black and white level, uncertain concepts like "little", "decent", and "very" in linguistic form. He deals with fuzzy sets and probability theories. Because of this, fuzzy clusters are communication media that speak of natural logic and complexity between human and social knowledge (Marimin 2005).

Nowadays, fuzzy group theory has developed as a measurement tool for various phenomena of mathematical ambiguity including the concept of opportunity. Fuzzy system is a structured and dynamic numerical estimator. This system has the ability to develop intelligence system in an uncertain and inappropriate environment.

Fuzzy concept and opportunity show the degree of certainty and uncertainty of an event. However, there are several differences, namely:

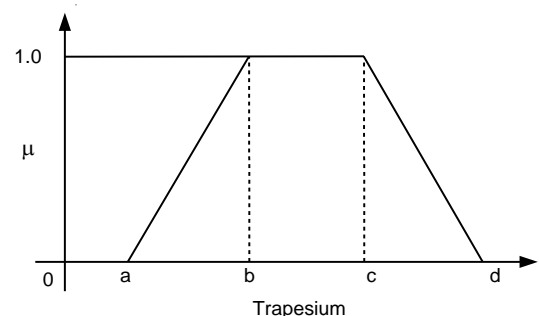
Table 3. The Differences in Fuzzy Concept and Opportunity

Aspect	Fuzzy Concept	Opportunity Concept
Certainty of membership	Membership in fuzzy group remains relevant although events have occurred	The degree of certainty is only meaningful before the event occurs. After the event, the opportunity is no longer relevant, because the result is known
Assumption (1)	Do not use assumption and free from each other between event	Assumed and mutually free between events
Second Assumption (2)	Do not assume everything after being known	Assumed a closed world model (known and opportunity based on frequency of occurrence)
Measurement	Based on descriptive domain measurement, not on subjective frequency measurement	Based on the frequency measure for each event

Membership and Operation Function of Fuzzy Logic Set is a function (curve) that shows the mapping of data input points into its membership value (membership degree) which has an interval between 0 to 1. There are several functions that can be used Linear, Triangle, Trapezoid, Sigmoid, Phi. As an example of Chart 1. Trapezoid

Logical operation is operation that combine and modify 2 or more fuzzy sets. The new membership value resulting from the operation of two sets is called firing strength or μ predicate, there are 3 basic operations in fuzzy set: OR (Union), AND (Intersection), NOT (Complement)

Fuzzy Inference System follow several models including: Mamdani and Sugeno. Mamdani method used fuzzy set as a consequence rule but more computationally heavy and human-like inference. Sugeno's method used mathematical or constant function but more efficient but it loses linguistic interpretation.



$$\mu[x] = \begin{cases} 0; & x \leq a \text{ atau } x \geq d \\ (x-a)/(b-a); & a < x < b \\ 1; & b < x < c \\ (d-x)/(d-c); & c < x < d \end{cases}$$

Chart 1. Trapezoidal Membership Function

The operation of fuzzy expert system depend on the execution of 4 main functions: (i) Fuzzification: the definition of fuzzy set and determination of membership degree of the crisp input on a fuzzy set, (ii) Inference: evaluation of fuzzy rules / rules to produce output from each rule, (iii) Composition: aggregation or combination of all output rules and (iv) Defuzzification: calculation of crisp output

III. RESEARCH METHODOLOGY

Fuzzy Logic modeling for stock price prediction follows the procedure as follows (Chart 1). In conducting model convergence, determining the variable input-range-membership function, fuzzy rule design is based on historical behavior and expert opinion. In this case, expert was selected based on who have experienced as dealer in the Financial Authority.

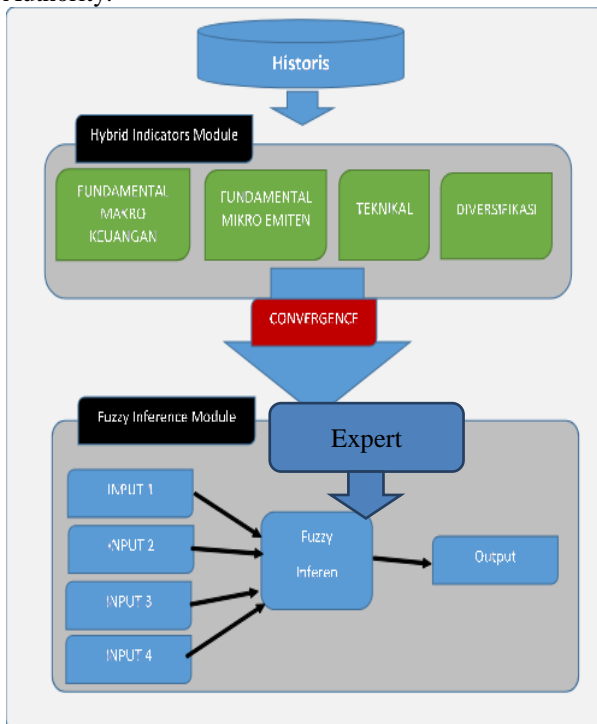


Chart 1. Hybrid Modeling Flow - Prediction of Stock Price

III.1 Hybrid Analysis Modul

Hybrid analysis module consists of 4 main aspects namely macro financial fundamental (proxy: PER ICI), micro issuers (proxy: z-score), technical (proxy: Relative Momentum Index) and asset diversification (proxy: correlation with market). After convergence is done, enter the stage of the fuzzy inference system.

III.2 Fuzzy Inference Systems

Fuzzy Inference System followed several Mamdani models. Mamdani method used fuzzy set that was more human-like inference but was more computationally heavy. In accordance with Marimin

(2005) To obtain the output several steps are needed as follows:

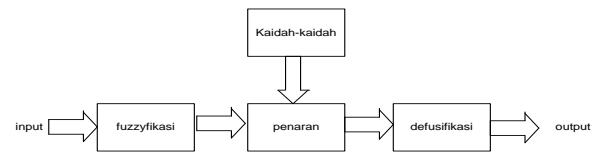


Chart 2. Process in Fuzzy Logic

Meanwhile, Input Variable, Membership Function, Range The hybrid predictive stock model was as table 1. Output Variable consisted of several recommendations: Buy, Hold, Sell.

Table 5. Input Variable, Membership Function and Range for Fuzzy Logic

Aspect	Input Variable	Membership Function	Range
Macro Financial Condition	PER ICI	Bubble and Normal	<ul style="list-style-type: none"> Bubble : PER IHSNG > 50 Normal : PER IHSNG ≤ 50
Micro Condition of Issuers	Z Score	High dan Low	<ul style="list-style-type: none"> High : Z-Score > 2,99 Low : Z-Score ≤ 2,99
Technical	Relative Momentum Index	High, Medium dan Low	<ul style="list-style-type: none"> High : RMI > 70 Medium : 30 ≤ RMI ≤ 70 Low : RMI < 30
Asset Diversification	P	Positive and Negative	<ul style="list-style-type: none"> High : ρ > 0 Low : ρ ≤ 0

III.3. Fuzzy Rules

Fuzzy rules are based on the processing of historical data and the result of expert discussion was as follows:

Table 6. Fuzzy Rules

	Macro Financial Aspect (PER Market)	Micro aspect (Z-Score)	Technical Indicator Aspect (RMI)	Aspect Diversification of Asset (Correlation Coefficient)	Recommendation
1	Normal	Safe	Oversold	ρ Positive	BUY
2	Normal	Safe	Oversold	ρ Negative	BUY
3	Normal	Safe	Neutral	ρ Positive	HOLD
4	Normal	Safe	Neutral	ρ Negative	HOLD
5	Normal	Safe	Overbought	ρ Positive	SELL
6	Normal	Safe	Overbought	ρ Negative	SELL
7	Normal	Grey	Oversold	ρ Positive	SELL
8	Normal	Grey	Oversold	ρ Negative	SELL
9	Normal	Grey	Neutral	ρ Positive	SELL
10	Normal	Grey	Neutral	ρ Negative	SELL
11	Normal	Grey	Overbought	ρ Positive	SELL
12	Normal	Grey	Overbought	ρ Negative	SELL
13	Bubble	Safe	Oversold	ρ Positive	HOLD
14	Bubble	Safe	Oversold	ρ Negative	BUY
15	Bubble	Safe	Neutral	ρ Positive	HOLD
16	Bubble	Safe	Neutral	ρ Negative	HOLD
17	Bubble	Safe	Overbought	ρ Positive	SELL
18	Bubble	Safe	Overbought	ρ Negative	SELL
19	Bubble	Grey	Oversold	ρ Positive	SELL
20	Bubble	Grey	Oversold	ρ Negative	SELL
21	Bubble	Grey	Neutral	ρ Positive	SELL
22	Bubble	Grey	Neutral	ρ Negative	SELL
23	Bubble	Grey	Overbought	ρ Positive	SELL
24	Bubble	Grey	Overbought	ρ Negative	SELL

III.4 Defuzzification

Defuzzification used the center of area method with the formula as follows:

$$F(nT) = \frac{\sum_i^L \mu C(Z_i)(Z_i)}{\sum_i^L \mu C(Z_i)}$$

L was the quantification level of C,Zi was the number of output control on the quantification level. $\mu C(Z_i)$ showed the membership value of fuzzy set. This calculation was only for specific $R(nT)$, $F(nT)$ will be formed. When $F(nT)$ approached 100,

it was worth buying and when approaching 0 it was worth selling.

IV. MATLAB PROCESSING RESULT

IV.4.1 Input, Output Variable and Membership Function

Range modeling input variables used a maximum or minimum value of ± 1 deviation, such as PER and Z-Score that have a maximum value of 10. FIS used Mamdani and membership type used trapezoidal model according to stock prediction model with Ijegwa, Rebecca, Olusegun and Isaac (2014).

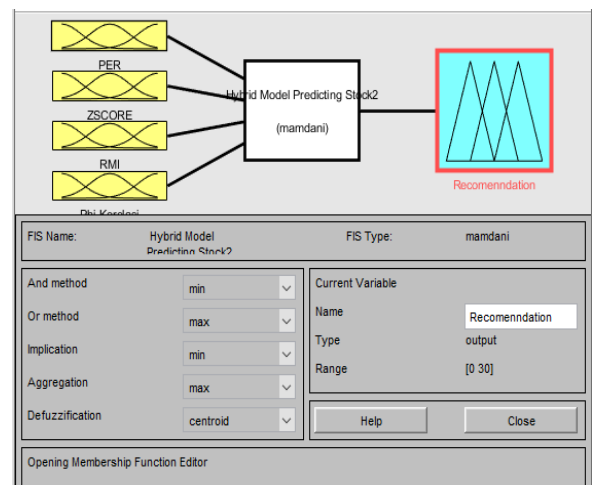
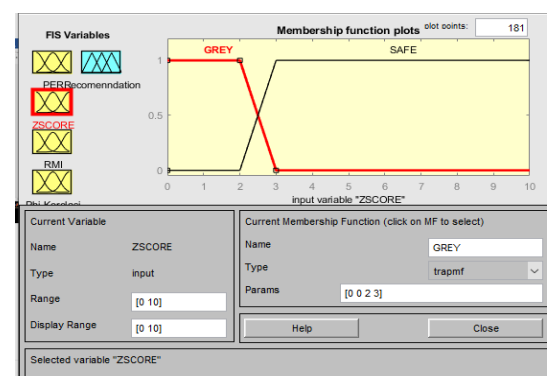


Chart 3. Input and Output Variables

While related to output used a range of 0-30 with a triangle in accordance with Ijegwa, Rebecca, Olusegun and Isaac (2014). The shape of the trapezium for input and triangle for output and the degree of membership were the result of discussion with expert who have experience as dealers in the Financial Authority. The following were the results of calculating the Matlab model:



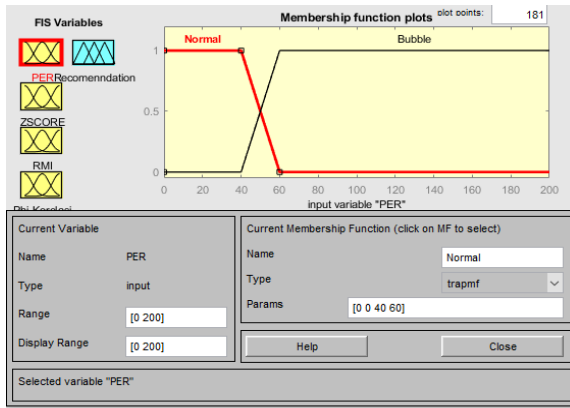


Chart 4. Membership Function of PER

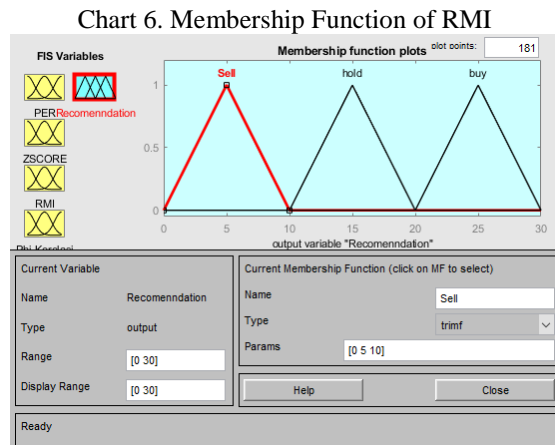


Chart 6. Membership Function of RMI

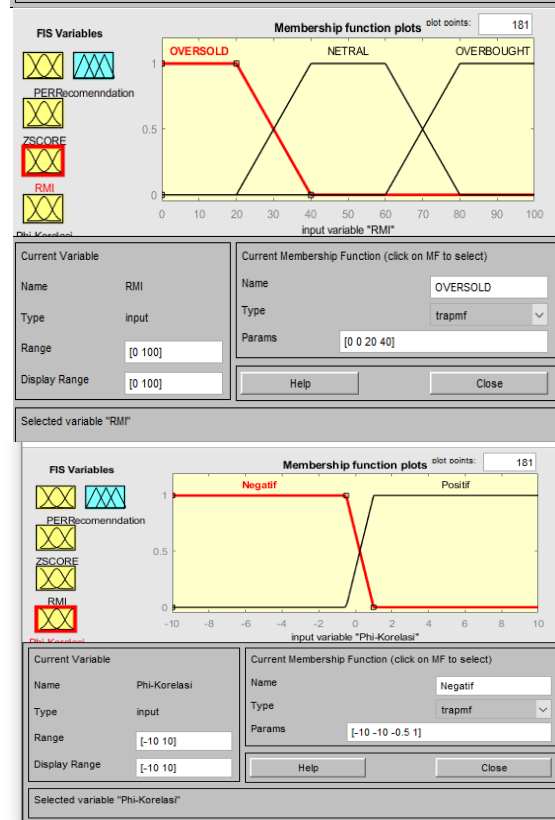


Chart 8. Output –Recommendation

IV.4.2 Fuzzy Rules Set

Model yang disusun mengandung 24 Rules dengan Fuzzy intersection (\cap): irisan dari 2 fuzzy set was the minimum of each pair of element in both sets. The general form of the rule used in the implication function: IF x is A THEN y is B with x and y are scalar, A and B are fuzzy set. Proposition followed IF are called antecedent, while proposition followed THEN are called consequent. Here were the results of calculating the Matlab model:

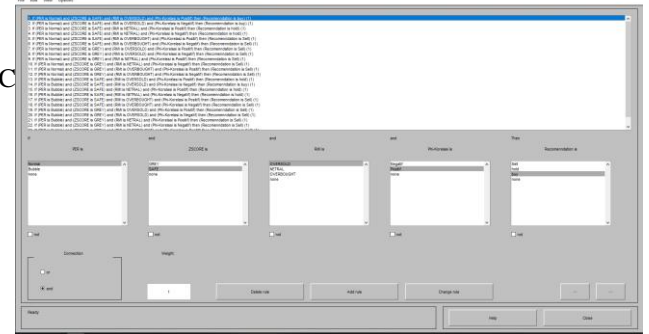


Chart 9. 24 Fuzzy Rule: Hybrid Model Prediction of Stock Price

IV.4.3 Simulation

Graphical simulation showed the role of two variables on recommendation score. In graph 1, it appeared that in line with the increase in the z-score, the recommendation value improved. While in the graph 2 PER below 50 was the biggest contribution to the recommendation score. In graph 3, the lower the RMI and the higher the Z-score was the higher the recommendation score. Then on graph 4, the negative correlation of the portfolio and the smaller the RMI influenced the recommendation score.

Graph 1. The Relationship of PER - ZScore on Recommendation

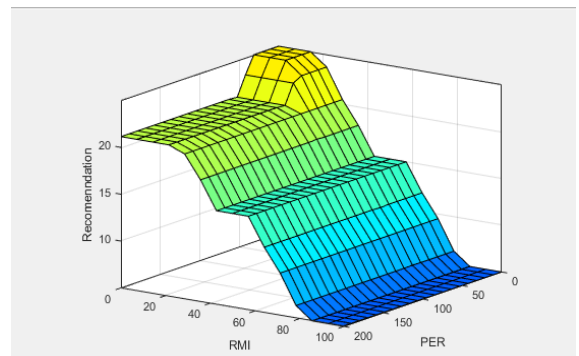
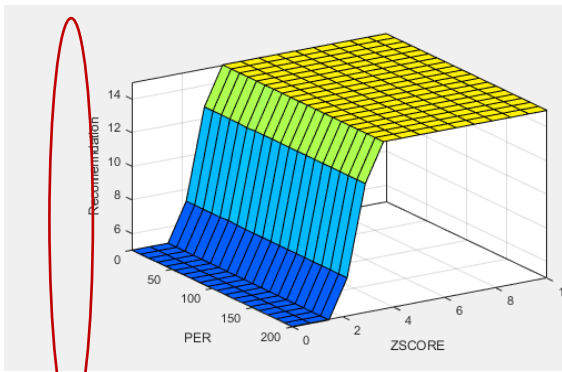
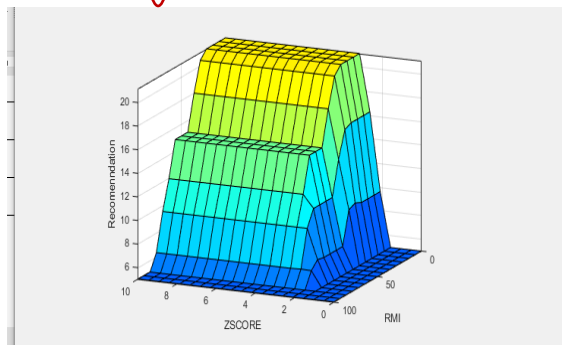
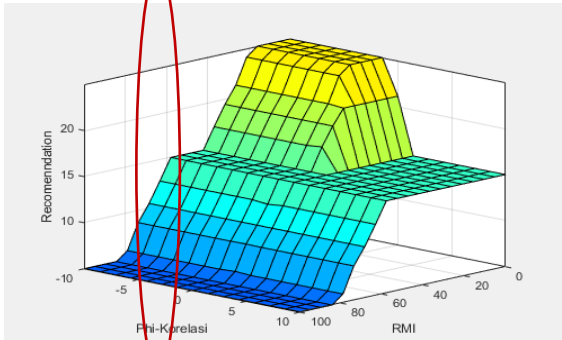


Chart 7. Membership Function of Correlation Coefficient



Graph 2. The Relationship of PER-RMI to Recommendation



Graph 3. The Relationship of RMI - ZScore to recommendation

Graph 4. The Relationship of Correlation - RMI to Recommendation

This was in line with the advanced simulation with the recommendation scenario: Hold, recommendation: Buy and recommendation: Sell on chart 8 - 10. On Chart 8, when the input variable was still at the midpoint, the recommendation was consistently in the middle point (Hold).

Chart 10. Hybrid Model Simulation: Hold



Chart 11. Hybrid Model Simulation: Buy

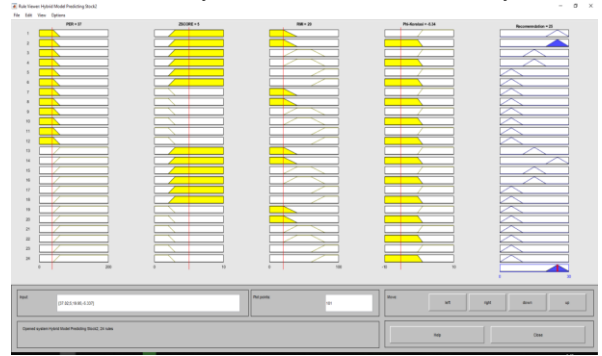
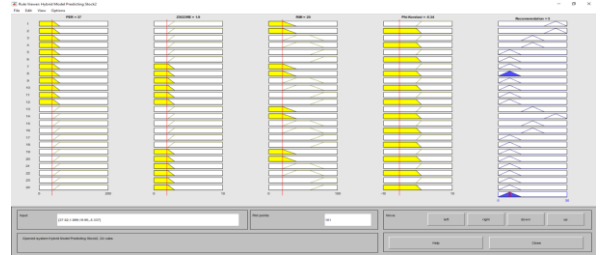


Chart 12. Hybrid Model Simulation: Sell



In Chart 9, it was stimulated PER that moved to normal condition, Z Score in Safe condition, RMI oversold condition and negative correlation, the recommendation consistently showed Buy. In Chart 10, it is simulated the same as chart 10, only PER Score in the condition of Grey, then the recommendation became Sell. This also indicated that the Z-score which was the issuer's fundamental factor as a key decision-making factor.

V. CONCLUSION AND SUGGESTION

Relationship of Correlation - RMI to Recommendation

Conclusion

1. Decision making in financial investment, especially on the stock market was complex. It is needed the expertise to understand information that affected the development of the financial sector. Stock investment also required speed and accuracy of momentum. In addition, disciplinary factor for the investment rule that has been prepared as the determinant of success in investing to the stock market
2. Currently, many trading algorithms have been developed to answer those needs. However, the algorithm was more technical in nature and has not included the fundamental aspect of the issuer or asset diversification as contained in Ijegwa, Rebecca, Olusegun and Isaac (2014). In practice, investor also depend not only on one technical aspect, but also by incorporating fundamental aspects such as macro-micro and asset diversification.
3. Hybrid model with algorithm that was more comprehensive considering with the aspects of macro financial fundamental, micro issuer, and

diversification complement technical aspect (hybrid model) with fuzzy logic approach provided consistent result. This can be seen in simulation on recommendation scenarios: Hold, recommendation: Buy and recommendation: Sell. When the input variable was still at the midpoint, the recommendations were consistently in the middle (Hold).

4. When it is simulated that PER moved to normal condition, Z Score in Safe condition, RMI oversold condition and negative correlation, recommendation consistently showed Buy.
5. Furthermore, when it is simulated the same as chart 10 only PER Score Gray condition, then the recommendation became Sell. This also indicated that the Z-score which was the issuer's fundamental factor as a key decision-making factor.

Suggestion

6. This result is expected to increase the reliability of the algorithm in predicting return. From a macro perspective, algorithms based on macroeconomic and micro-fundamentals are expected to contribute to financial system stability.
7. It needed to test the reliability of the algorithm by plotting the latest data update.

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Received : September 2019

Revised : November 2019

Accepted : December 2019