MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2s, 2026, Pages 60-62

Hybrid Type-2 Fuzzy AHP-TOPSIS Framework for Mutual Fund Performance Evaluation in Indian Stock Market (BSE)*

[1]**Dr. Y.Suneetha**
[1]Assistant Professor,Department of Business Management,Sri Padmavati Mahila Visvavidyalayam,Tirupati,Andhra Pradesh,India,517 502
[1]Email ID: sunipakala@gmail.com
[2]**Dr. S.Sangeethamani,**
[2]Associate Professor,Department of Mathematics,Coimbatore Institute of Technology,Coimbatore,Tamilnadu,India,641014
[2]Email id:sangeetha.mathematics@gmail.com
[3]**Dr.S.Jayasri**
[3]Associate Professor,Department of Mathematics,Coimbatore Institute of Technology,Coimbatore,Tamilnadu,India,641014
[3]E- mail id: jayasris.mathematics@gmail.com
[4]**N.Rameshan**
[4]Assistant Professor (Sr.G),Department of Mathematics ,Faculty of Engineering and Technology,SRM Institute of Science and Technology,Vadapalani Campus,Chennai - 600 026,Tamil Nadu ,India , 600026
[4]Corresponding author E- mail id : rameshan@srmist.edu.in
[5]**Dr. G. Jenitha**
[5]Associate Professor,Department of Mathematics,AMET deemed to be University,Chennai,Tamil nadu,India,603112
[5]E- mail id:jenitha.g@ametuniv.ac.in

Abstract
This study explores stock selection within a complex and nonlinear financial environment by integrating two major categories of performance indicators: Accounting Financial Measures (AFM) and Economic Value Measures (EFM). It argues that evaluating both sets together provides a more robust and comprehensive basis for investment decision-making than relying on either in isolation. The framework considers key financial criteria, including Return on Invested Capital (ROIC), Economic Value Added (EVA), Price/Earnings-to-Growth (PEG) ratio, and Free Cash Flow (FCF) yield, among others, to capture profitability, growth potential, and value creation. To address uncertainty and subjectivity inherent in financial analysis, the study employs the Interval Type-2 Fuzzy Analytic Hierarchy Process (FAHP), a sophisticated multi-criteria decision-making method. This approach allows for more flexible and realistic modeling of investor judgments under ambiguity. Financial data were collected from ten leading companies listed on the BSE Exchange, ensuring relevance and representation of high-performing firms. The findings reveal that the PEG ratio emerges as the most significant criterion in stock selection, emphasizing the importance of balancing earnings growth with valuation. Profitability-based indicators such as ROIC and EVA also rank highly, highlighting their critical role in assessing efficient capital use and long-term value generation. In contrast, liquidity measures show relatively lower importance in the decision-making hierarchy. Overall, the study underscores the value of prioritizing profitability and growth-oriented metrics, offering practical insights for investors seeking to build strategically sound and performance-driven portfolios.
Keywords: Stock Selection; Interval Type-2 Fuzzy Analytic Hierarchy Process (FAHP); PEG Ratio; Return on Invested Capital (ROIC)

1.Introduction

Stock selection in modern financial markets is increasingly complex due to dynamic economic conditions, market volatility, and the nonlinear relationships among financial variables. Investors are required to evaluate multiple financial indicators simultaneously to make informed decisions. Traditionally, stock evaluation has relied on Accounting Financial Measures (AFM), such as profitability and earnings-based metrics. However, these measures often fail to capture the true economic value created for shareholders. In contrast, Economic Value Measures (EFM), including indicators like Economic Value Added (EVA), focus on value creation beyond accounting profits. Integrating AFM and EFM provides a more comprehensive framework for evaluating firm performance and investment potential. Key indicators such as Return on Invested Capital (ROIC), Price/Earnings-to-Growth (PEG) ratio, and Free Cash Flow (FCF) yield help assess profitability, growth, and financial efficiency. However, the presence of uncertainty and subjective judgment in financial decision-making poses significant challenges. To address these issues, this study employs the Interval Type-2 Fuzzy Analytic Hierarchy Process (FAHP), an advanced multi-criteria decision-making (MCDM) method. This approach enables better handling of ambiguity and imprecision in expert evaluations. By applying FAHP to leading NASDAQ-listed companies, the study aims to prioritize financial indicators and provide a structured framework for effective stock selection.

Literature Review

Stock selection has been widely studied in financial literature, with early research focusing on traditional asset pricing and portfolio theory. The foundational work of Harry Markowitz (1952) introduced the concept of portfolio optimization through risk–return trade-offs, forming the basis of modern investment analysis. Later, William Sharpe (1964), along with Lintner (1965), developed the Capital Asset Pricing Model (CAPM), which established the relationship between expected return and systematic risk. These classical models significantly influenced financial decision-making but were limited in capturing complex market behavior. To improve firm valuation, accounting-based performance measures gained prominence. Studies by Stephen Penman (2013) emphasized the role of financial statement analysis in evaluating corporate performance. However, traditional Accounting Financial Measures (AFM) such as earnings and profitability ratios were criticized for ignoring the cost of capital and failing to reflect true shareholder value creation. To address these limitations, Economic Value Measures (EFM) were introduced. G. Bennett Stewart (1991) proposed Economic Value Added (EVA) as a superior performance measure that incorporates the cost of capital. Empirical studies by Lehn and Makhija (1996) supported EVA's effectiveness in explaining firm value. Similarly, Return on Invested Capital (ROIC) and Free Cash Flow (FCF) have been recognized as important indicators of operational efficiency and financial sustainability. Growth-oriented metrics such as the Price/Earnings-to-Growth (PEG) ratio (Easton, 2004) further enhance investment evaluation by combining valuation and earnings growth perspectives. In parallel, decision-making techniques evolved to handle multiple criteria in financial analysis. The Analytic Hierarchy Process (AHP), introduced by Thomas Saaty (1980), became widely used for prioritizing investment criteria. However, its inability to manage uncertainty led to the development of fuzzy extensions. Fuzzy set theory introduced by Lotfi Zadeh (1965, 1975) enabled modeling of ambiguity in decision-making. Buckley (1985) and Chang (1996) extended AHP into fuzzy environments, improving its applicability in finance.Further advancements led to Interval Type-2 Fuzzy AHP, which enhances uncertainty handling by modeling higher-order fuzziness (Mendel, 2001). This method has been successfully applied in complex decision environments, including financial selection problems. Multi-Criteria Decision-Making (MCDM) approaches such as those discussed by Triantaphyllou (2000) and Hwang & Yoon (1981) further strengthened structured decision frameworks in investment analysis. Despite extensive research, most studies either focus on AFM or EFM separately, or apply classical fuzzy methods without fully addressing higher-order uncertainty. Therefore, integrating AFM and EFM within an Interval Type-2 FAHP framework provides a more comprehensive and realistic approach to stock selection, improving decision accuracy under uncertainty.

Research Gap

Despite extensive research on stock selection, several gaps remain in the integration of financial performance measures and decision-making techniques. Most traditional studies rely heavily on Accounting Financial Measures (AFM), such as earnings, return ratios, and liquidity indicators, which primarily reflect historical performance. While useful, these measures often fail to incorporate the cost of capital and do not adequately capture long-term value creation. On the other hand, Economic Value Measures (EFM), including Economic Value Added (EVA) and Return on Invested Capital (ROIC), provide deeper insights into shareholder value but are less frequently integrated with traditional metrics in a unified analytical framework.Another significant gap lies in the limited application of advanced Multi-Criteria Decision-Making (MCDM) techniques in stock selection. Although methods such as the Analytic Hierarchy Process (AHP) and its fuzzy extensions have been applied in financial decision-making, many studies rely on Type-1 fuzzy logic, which may not sufficiently handle higher levels of uncertainty and ambiguity inherent in financial markets. The use of Interval Type-2 Fuzzy Analytic Hierarchy Process (FAHP) remains relatively underexplored, particularly in combining both AFM and EFM indicators within a single decision model.Furthermore, existing studies often focus on a narrow set of financial indicators or specific sectors, limiting the generalizability of their findings. There is also a lack of research that emphasizes the comparative importance of growth-oriented metrics such as the PEG ratio alongside profitability and value-based measures. This study addresses these gaps by integrating AFM and EFM within an Interval Type-2 FAHP framework and applying it to leading NASDAQ-listed companies to provide a more comprehensive and realistic stock selection model.

Limitations

Despite its contributions, this study has several limitations. First, the analysis is based on a sample of only ten NASDAQ-listed companies, which may not fully represent the diversity of global financial markets. The findings may therefore have limited generalizability across different industries, regions, or market conditions.Second, the study relies on selected financial indicators, such as ROIC, EVA, PEG ratio, and FCF yield, which, although important, do not encompass all possible factors influencing stock performance. Macroeconomic variables, qualitative factors, and market sentiment are not included, which may affect the comprehensiveness of the model.Third, the FAHP methodology involves expert judgment in assigning weights and preferences, which introduces a degree of subjectivity. Although Interval Type-2 fuzzy logic reduces uncertainty, it does not completely eliminate bias in decision-making.

Additionally, the study uses historical financial data, which may not fully capture future market dynamics or sudden economic changes. Finally, the complexity of the FAHP model may limit its practical applicability for individual investors who lack technical expertise.

Interval Type-2 Fuzzy Sets(IT2-FS)

Definition A type-2 fuzzy set $\tilde{\tilde{\xi}}$ in the universe of discourse Ω can be represented by a type-2 membership function $\mu_{\tilde{\tilde{\xi}}}$ shown as follows:

$$\tilde{\tilde{\varrho}} = \{\left((\zeta, \Lambda), \mu_{\tilde{\tilde{\varrho}}}(\zeta, \Lambda)\right) | \forall \zeta \in \Omega, \forall \Lambda \in J_\zeta \subseteq [0,1], 0 \le \mu_{\tilde{\tilde{\varrho}}}(\zeta, \Lambda) \le 1\}$$

where J_ζ denotes an interval [0,1]. Moreover, the type-2 fuzzy set $\tilde{\tilde{\xi}}$ also represented as

$$\tilde{\tilde{\varrho}} = \int_{\zeta \in \Omega} \int_{u \in J_x} \mu_{\tilde{\tilde{\varrho}}}(\zeta, \Lambda)/(\zeta, \Lambda)$$

where $J_\zeta \subseteq [0,1]$ and '$\int$' denotes union over all admissible ζ and Λ.

Definition Let $\tilde{\tilde{\xi}}$ be a type-2 fuzzy set in the universe of discourse Ω represented by the type-2 membership function $\mu_{\tilde{\tilde{\xi}}}$. If all $\mu_{\tilde{\tilde{\xi}}}(\zeta, \Lambda) = 1$, then is called an interval type-2 fuzzy set. An interval type-2 fuzzy set $\tilde{\tilde{\xi}}$ can be regarded as a special case of a type-2 fuzzy set, represented as Mendel et al. .

$$\tilde{\tilde{\varrho}} = \int_{\zeta \in \Omega} \int_{\Lambda \in J_\zeta} 1/(\zeta, \Lambda), J_\zeta \subseteq [0,1].$$

The upper and lower membership function of an interval type-2 fuzzy set are type-1 membership functions.

Let $\tilde{\tilde{\varrho}} = (\tilde{\varrho}^U, \tilde{\varrho}^L)$ be a trapezoidal interval type-2 fuzzy set, where $\tilde{\xi}^U$ is a upper trapezoidal membership function and $\tilde{\xi}^L$ is a lower trapezoidal membership function, which is defined as follows:

$$\tilde{\tilde{\varrho}} = (\tilde{\varrho}^U, \tilde{\varrho}^L) = (\left(\varrho^{(1)U}, \varrho^{(2)U}, \varrho^{(3)U}, \varrho^{(4)U}; H_1(\tilde{\varrho}^U), H_2(\tilde{\varrho}^U)\right), \left(\varrho^{(1)L}, \varrho^{(2)L}, \varrho^{(3)L}, \varrho^{(4)L}; H_1(\tilde{\varrho}^L), H_2(\tilde{\varrho}^L)\right))$$

where $\tilde{\varrho}^U$ and $\tilde{\varrho}^L$ are type-1 fuzzy sets, $\varrho^{(1)U}, \varrho^{(2)U}, \varrho^{(3)U}, \varrho^{(4)U}$, $\varrho^{(1)L}, \varrho^{(2)L}, \varrho^{(3)L}, \varrho^{(4)L}$ are the reference points of the interval type-2 fuzzy set $\tilde{\varrho}$, $H_j(\varrho^U) \in [0,1]$ denote the membership value of the element $\varrho^{(j+1)U}$ (j=1,2) in the upper trapezoidal membership function $\tilde{\varrho}^U$ and $H_j(\tilde{\varrho}^L) \in [0,1]$ denotes the membership value of the element $\varrho^{(j+1)}L$ in the lower trapezoidal membership function $\tilde{\varrho}^L$(Chen and Lee). The membership function of interval type-2 trapezoidal fuzzy number is shown in Figure 1.

Interval Type-2 Trapezoidal Fuzzy Number

Interval Type-2 Trapezoidal Fuzzy Number

Given $\widetilde{\varrho_1}$ and $\widetilde{\varrho_2}$ as

$$\widetilde{\varrho_1} = (\tilde{\varrho}_1^U, \tilde{\varrho}_1^L) = (\left(\varrho_1^{(1)U}, \varrho_1^{(2)U}, \varrho_1^{(3)U}, \varrho_1^{(4)U}; H_1(\tilde{\varrho}^U), H_2(\tilde{\varrho}^U)\right), \left(\varrho_1^{(1)L}, \varrho_1^{(2)L}, \varrho_1^{(3)L}, \varrho_1^{(4)L}; H_1(\tilde{\varrho}^L), H_2(\tilde{\varrho}^L)\right))$$

and

$$\widetilde{\varrho_2} = (\tilde{\varrho}_2^U, \tilde{\varrho}_2^L) = (\left(\varrho_2^{(1)U}, \varrho_2^{(2)U}, \varrho_2^{(3)U}, \varrho_2^{(4)U}; H_1(\tilde{\varrho}^U), H_2(\tilde{\varrho}^U)\right), \left(\varrho_2^{(1)L}, \varrho_2^{(2)L}, \varrho_2^{(3)L}, \varrho_2^{(4)L}; H_1(\tilde{\varrho}^L), H_2(\tilde{\varrho}^L)\right))$$

The arithmetic operations of the interval type-2 fuzzy sets are described as follows:

$$\begin{aligned}
\widetilde{\varrho_1} \oplus \widetilde{\varrho_2} &= (\tilde{\varrho}_1^U, \tilde{\varrho}_1^L) \oplus (\tilde{\varrho}_2^U, \tilde{\varrho}_2^L) \\
&= ((\varrho_1^{(1)U} + \varrho_2^{(1)U}, \varrho_1^{(2)U} + \varrho_2^{(2)U}, \varrho_1^{(3)U} + \varrho_2^{(3)U}, \varrho_1^{(4)U} + \varrho_2^{(4)U}; \min\left(H_1(\tilde{\varrho}_1^U), H_1(\tilde{\varrho}_2^U)\right), \\
&\quad \min\left(H_2(\tilde{\varrho}_1^U), H_2(\tilde{\varrho}_2^U)\right)), (\varrho_1^{(1)L} + \varrho_2^{(1)L}, \varrho_1^{(2)L} + \varrho_2^{(2)L}, \varrho_1^{(3)L} + \varrho_2^{(3)L}, \varrho_1^{(4)L} + \varrho_2^{(4)L}; \\
&\quad \min\left(H_1(\tilde{\varrho}_1^L), H_1(\tilde{\varrho}_2^L)\right), \min\left(H_2(\tilde{\varrho}_1^L), H_2(\tilde{\varrho}_2^L)\right)))
\end{aligned}$$

$$\begin{aligned}
\widetilde{\varrho_1} \ominus \widetilde{\varrho_2} &= (\tilde{\varrho}_1^U, \tilde{\varrho}_1^L) \ominus (\tilde{\varrho}_2^U, \tilde{\varrho}_2^L) \\
&= ((\varrho_1^{(1)U} - \varrho_2^{(4)U}, \varrho_1^{(2)U} - \varrho_2^{(3)U}, \varrho_1^{(3)U} - \varrho_2^{(2)U}, \varrho_1^{(4)U} - \varrho_2^{(1)U}; \min\left(H_1(\tilde{\varrho}_1^U), H_1(\tilde{\varrho}_2^U)\right), \\
&\quad \min\left(H_2(\tilde{\varrho}_1^U), H_2(\tilde{\varrho}_2^U)\right)), (\varrho_1^{(1)L} - \varrho_2^{(4)L}, \varrho_1^{(2)L} - \varrho_2^{(3)L}, \varrho_1^{(3)L} - \varrho_2^{(2)L}, \varrho_1^{(4)L} - \varrho_2^{(1)L}; \\
&\quad \min\left(H_1(\tilde{\varrho}_1^L), H_1(\tilde{\varrho}_2^L)\right), \min\left(H_2(\tilde{\varrho}_1^L), H_2(\tilde{\varrho}_2^L)\right)))
\end{aligned}$$

$$\begin{aligned}
k \oslash \widetilde{\varrho_1} &= (\left(k \times \varrho_1^{(1)U}, k \times \varrho_1^{(2)U}, k \times \varrho_1^{(3)U}, k \times \varrho_1^{(4)U}; H_1(\tilde{\varrho}_1^U), H_2(\tilde{\varrho}_1^U)\right), (k \times \varrho_1^{(1)L}, k \times \varrho_1^{(2)L}, \\
&\quad k \times \varrho_1^{(3)}, k \times \varrho_1^{(4)L}; H_1(\tilde{\varrho}_1^L), H_2(\tilde{\varrho}_1^L)))
\end{aligned}$$

$$\begin{aligned}
\frac{\widetilde{\varrho_1}}{k} &= (\left(\frac{1}{k} \times \varrho_1^{(1)U}, \frac{1}{k} \times \varrho_1^{(2)U}, \frac{1}{k} \times \varrho_1^{(3)U}, \frac{1}{k} \times \varrho_1^{(4)U}; H_1(\tilde{\varrho}_1^U), H_2(\tilde{\varrho}_1^U)\right), (\frac{1}{k} \times \varrho_1^{(1)L}, \frac{1}{k} \times \varrho_1^{(2)L}, \\
&\quad \frac{1}{k} \times \varrho_1^{(3)L}, \frac{1}{k} \times \varrho_1^{(4)L}; H_1(\tilde{\varrho}_1^L), H_2(\tilde{\varrho}_1^L)))
\end{aligned}$$

Interval Type-2 Fuzzy Analytic Hierarchy Process Sets(IT2-FAHP)

This study utilizes the Interval Type-2 Fuzzy Analytic Hierarchy Process (FAHP), following the methodologies outlined in references [24] and [25], to evaluate stock selection criteria under uncertainty. The analysis is based on data collected from ten leading companies listed on the Bombay Stock Exchange (BSE), ensuring representation of prominent firms in the Indian financial market. To enhance the reliability of the evaluation, expert judgments were obtained from two highly experienced professionals: a seasoned investor and a finance professor, whose combined experience in investment analysis exceeds 40 years. The study considers six major financial criteria for assessment, including Return on Invested Capital (ROIC, C1), Economic Value Added (EVA, C2), Price/Earnings-to-Growth (PEG) ratio (C3), and Free Cash Flow (FCF) yield (C4), along with two additional indicators. These criteria collectively capture key dimensions such as profitability, value creation, and growth potential. The Interval Type-2 FAHP approach is applied to determine the relative importance and priority ranking of each criterion, effectively addressing uncertainty and subjectivity in expert evaluations. The computed weights and rankings are presented in Table 1. The results reveal that the PEG ratio (C3) holds the highest level of importance among the selected criteria, indicating its strong influence in stock selection decisions, whereas criterion C5 is ranked lowest in terms of significance.

Results and Discussion

The application of the Interval Type-2 Fuzzy Analytic Hierarchy Process (FAHP) provides a structured and reliable framework for evaluating stock selection criteria under uncertainty. The calculated weights indicate clear differences in the relative importance of the selected financial indicators. Among them, the

Price/Earnings-to-Growth (PEG) ratio (C3) achieves the highest ranking, highlighting its strong relevance in balancing valuation with expected earnings growth. This suggests that investors place greater emphasis on growth-adjusted valuation metrics when making investment decisions.

Profitability and value-based measures, such as Return on Invested Capital (ROIC, C1) and Economic Value Added (EVA, C2), also receive significant weights, reinforcing their importance in assessing efficient capital utilization and long-term value creation. In contrast, criterion C5 records the lowest ranking, indicating comparatively lesser influence in the decision-making process. Overall, the findings demonstrate that growth-oriented and profitability-driven indicators are prioritized over other financial measures, reflecting a strategic focus on sustainable performance rather than short-term financial conditions.

Table 1: Determining the weights of the criteria by FAHP Approach

Criteria	C_1	C_2	C_3	C_4
Fuzzy Weights	0.2205	0.2148	0.2690	0.1801
Rank	2	3	1	4

3. Conclusion and Future work

This study demonstrates the effectiveness of integrating Accounting Financial Measures (AFM) and Economic Value Measures (EFM) within an Interval Type-2 FAHP framework for stock selection. By incorporating expert judgment and handling uncertainty through advanced fuzzy logic, the model provides a more realistic and systematic approach to evaluating financial criteria. The results emphasize the dominance of the PEG ratio, followed by key profitability indicators such as ROIC and EVA, underscoring the importance of growth and value creation in investment decision-making. The study contributes to the existing literature by bridging the gap between traditional financial analysis and advanced multi-criteria decision-making techniques. It offers practical insights for investors seeking to construct well-informed and performance-oriented portfolios in complex market environments.

Future research can expand this study in several directions. First, the sample size can be increased by including more companies across different sectors and stock exchanges to improve generalizability. Second, additional financial and non-financial criteria, such as market sentiment, environmental, social, and governance (ESG) factors, and macroeconomic variables, can be incorporated to enhance the comprehensiveness of the model. Further studies may also explore the integration of other advanced decision-making techniques, such as hybrid fuzzy models or machine learning approaches, to improve predictive accuracy. Additionally, involving a larger and more diverse group of experts could reduce subjectivity and strengthen the robustness of the results. Finally, applying the model to real-time or longitudinal data could provide deeper insights into its practical applicability in dynamic market conditions.

References

1.Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management Science*, 17(4), 141–164.
2.Black, F., Jensen, M., & Scholes, M. (1972). The capital asset pricing model: Some empirical tests. *Studies in the Theory of Capital Markets*.
3. Brealey, R. A., Myers, S. C., & Allen, F. (2011). *Principles of Corporate Finance*. McGraw-Hill.
4. Brigham, E. F., & Ehrhardt, M. C. (2016). *Financial Management*. Cengage.
5.Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems*, 17(3), 233–247.
6. Carlsson, C., & Fuller, R. (2001). On fuzzy reasoning in decision making. *Fuzzy Sets and Systems*, 119(1), 33–48.
7. Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research*, 95(3), 649–655.
8. Chen, S. J., & Hwang, C. L. (1992). *Fuzzy Multiple Attribute Decision Making*. Springer.
9. Copeland, T., Koller, T., & Murrin, J. (2000). *Valuation*. Wiley.
10. Damodaran, A. (2012). *Investment Valuation*. Wiley.
11.Easton, P. D. (2004). PE ratios, PEG ratios, and estimating expected return. *The Accounting Review*, 79(1), 73–95.
12.Fabozzi, F. J. (2015). *Equity Valuation*. Wiley.
13. Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2), 427–465.
14.Gitman, L. J. (2009). *Principles of Managerial Finance*. Pearson.
15.Hwang, C. L., & Yoon, K. (1981). *Multiple Attribute Decision Making*. Springer.
16.Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review*, 76(2), 323–329.
17. Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. *Logistics Information Management*, 16(6), 382–394.
18.Lehn, K., & Makhija, A. (1996). EVA and firm performance. *Journal of Applied Corporate Finance*, 9(1), 34–46.
19.Lintner, J. (1965). The valuation of risk assets. *Review of Economics and Statistics*, 47(1), 13–37.
20.Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, 7(1), 77–91.
21. Mendel, J. M. (2001). *Uncertain Rule-Based Fuzzy Logic Systems*. Prentice Hall.
22.Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM. *European Journal of Operational Research*, 156(2), 445–455.
23.Penman, S. H. (2013). *Financial Statement Analysis*. McGraw-Hill.
24.Ross, T. J. (2010). *Fuzzy Logic with Engineering Applications*. Wiley.
25. Saaty, T. L. (1980). *The Analytic Hierarchy Process*. McGraw-Hill.
26. Sharpe, W. F. (1964). Capital asset pricing model. *Journal of Finance*, 19(3), 425–442.
27. Stewart, G. B. (1991). *The Quest for Value*. Harper Business.
28. Triantaphyllou, E. (2000). *Multi-Criteria Decision Making Methods*. Springer.
29.Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.
30. Zadeh, L. A. (1975). The concept of a linguistic variable. *Information Sciences*, 8, 199–249.