Journal of Quality Measurement and Analysis *JQMA* 21(4) 2025, 145-165
e-ISSN: 2600-8602 *http://www.ukm.my/jqma*
https://doi.org/10.17576/jqma.2104.2025.09

FUZZY CLUSTERING FOR STOCK PERFORMANCE EVALUATION USING FINANCIAL INDICATORS: A RULE-BASED APPROACH

(Pengelompokan Kabur untuk Penilaian Prestasi Saham Menggunakan Petunjuk Kewangan: Pendekatan Berasaskan Peraturan)

SITI NAZIFAH ZAINOL ABIDIN, SAIFUL HAFIZAH JAAMAN*,
AHMAD SYAFADHLI ABU BAKAR & MUNIRA ISMAIL

ABSTRACT

Selecting well performing stocks in a diverse and volatile market is a challenging task. Established fuzzy clustering methods which rely on averaging the influence of variables under consideration, are often providing same performance evaluation for certain different cases of stocks' situations. Moreover, these methods struggle to appropriately handle market uncertainty, such that the evaluations are inconsistent with preference of investors. To cater these limitations, this study presents a novel fuzzy clustering method for evaluating stock performance by using Fuzzy Inference System (FIS). The proposed novel fuzzy clustering method utilises four established stock indicators, namely, return rates, standard deviation, Treynor index and beta coefficient, as the inputs of the FIS, where all of them are combined by using fuzzy relation to form novel stock performance's rule bases. Each developed novel rule-base aims at providing informed evaluation result, where all established and unique cases of stock performance under consideration are distinguished accordingly. Then, results obtained from the stock performance evaluation are further refined by incorporating the perspective of pessimistic and optimistic investor preferences, as to acknowledge the presence of market uncertainty. For validation, the performance of the proposed novel fuzzy clustering method is comparatively analysed based on the KLCI 30 top stocks, where the proposed method outperforms established clustering methods under consideration.

Keywords: stock performance; Fuzzy Inference System; rule-based approach

ABSTRAK

Memilih saham berprestasi baik dalam pasaran yang pelbagai dan tidak menentu adalah tugas mencabar. Kaedah pengelompokan sedia ada yang bergantung pada purata pengaruh pemboleh ubah yang dipertimbangkan, sering memberikan penilaian prestasi yang sama untuk kes-kes situasi saham berbeza. Lebih-lebih lagi, keadah pengelompokan sedia ada ini sukar untuk mengendalikan ketidakpastian pasaran dengan sewajarnya, sehinggakan penilaian yang diberikan tidak konsisten dengan pilihan pelabur. Bagi mengatasi batasan ini, kajian memperkenalkan kaedah pengelompokan novel untuk menilai prestasi saham dengan menggunakan Sistem Penakulan Kabur (FIS). Kaedah pengelompokan kabur novel yang dicadangkan ini menggunakan empat indikator saham sedia ada, iaitu kadar pulangan, sisihan piawai, indek Treynor, dan pekali beta, sebagai input kepada FIS, dan kesemuanya digabungkan dengan menggunakan hubungan kabur untuk membentuk asas peraturan prestasi saham yang novel. Setiap asas peraturan novel yang dibangunkan bertujuan untuk memberikan hasil penilaian yang bermaklumat, dengan semua kes prestasi saham yang sedia ada dan unik di bawah pertimbangan dapat dibezakan dengan sewajarnya. Kemudian, hasil yang diperoleh daripada penilaian prestasi saham diperhalusi lagi dengan menggabungkan perspektif pilihan pelabur pesimis dan optimis, sebagai pengiktirafan terhadap kehadiran ketidakpastian pasaran. Untuk pengesahan, prestasi kaedah pengelompokan kabur novel yang dicadangkan ini dianalisis secara perbandingan berdasarkan 30 saham teratas KLCI, melalui kaedah yang dicadangkan ini mengatasi kaedah pengelompokan sedia ada yang dipertimbangkan.

Kata kunci: prestasi saham; sistem inferens kabur; berasaskan peraturan

1. Introduction

Stocks in financial market are often perceived as unpredictable and volatile, primarily due to the uncertain fluctuations in daily stock prices influenced by dynamic market changes (Mohamed *et al.* 2009 & Kumari *et al.* 2019). This unpredictability leads to investor hesitation when selecting suitable stocks for investment (Zainudin *et al.* 2024). Additionally, the challenge of balancing risk and return further contributes a well-balanced interaction between risks and returns further contributes to investor indecision (Zainudin *et al.* 2023). When making investment decisions, investors typically seek stocks with consistent performance such as those offering low risk and high returns (Chen & Huang 2009; Kiliçman & Sivalingam 2010; Mirnoori & Shariati 2012). Stocks with these attributes are often regarded as profitable investments. Investors generally seek such profitable investment opportunities, making it essential to develop systematic and reliable stock selection rules to support informed and measurable investment decisions.

In the literature, stock selections for investment are often defined as a process of clustering stocks based financial indicators (Nanda *et al.* 2010; Zainuddin *et al.* 2024). This can be seen when Chen and Huang (2009) utilized return rate, standard deviation, Treynor's index and turnover rate as financial indicators to cluster the stocks based on k mean clustering techniques. Kiliçman and Sivalingam (2010) used return rate, variance and Treynor's index to cluster the stocks, whereas rate of return, standard deviation, turnover rate and Sortino index as the indicators to cluster the stocks based on k mean clustering techniques (Mirnoori & Shariati 2012). Return rate, standard deviation, Sharpe index beta coefficient, Modigliani and Modigliani index, Treynor index, Jensen index and Sortino index as the indicators to cluster the funds based on k mean clustering techniques (Gabriel *et al.* 2015). Meanwhile, dividend yield, price to book value, price-earnings ratio and beta coefficient as used by Zainudin *et al.* (2023) as the indicators to cluster the stocks based on k means, agglomerative and mean shift clustering techniques. It is worth mentioning that the incorporation of various distinctive financial indicators by each method offers flexibility for investors to effectively deal with variety of cases when selecting stocks. For example, Chen and Huang (2009) consider on cases of good performance stocks that involve high return rate, low risk, high Treynor's index and moderate turnover rate. Kiliçman and Sivalingam (2010) define a good performance stock as those having high rate of return, low risk, with high Treynor index. Meanwhile, Mirnoori and Shariati (2012) describe good performance funds as high return, very low risk, moderate turnover rate and moderate Sortino index.

Although cases covered by each mentioned clustering method are mainly aiming at selecting stocks that possess high return with low risk, each case of scenario is only applicable to individual method. This is reflected when cases of stable performance funds covered by Chen and Huang (2009), Kiliçman and Sivalingam (2010) and Gabriel *et al.* (2015) are not consistent with each other. Chen and Huang (2009) define their stable performance stocks as moderate return, moderate risk, lowest turnover rate and moderate Treynor index, while Kiliçman and Sivalingam (2010) declares the stable performance as low return, very low risk, and high Treynor's index. On the other hand, Gabriel *et al.* (2015) indicates stable performance funds as those having moderate return, low risk and high Sortino index. Not only that, inconsistencies in terms of stock performance evaluations from other cases can also be observed such as inferior performance (Chen & Huang 2009; Kiliçman & Sivalingam 2010; Mirnoori & Shariati 2012; Gabriel *et al.* 2015) and stable performance (Chen & Huang 2009; Kiliçman & Sivalingam 2010; Gabriel *et al.* 2015). Apart from obtaining inconsistent stock performance evaluation results, there is another crucial aspect that is often neglected by established clustering methods, which is the capability to handle uncertainty, such that the stock performance evaluation results are not consistent with investor preferences. The acknowledgement of investor preferences is important when clustering stocks because each investor may perceive a situation differently from other investors (Mohamed *et al.* 2009; Li & Yi 2019; Widhiarti *et al.* 2018). Therefore, the consistencies and limitations by established clustering method mentioned above imply that a critical need for a unique clustering method that is not only capable at evaluating all possible cases of stock performance appropriately, but also able considering preference by investors is worth developing.

In the light of this challenge, this study aims at developing a novel clustering method for evaluating stock performance by using Fuzzy Inference System (FIS). The proposed novel fuzzy clustering method utilises four established stock indicators, namely, return rates, standard deviation, Treynor index and beta coefficient, as the inputs of the FIS, where all of them are combined by using fuzzy relation to form novel stock performance's rule bases. Each developed novel rule-base aims at providing informed evaluation results, where all established and unique cases of stock performance under consideration are distinguished accordingly. Then, results obtained from the stock performance evaluation are further refined by incorporating the perspective of pessimistic and optimistic investor preferences, as to acknowledge the presence of market uncertainty. For validation, the performance of the proposed novel fuzzy clustering method is comparatively analysed with established clustering methods based on the KLCI 30 top stocks. The rest of the paper is as followed: Section 2 covers on related works, Section 3 on research formulation, Section 4 on case study on Malaysia's stock market and Section 5 on validation. Discussion and conclusion are presented in Section 6 and Section 7, respectively.

2. Related Works

Fuzzy clustering analysis-based methods have been introduced as alternative approaches to stock selection with high dimensional portfolio construction, aiming to identify and group the well-performing stock simultaneously (Kumari *et al.* 2019; Nanda *et al.* 2010). Among others are k-means (Chen & Huang, 2009; Nanda et al. 2010; Kiliçman & Sivalingam 2010; Mirnoori & Shariati 2012; Al-Augby *et al.* 2014; Marvin 2015; Gabriel *et al.* 2015; León *et al.* 2017; Alqaryouti *et al.* 2019; Kumari *et al.* 2019; Zainudin *et al.* 2023; Zainudin et al., 2024), hierarchical (Da Costa Jr *et al.* 2005; Chen & Huang 2009; Kiliçman & Sivalingam 2010; Mirnoori & Shariati 2012; León *et al.* 2017; Tekin & Gümüş 2017), and k-mediods clustering (Alqaryouti *et al.* 2019; Gubu *et al.* 2021), where all of them are summarised in Table 1.

Table 1: Established clustering methods in finance

Authors	K-Mean	Hierarchical	K-Mediods	C-Mean	SOM
Da Costa Jr *et al.* (2005)		/			
Chen & Huang (2009)	/	/			
Nanda *et al.* (2010)	/			/	/
Kiliçman & Sivalingam (2010)	/	/			
Mirnoori & Shariati (2012)	/	/			
Al-Augby *et al.* (2014)	/			/	
Marvin (2015)	/				
Gabriel *et al.* (2015)	/				
Tekin & Gümüş (2017)		/			
León *et al.* (2017)	/	/			
Alqaryouti *et al.* (2019)	/		/		
Kumari *et al.* (2019)	/				
Gubu *et al.* (2021)			/		
Zainudin *et al.* (2023)	/				

Zainudin *et al.* (2024)	/

Although, all the established fuzzy clustering methods given in Table 1 are considered various and unique from the perspective of the nature of the method used, all of them shared a common capability which is evaluating stocks performance based on averages of stock indicators. In other word, these methods assume that stocks with similar average scores as having similar performance. These evaluations, however, are potentially producing mislead and inaccurate stock performance results, especially when the stock indicators under consideration are outliers and extreme values (Falk & Guillou 2008; Stelzer 2008; Chan & Zhang 2009). In this case, average scores fell short when evaluating stock performance that are too high or too low (Falk & Guillou 2008; Stelzer 2008; Chan & Zhang 2009).

Apart from the above mentioned limitation, some of these established clustering methods are producing inconsistent stock performance results from each other. This can be observed when cases of stable performance stocks and inferior performance of stocks. Chen and Huang (2009) defines inferior as low in return, high in risk and high in Treynor index, as the same as Mirnoori and Shariati (2012) and Gabriel *et al.* (2015) without Treynor index but with low in Sortino index. However, Kiliçman and Sivalingam (2010) defines inferior as lowest in return, low in risk and very low in Treynor index. Inconsistent also for stable performance of stocks defines by Chen and Huang (2009), Kiliçman and Sivalingam (2010) and Gabriel *et al.* (2015). Table 2 summarises cases stock performance evaluation considered by established clustering methods with their respective conflicting evaluation results.

Table 2: Cases of stock performance evaluation considered by established clustering method with their respective conflicting evaluation results

Performance	Authors	Return	Risk	Treynor Index	Sortino Index
Inferior	Chen & Huang (2009)	Low	High	High	N/A
	Kiliçman & Sivalingam (2010)	Lowest	Low	Very Low	N/A
	Mirnoori & Shariati (2012)	Low	High	N/A	Low
	Gabriel *et al.* (2015)	Low	High	N/A	Low
Stable	Chen & Huang (2009)	Moderate	Moderate	Moderate	N/A
	Kiliçman & Sivalingam (2010)	Low	Very Low	Very High	N/A
	Gabriel *et al.* (2015)	Moderate	Low	N/A	Moderate
Good	Chen & Huang (2009)	Highest	Lowest	High	N/A
	Kiliçman & Sivalingam (2010)	High	Low	High	N/A
	Mirnoori & Shariati (2012)	High	Low	N/A	High
	Gabriel *et al.* (2015)	High	Lowest	N/A	Highest
Aggressive	Chen & Huang (2009)	Highest	Highest	Highest	N/A
	Kiliçman & Sivalingam (2010)	Highest	Highest	High	N/A
	Mirnoori & Shariati (2012)	Very High	High	N/A	Moderate

3. Research Formulation

As mentioned in the introduction and related work sections, limitations of established clustering methods are producing mislead and inaccurate stock performance results, especially when the stock indicators under consideration are outliers and extreme values, provide inconsistent stock performance evaluations results and the incapability to address investor preferences. Since, all of these limitations are crucial to be resolved, this study introduces a novel fuzzy clustering method where it is not only capable at providing correct stock performance evaluation but also able at incorporating investor preferences. It is worth mentioning that the proposed clustering method is constructed by using FIS, where all stock performance evaluations under consideration are aggregated based on rule bases. Details on the method's procedure is given as follows.

3.1. *Step 1: Data collection, input and output identifying and normalization*

This study used return rates, standard deviation, the Treynor index, and the beta coefficient as input variables to evaluate the stock performance. The beta coefficient served as a market benchmark, and the Treynor Index was used to measure market performance.

Definition 3.1. Return Rates, R_t

The return rate denotes as R_t, represents the return gained from an investment. A high value of R_t indicates a significant profit and, therefore positive stock performance which is a favourable indicator for investors. As defined by Chen and Huang (2009), R_t is calculated as follows:

$$R_t = \frac{P_{t+1} - P_t}{P_t} \times 100 \tag{1}$$

where P_t is the stock price at time t, and P_{t+1} is the stock price at time $t+1$.

Definition 3.2. Standard Deviation, S_t

Standard deviation denotes as S_t, measures the volatility of returns representing the investment risk level (Chen & Huang 2009; Ma & Tang 2019). The standard deviation, S_t, is calculated using Eq. (2):

$$S_t = \sqrt{\frac{\sum_{t=1}^{n} \left(R_{ti} - \overline{R}_t\right)^2}{n-1}} \tag{2}$$

where R_{ti} is the return rate of stock t on the ith day, and $\overline{R}_{ti}$ is the average return rate for n period.

Definition 3.3. Beta Coefficient, β

Beta coefficient, denoted as β, represents systematic risk and is calculate as the ratio of covariance to variance, as shown in Eq. (3). Here, R_b represents the market return rate and is the average market return rate (Haight *et al.* 2007; Brigham & Ehrhadt 2011).

$$\beta = \frac{n\left(\sum R_{1,t} R_{2,r}\right) - \left(\sum R_{1,t}\right)\left(\sum R_{2,t}\right)}{n\left(\sum R_{2,t}^2\right) - \left(\sum R_{2,t}\right)^2} \tag{3}$$

Definition 3.4. Treynor Index, T_t

The Treynor Index denotes as T_t , measures of the excess return earned per unit of systematic risk (Chen & Huang 2009). The Treynor index was chosen in this study because it evaluates the stock portfolio against the overall market and is highly sensitive to market risk (Robiyanto 2018; Kuhle & Lin 2018). A high value of of T_t indicates indicates a high return per unit of market risk (Chen & Huang 2009). The Treynor Index is given by Eq. (4):

$$T_t = \frac{\overline{R_t} - \overline{R_{rf}}}{\beta} \tag{4}$$

where β is the systematic risk or the market risk, and $\overline{R}_{rf}$ is the daily average risk-free rate for a week.

Definition 3.5. Normalization, $\varpi_t^{'}$.

Let $\varpi_t^{'}$ be the normalized value of input variables i defined Chen and Huang (2009) as,

$$\varpi_i^{'} = \frac{\varpi_i - Min\left(\varpi_{i,j}\right)}{Max\left(\varpi_{i,j}\right) - Min\left(\varpi_{i,j}\right)} \tag{5}$$

where $i = R_t', S_t' \text{ and } T_t'$, $Min_i\left(\varpi_{i,j}\right)$ is the minimum i with $j = 1,2,3 \cdots n$ and $Max_i\left(\varpi_{i,j}\right)$ is the maximum i with $j = 1,2,3 \cdots n$. All defined inputs were normalized using Eq. (5) as shown in Eq. (6) – (9):

$$R_t \to R_t^{'} \tag{6}$$
$$S_t \to S_t^{'} \tag{7}$$
$$T_t \to T_t^{'} \tag{8}$$
$$\beta_t \to \beta_t^{'} \tag{9}$$

where $R_t^{'}$, $S_t^{'}$, $T_t^{'}$ and $\beta_t^{'}$ are the normalized values for the return rates, standard deviation, Treynor Index, and beta coefficient, respectively.

3.2. *Step 2: Fuzzification*

The normalized results from Step 1 were subsequently mapped into linguistic triangular fuzzy numbers.

Definition 3.6. Triangular Fuzzy Numbers.

Let a,b and c be a real numbers with $a < b < c$ as illustrated in Figure 1.

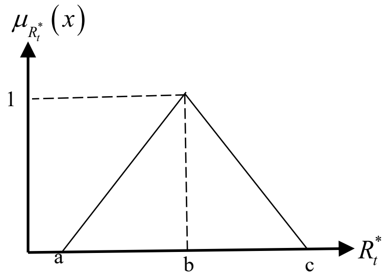

Figure 1: Graph of membership function

As shown in Figure 1, the value a,b and c represent the minimum, modal and maximum value, respectively, of the triangular fuzzy numbers corresponding to the input variables. In this study, the triangular fuzzy numbers for $R_t^{'}$, $S_t^{'}$, $T_t^{'}$ and $\beta_t^{'}$ act as modal value and the value of a and c are defines as the spread of that modal value. The membership function is defined as follows:

$$\mu_{R_t^*}(x)=\begin{cases}(x-a)/(b-a) & \text{if } a\le x\le b\\ (c-x)/(c-b) & \text{if } b\le x\le c\\ 0 & \text{otherwise}\end{cases} \tag{10}$$

The mapping of $R_t^{'}$, $S_t^{'}$, $T_t^{'}$ and $\beta_t^{'}$ into $R_t^{'}$, $S_t^{'}$, $T_t^{'}$ and $\beta_t^{'}$ are given as the following Eq. (11) – (14):

$$R_t^{'} \rightarrow R_t^* = \left(a_{R_t^*}, b_{R_t^*}, c_{R_t^*}\right) \tag{11}$$

$$S_t^{'} \rightarrow S_t^* = \left(a_{S_t^*}, b_{S_t^*}, c_{S_t^*}\right) \tag{12}$$

$$T_t^{'} \rightarrow T_t^* = \left(a_{T_t^*}, b_{T_t^*}, c_{T_t^*}\right) \tag{13}$$

$$\beta_t^{'} \rightarrow \beta_t^* = \left(a_{\beta_t^*}, b_{\beta_t^*}, c_{\beta_t^*}\right) \tag{14}$$

where R_t^*, S_t^*, T_t^* and β_t^* are the linguistic triangular fuzzy numbers for the return rates, standard deviation, Treynor index and beta coefficient values, respectively.

3.3. *Step 3: Fuzzy rule base, fuzzy inference system and defuzzification*

In this step, linguistic rule bases were developed based on previous stock performance evaluation (Kiliçman & Sivalingam 2010; Chen & Huang 2009). The fuzzy inputs from Step 2 were combined using these rule bases to determine stock performance outputs. These outputs were then defuzzied converting the linguistic triangular fuzzy numbers into crisp values. The interaction between inputs, rule bases, and outputs can be summarized as follows:

IF R_t^* *is ....* **AND** S_t^* *is ....* **AND** T_t^* *is ....* **AND** β_t^* *is ....* **THEN** .... *stock performance*.

Centroid method was used for defuzzification, which converts the fuzzy output of a fuzzy inference system into a single crisp value. The centroid method is given by Eq. (15):

$$y^{*}=\frac{\int \mu_{A}(y).ydy}{\int \mu_{A}(y)dy} \tag{15}$$

where A is the stock performance evaluation, $\mu_A(y)$ is the membership function of the fuzzy output, and y^* is defuzzification value.

3.4. *Step 4: Stock performance and investor selection preferences*

The stock performance derived from the defuzzification process in Step 3 was represented as a single crisp value, reflecting the investors' evaluation of the stocks. This evaluation was then mapped onto the height of the linguistic triangular fuzzy numbers, resulting in two satisfaction levels. These satisfaction levels correspond to the selection preferences of three types of investors: pessimistic, neutral, and optimistic. Specifically, pessimistic investors are assumed to have a satisfaction level less than 0.5, neutral investors a level of 0.5, and optimistic investors a level greater than 0.5 (Mohamed *et al.* 2009).

4. Case Study on Malaysia's Stock Market

In this section, the application of the proposed novel fuzzy clustering method is demonstrated. It is worth mentioning that this study utilises dataset of 30 stocks from FTSE Bursa Malaysia (KLCI).

Step 1: Data collection, input and output identification and normalization.
The top 30 stocks from FTSE Bursa Malaysia (KLCI) were used as a sample case. The input variables were the rate of return, standard deviation, beta coefficient, and Treynor Index, while the output was stock performance. Normalization was performed using Eq. (5), resulting in Eq. (6) through (9).

Step 2: Fuzzification
Membership values were determined based on the KLCI index, which serves as a benchmark for market performance. Specifically, R_t^* was 0.6198, S_t^* was 0.1125, T_t^* was 0.2083 and beta was 1. After normalization, the β_t^* is 0.5. These values, particularly the benchmarks beta of 1 in which indicating average market risk, were used to the range and modal points of the triangular fuzzy numbers for each linguistic term. Linguistic term for input variables, "very low", "low", "moderate", "high" and "very high" and for output variables, "very inferior", "inferior", "stable", "very stable", "good", "very good", "aggressive" and "very aggressive" are presented in Table 3. The usage of KLCI index ensures that the fuzzy membership functions are grounded in real market conditions and enhances the credibility of the fuzzy rule base. Table 3 presents the membership value for input and output variables.

The membership for R_t^*, using Eq. (10) is as follows:

$$\mu_{R_t^*\_\text{verylow}}(x)=\begin{cases}(0.3099-x)/0.3099 & \text{if } 0\le x\le 0.3099\\ 0 & \text{otherwise}\end{cases}$$

$$\mu_{R_t^*\_low}(x)=\begin{cases} x/0.3099 & \text{if } 0\le x\le 0.3099 \\ (0.6198-x)/0.3099 & \text{if } 0.3099\le x\le 0.6198 \\ 0 & \text{otherwise} \end{cases}$$

$$\mu_{R_t^*\_moderate}(x)=\begin{cases} (x-0.3099)/0.3099 & \text{if } 0.3099\le x\le 0.6198 \\ (0.8099-x)/0.1901 & \text{if } 0.6198\le x\le 0.8099 \\ 0 & \text{otherwise} \end{cases}$$

$$\mu_{R_t^*\_high}(x)=\begin{cases} (x-0.6198)/0.1901 & \text{if } 0.6198\le x\le 0.8099 \\ (1-x)/0.1901 & \text{if } 0.8099\le x\le 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\mu_{R_t^*\_veryhigh}(x)=\begin{cases} (x-0.8099)/0.1901 & \text{if } 0.8099\le x\le 1 \\ 0 & \text{otherwise} \end{cases}$$

The membership functions for the remaining inputs and the output can be obtained using Eq. (10).

Table 3: Membership value for input and output variables

Linguistic Variables	Linguistic Terms	Fuzzy Triangle Numbers
R_t^*	Very Low	(0 0 0.3099)
	Low	(0 0.3099 0.6198)
	Moderate	(0.3099 0.6198 0.8099)
	High	(0.6198 0.8099 1)
	Very High	(0.8099 1 1)
S_t^*	Very Low	(0 0 0.0563)
	Low	(0 0.0563 0.1125)
	Moderate	(0.0563 0.1125 0.5563)
	High	(0.1125 0.5563 1)
	Very High	(0.5563 1 1)
T_t^*	Very Low	(0 0 0.1042)
	Low	(0 0.1042 0.2083)
	Moderate	(0.1042 0.2083 0.6042)
	High	(0.2083 0.6042 1)
	Very High	(0.6042 1 1)
β_t^*	Very Low	(0 0 0.25)
	Low	(0 0.25 0.5)
	Moderate	(0.25 0.5 0.75)
	High	(0.5 0.75 1)
	Very High	(0.75 1 1)
Stock performance	Very Inferior	(0 0 0.167)
	Inferior	(0 0.167 0.334)
	Stable	(0.167 0.334 0.5)
	Very Stable	(0.334 0.5 0.625)
	Very Good	(0.5 0.625 0.75)
	Good	(0.625 0.75 0.875)
	Aggressive	(0.75 0.875 1)
	Very Aggressive	(0.875 1 1)

Step 3: Fuzzy rule base, fuzzy inference system and defuzzification

Following the fuzzification process, the core of this study's stock performance evaluation lies in a fuzzy rule based that translates expert knowledge and established financial theories into a set of “IF-THEN” rules. These rules utilized the fuzzy linguistic terms defined for the input variables and map to fuzzy linguistic terms of the output variables. The membership values for all input and output variables were derived based on real market data, using KLCI index as the benchmark. The sample set of rules is presented in Table 4, where the combination of 4 variables and 5 linguistic terms yield 625 possible rules that capturing all potential evaluation scenarios.

Table 4: Fuzzy rule base of stock performance

Rules	R_t^*	S_t^*	T_t^*	β_t^*	Stock Performance
1	Very Low	Very Low	Very Low	Very Low	Very Inferior
2	Very Low	Very Low	Very Low	Low	Very Inferior
3	Very Low	Very Low	Very Low	Moderate	Very Inferior
4	Very Low	Very Low	Very Low	High	Very Inferior
5	Very Low	Very Low	Very Low	Very High	Very Inferior
6	Very Low	Very Low	Low	Very Low	Very Inferior
7	Very Low	Very Low	Low	Low	Very Inferior
8	Very Low	Very Low	Low	Moderate	Very Inferior
9	Very Low	Very Low	Low	High	Very Inferior
10	Very Low	Very Low	Low	Very High	Very Inferior
⋮	⋮	⋮	⋮	⋮	⋮
125	Very Low	Very High	Very High	Very High	Very Inferior
126	Low	Very Low	Very Low	Very Low	Inferior
127	Low	Very Low	Very Low	Low	Inferior
128	Low	Very Low	Very Low	Moderate	Inferior
129	Low	Very Low	Very Low	High	Inferior
130	Low	Very Low	Very Low	Very High	Inferior
131	Low	Very Low	Low	Very Low	Inferior
132	Low	Very Low	Low	Low	Inferior
133	Low	Very Low	Low	Moderate	Inferior
134	Low	Very Low	Low	High	Inferior
135	Low	Very Low	Low	Very High	Inferior
⋮	⋮	⋮	⋮	⋮	⋮
250	Low	Very High	Very High	Very High	Inferior
251	Moderate	Very Low	Very Low	Very Low	Stable
252	Moderate	Very Low	Very Low	Low	Stable
253	Moderate	Very Low	Very Low	Moderate	Stable
254	Moderate	Very Low	Very Low	High	Stable
255	Moderate	Very Low	Very Low	Very High	Stable
256	Moderate	Very Low	Low	Very Low	Stable
257	Moderate	Very Low	Low	Low	Stable
258	Moderate	Very Low	Low	Moderate	Stable
259	Moderate	Very Low	Low	High	Stable
260	Moderate	Very Low	Low	Very High	Stable
⋮	⋮	⋮	⋮	⋮	⋮
312	Moderate	Moderate	Moderate	Low	Stable
313	Moderate	Moderate	Moderate	Moderate	Very Stable
314	Moderate	Moderate	Moderate	High	Very Stable
315	Moderate	Moderate	Moderate	Very High	Very Stable
316	Moderate	Moderate	High	Very Low	Very Stable
317	Moderate	Moderate	High	Low	Very Stable
318	Moderate	Moderate	High	Moderate	Very Stable
319	Moderate	Moderate	High	High	Very Stable
320	Moderate	Moderate	High	Very High	Very Stable
321	Moderate	Moderate	Very High	Very Low	Very Stable
322	Moderate	Moderate	Very High	Low	Very Stable
⋮	⋮	⋮	⋮	⋮	⋮

Table 4 (Continued)

375	Moderate	Very High	Very High	Very High	Very Stable
376	High	Very Low	Very Low	Very Low	Very Good
377	High	Very Low	Very Low	Low	Very Good
378	High	Very Low	Very Low	Moderate	Very Good
379	High	Very Low	Very Low	High	Very Good
380	High	Very Low	Very Low	Very High	Very Good
381	High	Very Low	Low	Very Low	Very Good
382	High	Very Low	Low	Low	Very Good
383	High	Very Low	Low	Moderate	Very Good
384	High	Very Low	Low	High	Very Good
385	High	Very Low	Low	Very High	Very Good
⋮	⋮	⋮	⋮	⋮	⋮
425	High	Low	Very High	Very High	Very Good
426	High	Moderate	Very Low	Very Low	Good
427	High	Moderate	Very Low	Low	Good
428	High	Moderate	Very Low	Moderate	Good
429	High	Moderate	Very Low	High	Good
430	High	Moderate	Very Low	Very High	Good
431	High	Moderate	Low	Very Low	Good
432	High	Moderate	Low	Low	Good
433	High	Moderate	Low	Moderate	Good
434	High	Moderate	Low	High	Good
435	High	Moderate	Low	Very High	Good
⋮	⋮	⋮	⋮	⋮	⋮
450	High	Moderate	Very High	Very High	Good
451	High	High	Very Low	Very Low	Aggressive
452	High	High	Very Low	Low	Aggressive
453	High	High	Very Low	Moderate	Aggressive
454	High	High	Very Low	High	Aggressive
455	High	High	Very Low	Very High	Aggressive
456	High	High	Low	Very Low	Aggressive
457	High	High	Low	Low	Aggressive
458	High	High	Low	Moderate	Aggressive
459	High	High	Low	High	Aggressive
460	High	High	Low	Very High	Aggressive
⋮	⋮	⋮	⋮	⋮	⋮
550	Very High	High	Very High	Very High	Aggressive
551	Very High	Moderate	Very Low	Very Low	Very Aggressive
552	Very High	Moderate	Very Low	Low	Very Aggressive
553	Very High	Moderate	Very Low	Moderate	Very Aggressive
554	Very High	Moderate	Very Low	High	Very Aggressive
555	Very High	Moderate	Very Low	Very High	Very Aggressive
556	Very High	Moderate	Low	Very Low	Very Aggressive
557	Very High	Moderate	Low	Low	Very Aggressive
558	Very High	Moderate	Low	Moderate	Very Aggressive
559	Very High	Moderate	Low	High	Very Aggressive
560	Very High	Moderate	Low	Very High	Very Aggressive
⋮	⋮	⋮	⋮	⋮	⋮
625	Very High	Very High	Very High	Very High	Very Aggressive

Based on Table 4, consider Rule 313 as illustrated example

IF R_t^* *is moderate* **AND** S_t^* *is moderate* **AND** T_t^* *is moderate* **AND** β_t^* *is moderate* **THEN** *very stable stock performance.*

This rule represents a logical financial scenario where all indicators show moderate behaviour. These rules align closely with a stock that performs in tandem with the market where the stock is neither outperforming nor underperforming, hence making it reasonable to classify performance as "very stable".

The fuzzy rule based reflects principles from the CAPM (Zainudin *et al.* 2023; Zainudin *et al.* 2024) where beta indicates systematic risk and from MPT (Chen & Huang 2009; Mohamed *et al.* 2009). which emphasizes the balance between risk and return. Figure 2 and Figure 3 illustrates the fuzzy rule based that show interaction of return and risk in line with MPT.

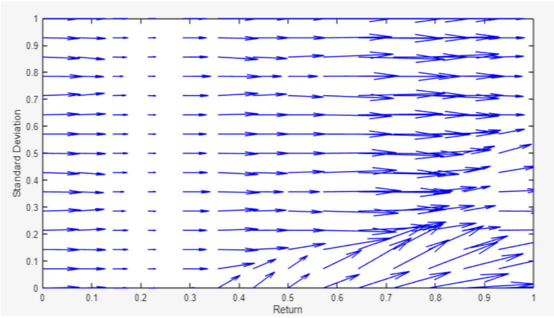

Figure 2: Quiver plot

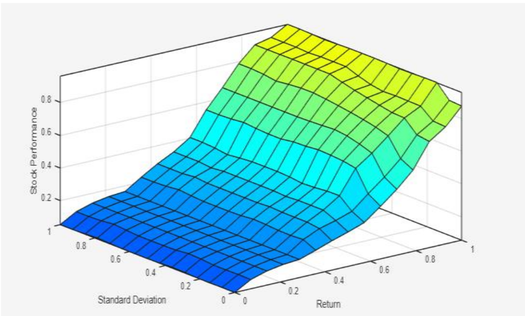

Figure 3: 3D surface plot

Figure 2 shows stable vector patterns in regions with moderate return and low to moderate risk, reflecting MPT's idea of efficient risk return combinations. Meanwhile, Figure 3 illustrates a smooth performance surface that capturing the trade off between return and risk, confirming the system's ability to model continuous and realistic investment scenarios.

Although return often acts as the primary factor in categorizing stock performance, where low return indicates inferior and high return indicates aggressive stocks, the rule base also incorporates risk, Treynor index and beta coefficient. These additional indicators provide a deeper understanding of risk exposure and risk-adjusted returns. For example, high return may still result in a lower performance classification if risk is excessive or Treynor index is low.

Step 4: Stock performance and investor selection preference.

Table 5 presents the stock performance result based on pessimistic and optimistic investor preferences, as determined by the fuzzy inference system.

Table 5: Stock performance categorized-based investor's preferences

Stocks	$R_t^{'}$	$S_t^{'}$	$T_t^{'}$	$\beta_t^{'}$	y^*	Pessimistic	Optimistic
Nestle Malaysia Bhd	0.5789	0.0000	0.0000	0.0000	0.3050	Inferior	Stable
Press Metal	1.0000	0.6092	1.0000	1.0000	0.9610	Aggressive	Very Aggressive
Sime Darby Bhd	0.1930	0.4529	0.7746	0.5111	0.1530	Very Inferior	Inferior
Petronas Chemicals Group Bhd	0.5439	0.3547	0.9335	0.8686	0.3610	Very Stable	Very Stable
Public Banks Bhd	0.4386	0.2425	0.8873	0.3170	0.2990	Inferior	Inferior
IHH Healthcare Bhd	0.4211	0.1383	0.7283	0.3579	0.3110	Inferior	Inferior
RHB Bank Bhd	0.4561	0.1683	0.8497	0.5747	0.3090	Inferior	Inferior
Genting Malaysia Bhd	0.0526	0.4770	0.8064	0.6339	0.1140	Very Inferior	Very Inferior
PPB Group Bhd	0.4561	0.0361	0.6156	0.2250	0.2460	Stable	Inferior
Digi.com Bhd	0.3158	0.2946	0.8121	0.5395	0.1800	Stable	Inferior
Maxis Bhd	0.0877	0.1443	0.7254	0.4581	0.1710	Stable	Very Inferior
Hong Leong Financial Group Bhd	0.5088	0.2285	0.8815	0.6554	0.3450	Very Stable	Very Stable
Malayan Banking Bhd	0.2982	0.0100	0.7283	0.3929	0.1670	Inferior	Inferior
Hong Leong Bank Bhd	0.5789	0.1503	0.8353	0.4888	0.4030	Very Stable	Very Stable
Kuala Lumpur Kepong Bhd	0.2982	0.1723	0.8006	0.5280	0.1670	Stable	Inferior
Dialog Group Bhd	0.3333	0.3487	0.8150	0.5399	0.2100	Stable	Inferior
Axiata Group Bhd	0.0702	0.4870	0.8728	0.8492	0.1180	Very Inferior	Very Inferior
Genting Bhd	0.0526	0.4770	0.8064	0.6339	0.1140	Very Inferior	Very Inferior
CIMB Group Holdings Bhd	0.3333	0.2545	0.8642	0.6899	0.2060	Stable	Inferior
Inari Amertron Bhd	0.7544	0.7154	0.8468	0.4390	0.7150	Very Good	Aggressive
Tenaga Nasional Bhd	0.0000	0.1583	0.7023	0.4484	0.0557	Inferior	Very Inferior
Petronas Gas Bhd	0.3684	0.0982	0.6272	0.2581	0.3140	Inferior	Inferior
Petronas Dagangan Bhd	0.3684	0.2365	0.7139	0.3496	0.2940	Inferior	Inferior
MISC	0.3860	0.1663	0.6734	0.2959	0.2940	Inferior	Inferior
Telekom Malaysia	0.4211	0.5251	0.8382	0.5659	0.2880	Inferior	Inferior
Top Glove Corp Bhd	0.5789	1.0000	0.9046	0.7068	0.3780	Stable	Very Stable
Hartalega Holdings Bhd	0.0702	0.9479	0.7746	0.5577	0.1200	Very Inferior	Very Inferior
KLCI	0.6198	0.1125	0.2083	0.5000	0.4860	Stable	Very Stable

Based on Table 5, pessimistic and optimistic investor preferences are shown. Neutral investor is not listed in Table 5 since no stocks in the dataset met the strict criteria for a neutral investor preference (a level of satisfaction of exactly 0.5). This can be illustrated as the membership function for each indicator, example for Press metal is as illustrated in Figure 4. Hence, using Eq. (15), the defuzzification is 0.9560 as illustrates in Figure 5.

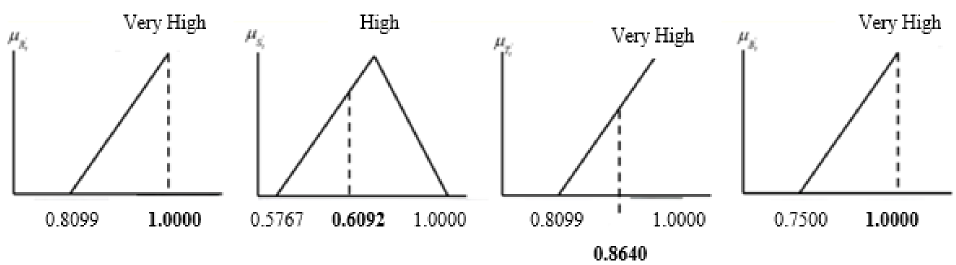

Figure 4: Membership function for each indicator for Press Metal

Figure 5 highlights the distinction between investor preferences. A pessimistic investor classifies Press Metal as a very aggressive stock, whereas an optimistic investor interprets it as an aggressive stock. This variation reflects how different sentiment influence stock performance evaluation within the fuzzy inference system.

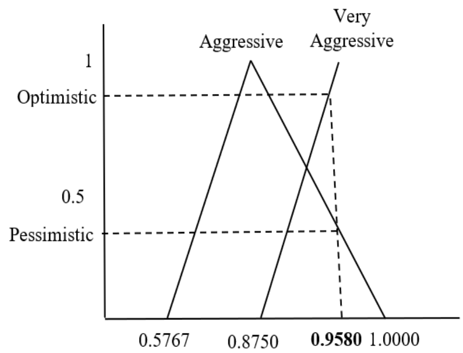

Figure 5: Membership of stock performance

5. Validation

For validation purposes, a comparative analysis was conducted between past research findings and the fuzzy inference system results, using the 30 stocks as a test case. The fuzzy rule based were also tested to penny stocks, high-priced stocks, and Hang Seng top 30 stocks to evaluate their stability and reliability across diverse market conditions.

Based on Table 2, the rules established by previous research were employed. This study standardized these rules using linguistic terms to enhance consistency and reduce ambiguity. Table 6 and Table 7 present the validation rules based on theories of Chen and Huang (2009) and Kiliçman and Sivalingam (2010).

Table 6 and Table 7 demonstrate that approximately 87.5% of the rule bases align with those reported by Chen and Huang (2009) and Kiliçman and Sivalingam (2010), as well as the rule bases outlined in Table 4. Due to the use of eight stocks performance evaluation in this study, there are slight differences in the stock performance outcomes. However, these results generally fall within the performance ranges defined in previous studies, as shown in Table 2. Specifically, in Table 7, where the return rate is low, the standard deviation is very low, and the Treynor Index is very high, a stock classified as having stable performance by Kiliçman and Sivalingam (2010) was categorized as inferior in fuzzy rule based.

This case had been highlighted in the introduction sections where Chen and Huang (2009) define stable performance funds differently from Kiliçman and Sivalingam (2010) and Gabriel *et al.* (2015) offer yet another interpretation. This widespread inconsistency underscores the critical need for a unique rule based than specific classifications. The fuzzy rule based directly addressed this need. As stated in Table 7, low return rate, very low standard deviation and a very high Treynor index was classified as stable by Kiliçman and Sivalingam (2010), however, within the rule based, this same stock was categorized as inferior. This discrepancy is not a shortcoming, but a deliberate classification driven by rule base's integrated logic. A low return, despite otherwise favourable risk indicates slower investment growth that could cause dissatisfaction among investors. Therefore, fuzzy rule base classifies such stock as inferior performance stock. It demonstrates that fuzzy rule base is ability to capture the complexities missing in previous stock performance evaluation.

Using the KLCI top 30 stocks as a case study, as presented in Table 5, the values of the R_t^*, S_t^*, T_t^* and β_t^* are transformed into linguistic variables to test the accuracy of the novel fuzzy clustering stocks performance. This testing was conducted by comparing the result of the KLCI top 30 stocks with previous studies, as shown in Table 2, and the fuzzy rule based developed in Table 4. Table 8 presents the validation results.

Table 6: Validation based Chen and Huang (2009)

R_t'	S_t'	T_t'	Stock Performance in Table 2	Rules	Satisfied performance in Table 4
Low	High	High	Inferior	216 – 220	Inferior
Moderate	Moderate	Moderate	Stable	311 – 315	Very Stable
High	Very Low	High	Good	391 – 395	Very Good
Very High	Very High	Very High	Aggressive	621 – 625	Very Aggressive

Table 7: Validation based Kiliçman and Sivalingam (2010)

R_t'	S_t'	T_t'	Stock Performance in Table 2	Rules	Satisfied performance in Table 4
Very Low	Low	Very Low	Inferior	27 – 31	Very inferior
Low	Very Low	Very High	Stable	146 – 150	Inferior
High	Low	Moderate	Good	411 – 415	Good
Very High	Very High	High	Aggressive	616 - 620	Very Aggressive

Table 8 reveals that approximately 92.59% of the results align with the rule bases outlined in Table 4. The discrepancies in stock performance evaluation are observed for Maxis Bhd and Inari Amerton Bhd. Maxis Bhd's stock performance, as evaluated by the novel fuzzy clustering method, was classified as "stable" and "inferior", whereas the fuzzy rule base categorized it as "very inferior". Futhermore, four rules, encompassing Press Metal, Sime Darby Bhd, Dialog Group Bhd, and KLCI index, evaluated based on R_t^*, S_t^* and T_t^* are consistent with the findings of Chen and Huang (2009) and Kiliçman and Sivalingam (2010). Conversely, Inari Amerton Bhd, exhibited a difference in stock performance evaluation. The novel fuzzy clustering method assessed its performance as "very good" and "good" while the fuzzy rule based and the studies by Chen and Huang (2009) and Kiliçman and Sivalingam (2010) classified it as "aggressive". This demonstrates that the fuzzy rule based maintain accuracy compared to previous studies. This discrepancy arises because the novel fuzzy clustering method incorporates behavioural factors and the reality of boundary conditions. Even when two inputs appear numerically similar, their degrees of membership in different fuzzy set may vary slightly. A minor variation can trigger different rules activations. This ability capture accommodates fuzziness of real financial situation that allows for precise reflection of stock performance than conventional clustering method. Table 9, 10 and 11 show the validation of rule based on Malaysia's penny stocks, Malaysia's blue-chip stocks and Hang Seng top 30 stocks respectively.

Table 9 and Table 10 indicate that approximately 90% of stock performance evaluations obtained using the novel fuzzy clustering method are consistent with the fuzzy rule based. Table 11 demonstrates a 96% alignment with the fuzzy rule based. According to Table 9, for Berjaya Land Bhd, evaluation for R_t', S_t', T_t' and β_t' as moderate, high, high and very low, respectively, the pessimistic investor evaluation is "inferior", and the optimistic investor evaluation is "stable". However, the fuzzy rule based evaluate it as "very stable". Similarly, discrepancies are observed for Fraser & Neave in Table 10 and Longfar Group Holdings in Table 11. As previously stated, these differences are attributed to the novel fuzzy clustering method's consideration of membership degrees and investor preferences. Despite the variations in stock performance evaluations, the method remains valid and is substantiated by past research.

Table 8: Comparison between result using novel fuzzy clustering stocks performance, fuzzy rules based and previous research

Stocks	$R_t^{'}$	$S_t^{'}$	$T_t^{'}$	$\beta_t^{'}$	Pessimistic	Optimistic	Rule No.	Table 4	Table 2
Nestle Malaysia Bhd	M	VL	VL	VL	Inferior	Stable	251	Stable	
Press Metal	VH	H	VH	VH	Aggressive	Very Aggressive	600	Very Aggressive	Kiliçman & Sivalingam (2010); Chen & Huang (2009)
Sime Darby Bhd	L	H	H	M	Very Inferior	Inferior	218	Inferior	Chen & Huang (2009)
Petronas Chemicals Group Bhd	M	H	VH	H	Very Stable	Stable	349	Very Stable	
Public Banks Bhd	L	M	VH	L	Inferior	Stable	197	Inferior	
IHH Healthcare Bhd	L	M	H	L	Inferior	Stable	192	Inferior	
RHB Bank Bhd	L	M	VH	M	Inferior	Stable	198	Inferior	
Genting Malaysia Bhd	VL	H	VH	H	Very Inferior	Inferior	99	Very Inferior	
PPB Group Bhd	L	VL	H	L	Stable	Inferior	142	Inferior	
Digi.com Bhd	L	M	VH	M	Stable	Inferior	198	Inferior	
Maxis Bhd	VL	M	H	M	Stable	Inferior	68	Very Inferior	
Hong Leong Financial Group Bhd	M	M	VH	H	Very Stable	Stable	324	Very Stable	
Malayan Banking Bhd	L	VL	H	M	Inferior	Inferior	143	Inferior	
Hong Leong Bank	M	M	VH	M	Very Stable	Stable	323	Very Stable	
Kuala Lumpur Kepong Bhd	L	M	H	M	Stable	Inferior	193	Inferior	
Dialog Group Bhd	L	H	VH	M	Stable	Inferior	223	Inferior	Chen & Huang (2009)
Axiata Group Bhd	VL	H	VH	H	Very Inferior	Inferior	99	Very Inferior	
Genting Bhd	VL	H	VH	H	Very Inferior	Inferior	99	Very Inferior	
CIMB Group Holdings Bhd	L	M	VH	H	Stable	Inferior	199	Inferior	
Inari Amertron Bhd	H	H	VH	M	Very Good	Good	473	Aggressive	Kiliçman & Sivalingam (2010); Chen & Huang (2009)
Tenaga Nasional Bhd	VL	M	H	M	Inferior	Very Inferior	68	Very Inferior	
Petronas Gas Bhd	L	M	H	L	Inferior	Stable	192	Inferior	
Petronas Dagangan Bhd	L	M	H	L	Inferior	Stable	192	Inferior	
MISC	L	M	H	L	Inferior	Stable	192	Inferior	
Telekom Malaysia	L	H	VH	M	Inferior	Stable	223	Inferior	
Top Glove Corp Bhd	M	VH	VH	H	Stable	Very Stable	374	Very Stable	
Hartalega Holdings Bhd	VL	VH	H	M	Very Inferior	Inferior	118	Very Inferior	
KLCI	M	M	M	M	Stable	Very Stable	313	Very Stable	Chen & Huang (2009)

[a]VL= Very Low; L= Low; M=Moderate; H=High; VH=Very High

Table 9: Validate rule based on penny stocks

Penny Stocks	R_t'	S_t'	T_t'	β_t'	Pessimistic	Optimistic	Rule No.	Table 4	Table 2
Astro	VL	VL	H	M	Very Inferior	Inferior	18	Very Inferior	
Velestro	M	H	VH	H	Very Stable	Stable	349	Very Stable	
Malaysian Resources	L	M	VH	H	Very Inferior	Inferior	199	Inferior	
Berjaya Corporation	L	M	VL	VL	Inferior	Stable	176	Inferior	
Berjaya Land Bhd	M	H	H	VL	Inferior	Stable	341	Very Stable	
Dagang NeXchange	VH	VH	VH	VH	Aggressive	Very Aggressive	625	Very Aggressive	Kiliçman & Sivalingam (2010); Chen & Huang (2009)
Datasonic Group	M	H	VH	M	Very Stable	Very Good	348	Very Stable	
Hextar Industries	VH	H	VH	M	Very Aggressive	Aggressive	598	Very Aggressive	Kiliçman & Sivalingam (2010); Chen & Huang (2009)
GDEX Bhd	VL	M	H	H	Inferior	Very Inferior	69	Very Inferior	
Eco Wrold International	L	L	VH	H	Very Inferior	Inferior	174	Inferior	Kiliçman & Sivalingam (2010)

[a]VL= Very Low; L= Low; M=Moderate; H=High; VH=Very High

Table 10: Validate rule based on blue-chip stocks

Expensive Stocks	R_t'	S_t'	T_t'	β_t'	Pessimistic	Optimistic	Rule No.	Table 4	Table 2
Nestle	L	VL	VL	VL	Very Inferior	Inferior	126	Inferior	
Malaysian Pacific	L	H	H	L	Inferior	Stable	217	Inferior	
Fraser & Neave	VL	M	M	L	Stable	Inferior	62	Very Inferior	
Hextar Technologies	VH	VH	VH	VH	Aggressive	Very Aggressive	625	Very Aggressive	Kiliçman & Sivalingam (2010); Chen & Huang (2009)
Petronas Dagangan	VL	M	H	M	Very Inferior	Inferior	68	Very Inferior	
Dutch Lady Milk	VL	L	VL	L	Inferior	Very Inferior	27	Very Inferior	Kiliçman & Sivalingam (2010)
Kuala Lumpur Kepong	VL	M	H	VH	Very Inferior	Inferior	70	Very Inferior	
Batu Kawan	L	M	H	M	Very Inferior	Inferior	193	Inferior	
Petronas Gas	VL	M	H	M	Very Inferior	Inferior	68	Very Inferior	
United Plantation	VL	VL	L	VL	Very Inferior	Inferior	6	Very Inferior	Kiliçman & Sivalingam (2010)

[a]VL= Very Low; L= Low; M=Moderate; H=High; VH=Very High

Table 11: Validate rule based on Hang Seng top 30 stocks

Stocks	$R_t^{'}$	$S_t^{'}$	$T_t^{'}$	$\beta_t^{'}$	Pessimistic	Optimistic	Rule No.	Table 4	Table 2
Techtronic Industries Company	M	H	M	M	Stable	Very Stable	338	Very Stable	
China Mengniu Dairy	M	H	M	M	Very Stable	Stable	338	Very Stable	
Hong Lung Properties	L	M	M	L	Very Inferior	Inferior	187	Inferior	
Hengan International Group	VL	VL	L	L	Very Inferior	Inferior	7	Very Inferior	
China Petroleum & Chemical Corp	VL	M	L	L	Very Inferior	Inferior	57	Very Inferior	
China Life Insurance Company	VL	M	M	M	Inferior	Very Inferior	63	Very Inferior	
Wuxi Biologics (Cayman) Inc	H	VH	H	H	Very Aggressive	Aggressive	494	Aggressive	Kiliçman & Sivalingam (2010); Chen & Huang (2009)
ANTA Sports Products Limited	M	H	M	H	Very Stable	Very Good	339	Very Stable	
Industrial and Commercial Bank	VL	M	L	L	Very Inferior	Inferior	57	Very Inferior	
ENN Energy Holdings	M	H	M	L	Very Stable	Stable	337	Very Stable	
Longfar Group Holdings	M	H	M	H	Inferior	Stable	339	Very Stable	
The Hong Kong and China Gas Company	VL	M	L	VL	Very Inferior	Inferior	56	Very Inferior	
CK Infrastructure Holdings	VL	M	L	L	Very Inferior	Inferior	57	Very Inferior	
China Resources Land Limited	M	H	M	M	Very Stable	Stable	338	Very Stable	
CNOOC Limited	L	H	M	M	Stable	Inferior	213	Inferior	
CLP Holdings Limited	VL	L	VL	VL	Very Inferior	Inferior	26	Very Inferior	
Lenovo Group Limited	M	H	M	L	Very Stable	Stable	337	Very Stable	
Li Ning Company Limited	VH	H	VH	H	Aggressive	Very Aggressive	599	Very Aggressive	
CSPC Pharmaceutical Group	L	H	M	M	Inferior	Stable	213	Inferior	
CITIC Limited	L	M	L	L	Very Inferior	Inferior	182	Inferior	
Galaxy Entertainment Group	L	H	M	H	Inferior	Inferior	214	Inferior	
Henderson land Development	VL	M	L	L	Very Inferior	Inferior	57	Very Inferior	
Alibaba Health Information Technology	M	VH	H	VH	Very Good	Very Stable	370	Very Stable	
New world Development Company	VL	M	L	M	Very Inferior	Inferior	58	Very Inferior	
Hang Seng	M	M	M	M	Very Stable	Very Stable	313	Very Stable	Chen & Huang (2009)

6. Discussion

This study successfully developed a novel fuzzy clustering method through the implementation of a Fuzzy Inference System (FIS) to evaluate stock performance while incorporating investor preferences, as shown in Table 5. This crucial inclusion of diverse investor preferences allows for a more personalized and realistic stock selection process.

Furthermore, the usage of numerical values that represent the precise strength of stock performance. This numerical allows to differentiate between stocks, and eliminate simple average values used in conventional method. This comprehensive numerical approach ensures that the fuzzy rule based consider all possible outcomes during stock performance evaluation aligning with investor preferences simultaneously.

The performance of the novel fuzzy clustering method was validated against previous studies and fuzzy rule based, as presented in Tables 8, 9, 10, and 11. The results indicate that while the novel fuzzy clustering method produces outcomes that differ slightly from the established fuzzy rule based, this variation arises due to its consideration of investors' preferences factors. Additionally, even when two input values appear similar, their degrees of membership in different fuzzy sets may vary slightly, leading to different rule activations. This demonstrates that when an input is positioned at the boundary between two fuzzy sets, small variations can trigger different rules with varying intensities. Despite differences in stock performance evaluations, the method remains valid and is supported by previous research. This robustness to boundary conditions allows for a more precise and realistic reflection of stock performance.

Regarding the stock performance categories, fuzzy rule based classifies stock performance into eight linguistic labels namely as "very inferior", "inferior", "stable", "very stable", "good", "very good", "aggressive", and "very aggressive" as shown in Table 5. Stock classifies as "very inferior" and "inferior" generally exhibit unstable financial conditions, characterized by high risk and low returns, make that stocks unattractive investment options. Consequently, investing in this category is considered unprofitable. Stocks in the "stable" and "very stable" categories show improved performance but still carry moderate to high risk with relatively low returns though "very stable" stocks may align with overall market trends in which not optimal for short term gains. In contrast, "good" and "very good" stocks are the most favourable for investment that offering high returns with low risk, thereby maximizing profit potential while minimizing the likelihood of loss. Meanwhile, "aggressive" and "very aggressive" stocks provide higher returns at increased risk, making that stocks suitable for risk tolerant investors. As such, stocks within the "good", "very good", "aggressive" and "very aggressive" classifications are generally recommended for investment consideration.

The overall performance of the novel fuzzy clustering method was validated against previous studies and fuzzy rule based, demonstrating its validity and support by previous research, despite the differences in stock performance evaluations. Moreover, the fuzzy rule based able to capture all potential evaluation scenarios. This demonstrated that this study able to use a single method to determine stock performance, to cluster stock performance, and to determine stocks-based investor preferences.

7. Conclusion

This paper introduced and validated a novel fuzzy clustering method for stock performance evaluation incorporating investor preferences by implementing fuzzy inference system. The incorporation of investor preferences providing more realistic stock selection process by delivering precise numerical results quantifying the strength of stock performance. The evaluation of stock performance considering all potential evaluation scenarios shows the complete and structure approach, one that incorporates all key financial indicators uses consistent measurement scales and models the interrelationship among financial indicators and incorporated with investor preferences. The versatility and robustness of novel fuzzy clustering method were demonstrated through its successful application across diverse stock categories, including KLCI top 30 stocks, penny stocks, blue-chip stocks, and Hang Seng top 30 stocks. The validation results, obtained through comparative analysis with fuzzy rule based and previous research, confirmed the method's effectiveness in considering a comprehensive range of stock performance outcomes. This method empowers investors with valuable, data-driven insights, facilitating more informed and personalised investment decisions. While the novel fuzzy clustering method successfully captures the uncertainty associated with pessimistic and optimistic investor behaviour, future research could further enhance its applicability by integration components that address reliability, hesitancy, and bipolarity within the stock selection process. This expansion would enable a more comprehensive understanding of investor decision-making, leading to even more refined and robust stock performance evaluations.

Acknowledgments

This research was funded by research grant provided by Universiti Kebangsaan Malaysia code GUP-2019-038, the APC was funded by grant GUP-2019-038 and research grant provided by Universiti Teknologi MARA GDT2021/1-27.

References

Al-Augby S., Majeswski S., Majewska A. & Nermend K. 2014. Comparison of k-means and fuzzy c-means clustering methods for a sample of Gulf Cooperation Council stock markets. *Folio Oeconomica Stetinensia* **14**(2): 19-36.

Alqaryouti O., Farouk T. & Siyam N. 2019. Clustering stock markets for balanced portfolio construction. *Proceeding of the International Conference on Advanced Intelligent Systems and Informatics 2018*, pp. 577–587.

Brigham E.F. & Ehrhardt M.C. 2011. *Financial management: Theory and Practice*. 13th Ed. Mason, OH: South-Western Cengage Learning.

Chan N.H. & Zhang R.M. 2009. Quantile inference for near-integrated autoregressive time series under infinite variance and strong dependence. *Stochastic Processes and their Applications* **119**(12): 4124–4148.

Chen L.H. & Huang L. 2009. Portfolio optimization of equity mutual funds with fuzzy return rates and risks. *Expert Systems with Applications* **36**(2): 3720–3727.

Da Costa Jr N., Cunha J. & Da Silva S. 2005. Stock selection based on cluster analysis. *Economics Bulletin* **13**(1): 1-9.

Falk M. & Guillou A. 2008. Peaks-over-threshold stability of multivariate generalized Pareto distributions. *J. Multivar. Anal.* **99**(4): 715-734.

Gabriel F.S., Post K.C.D.S.R. & Rogers P. 2015. Clustering real estate investment trusts: Brazil versus United States. *J. Manag. Res.* **7**(4): 166–190.

Gubu L., Rosadi D. & Abdurakhman. 2021. Robust mean-variance portfolio selection with time series clustering. *AIP Conference Proceedings* **2329**(1): 060027.

Haight G.T., Morrell S.O. & Ross G. 2007. *How to Select Investment Managers and Evaluate Performance: A Guide for Pension Funds, Endowments, Foundations, and Trusts.* Hoboken, NJ: John Wiley & Sons.

Kiliçman A. & Sivalingam J. 2010. Portfolio optimization of equity mutual funds: Malaysian case study. *Adv. Fuzzy Syst.* **2010**: 879453.

Kuhle J.L. & Lin E.C. 2018. An evaluation of risk and return performance measure alternatives: Evidence from real estate mutual funds. *Rev. Bus. Financ. Stud.* **9**(1): 1-11

Kumari S.K., Kumar P., Priya J., Surya S. & Bhurjee A.K. 2019. Mean-value at risk portfolio selection problem using clustering technique: A case study. *AIP Conf. Proc.* **2112**: 020178.

León D., Aragón A., Sandoval J., Hernández G., Arévalo A. & Niño J. 2017. Clustering algorithms for risk-adjusted portfolio construction. *Procedia Computer Science* **108**: 1334–1343.

Li H.Q. & Yi Z.H. 2019. Portfolio selection with coherent Investor's expectations under uncertainty. *Expert Systems with Applications* **133**: 49-58.
Ma L. & Tang Y. 2019. Portfolio manager ownership and mutual fund risk taking, *Manag. Sci*. **65**(12): 5518-5534.
Marvin K. 2015. Creating diversified portfolios using cluster analysis. PhD Thesis. Princeton University.
Mirnoori S.M. & Shariati A. 2012. Fuzzy portfolio optimization using Chen and Huang model: Evidence from Iranian mutual funds. *Afr. J. Bus. Manag.* **6**(22): 6608–6616.
Mohamed Z., Mohamad D. & Samat O. 2009. A fuzzy approach to portfolio selection. *Sains Malaysiana* **38**(6): 895–899.
Nanda S.R., Mahanty B. & Tiwari M.K. 2010. Clustering Indian stock market data for portfolio management. *Expert Syst. Appl.* **37**(12): 8793–8798.
Robiyanto R. 2018. Performance evaluation of stock price indexes in the Indonesia stock exchange. *Int. Res. J. Bus. Stud*. **10**(3): 173-182.
Stelzer R. 2008. Multivariate Markov-switching ARMA processes with regularly varying noise. *J. Multivar. Anal.* **99**(6): 1177–1190.
Tekin B. & Gümüş F.B. 2017. The classification of stocks with basic financial indicators: An application of cluster analysis on the BIST 100 index. *Int. J. Acad. Res. Bus. Soc. Sci.* **7**(5): 104–131.
Widhiarti R.P., Anggraeni L. & Pasaribu S.H. 2018. Analysis of investor sentiment impact in Indonesia composite stock price index return volatility. *Indonesian Journal of Business and Entrepreneurship* **4**(3): 239-248.
Zainudin N.S., Ng K.H., Ting C.Y., Khor K.C., Tong G.K. & Kalid S.N. 2023. Portfolio construction of good defensive Malaysian Shariah-compliant stocks using data mining techniques. *Journal of System and Management Sciences* **13**(5): 260-275.
Zainudin N.S., Ting C.Y., Khor K.C., Ng K.H., Tong G.K. & Kalid S.N. 2024. Clustering defensive Shariah-compliant stocks using financial performance as the indicator. JOIV: *International Journal on Informatics Visualization* **8**(1): 115-122.

Department of Mathematical Sciences
Faculty of Science and Technology
Universiti Kebangsaan Malaysia
43600 Bangi
Selangor, MALAYSIA
E-mail: sitinazifah@uitm.edu.my, shj@ukm.edu.my, munira@ukm.edu.my*

Center of Mathematical Sciences
Faculty of Computer and Mathematical Sciences
Universiti Teknology MARA Negeri Sembilan Branch, Seremban Campus
70300 Seremban
Negeri Sembilan, MALAYSIA
E-mail: sitinazifah@uitm.edu.my

Mathematics Division
Centre for Foundation Studies in Sciences
University of Malaya
50603 Kuala Lumpur, MALAYSIA
E-mail: ahmadsyafadhli@um.edu.my

Received: 19 March 2025
Accepted: 24 July 2025

*Corresponding author