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A Three-Phase Algorithm for Selecting Optimal Investment Options Based on Financial Ratios of Stock Companies

Zahra Joorbonyan[1], Sapan Kumar Das[2], Seyed Ali Noorkhah[3], Ali Sorourkhah[4*]

[1] Industrial Engineering and Management Department, Morvarid Intelligent Industrial Systems Research Group, 4681853617 Tehran, Iran
[2] Department of Mathematics, National Institute of Technology Jamshedpur, 831014 Jharkhand, India
[3] Department of Civil Engineering, Science and Research Branch, Islamic Azad University, 1477893855 Tehran, Iran
[4] Department of Management, Ayandegan Institute of Higher Education, 4681853617 Tonekabon, Iran

[*] Correspondence: Ali Sorourkhah (ali.sorourkhah@gmail.com)

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Abstract: The identification of optimal stock or portfolio options is a critical concern for investors aiming to maximize profitability within financial markets. With the increasing complexity of available alternatives and the growing volume of financial data, selecting the most suitable investment has become more challenging. Decision-makers often face difficulties in navigating these vast data sets and require robust support tools to simplify and enhance the decision-making process. This study proposes a three-phase approach designed to reduce data complexity and facilitate more detailed analysis. In the initial phase, firms demonstrating low operational efficiency, as indicated by their inventory turnover ratio, were excluded from further consideration. In the subsequent phase, data envelopment analysis (DEA) was employed to assess the efficiency of remaining firms, with those exhibiting efficiency scores lower than one being removed from further investigation. Finally, the third phase involved determining the relative importance of each financial ratio through the calculation of their respective weights, allowing for the ranking of firms based on these adjusted values. The results of this approach provide decision-makers with a refined list of viable investment options, contributing to more informed stock portfolio optimization decisions.

Keywords: Portfolio selection; Multicriteria decision-making; Data envelopment analysis; Financial ratios; Decision-making

1 Introduction

In today's world, people face many challenges when making decisions [1]. One of the most significant challenges that decision-makers face is selecting an appropriate option, especially when facing a complex situation [2]. The numbers and diversity of criteria and various dependencies among them have made selecting the best option very complicated [3]. Furthermore, the increasing number of available options can add to the complexity of the problem [4]. In such a situation, obtaining problem owners' judgments becomes more complicated, and option ranking is limited [5]. Related studies have shown that one of the research areas that can be defined in such conditions is the investment decision-making problem [6].

Choosing the right stock or portfolio for profitability is a crucial concern of investors [7]. It is increasingly important for investors to select a portfolio that minimizes risk and maximizes return on investment. For decades, researchers, practitioners, and ordinary investors have been interested in the stock market [8]. Various studies have been conducted on portfolio selection, including operational research, behavioral finance, and intelligent optimization technologies [9]. In portfolio selection, investors evaluate alternatives based on several objectives or criteria, specifically the multicriteria decision-making (MCDM) method [10]. There is a limit of two criteria for classical portfolio models. Nevertheless, many investors prefer to look at additional factors currently. The multicriteria sorting method benefits stock portfolio formation because it is also a sorting problem [11]. Alternatives are assigned to classes using multicriteria sorting methods based on comparisons with reference profiles. With this process, one can easily construct a portfolio of stocks [12].

MCDM is an active field of research in operational research. Portfolio selection problems have an inherent multicriteria nature and they can be primarily addressed using MCDM [13]. Besides return and risk, other financial criteria, such as return on equity (ROE) and net profit margin, can also be considered under the MCDM framework. A further advantage of MCDM is that it allows investors to view their preferences. In other words, the MCDM could contribute to developing more realistic portfolio selection models [14]. According to the MCDM framework, portfolio selection involves two stages: financial performance evaluation of firms, which is the topic of this study, and portfolio allocation of stocks. Funds, insurance companies, and securities companies are interested in firms' financial performance. A firm's financial performance is generally measured by its financial ratios. Investing in a company starts with obtaining information on its financial position, operating results, and investment value through a financial statement. A firm's financial performance can be well described by combining all pertinent financial factors [10].

2 Literature Review

In the decision-making filed, several studies have proposed various approaches to choosing the best alternative among the available options, which are difficult for many decision-makers to understand and apply [15]. Therefore, in practice, many of these approaches are not used [16]. Accordingly, an essential feature of a decision-making technique is its simplicity and ease of use [17]. Besides this, a suitable approach should be able to consider the main dimensions of a decision problem, that is, complexity and uncertainty [18]. Hence, it is recommended in this study that a decision-maker should take the steps below to select the best private partner.

2.1 MCDM

Gupta et al. [8] built an investment portfolio from stocks of 100 listed companies of a non-parametric nature, serving the basic premise of portfolio-making by reducing risk. To study the profitability of stocks rank-wise for each year, the outcome was selected based on financial data and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. Wu et al. [10] conducted an analysis of financial performance to determine portfolios based on the Technique for Order Preference by Similarity to Ideal Solution (TODIM) method. Financial performance evaluation was conducted using a multidimensional financial evaluation index system. Affinity propagation clustering (APC) was used to select features from the financial ratios. In addition, the dominance relation between stocks was calculated using a generalized TODIM method to reflect investors' bounded rational behavior. Finally, the model was extended to include financial and stock market performance in a multi-objective selection process. Emamat et al. [12] used the Best Worst Method (BWM) to calculate the criteria weights. A large pool of stocks was chosen using 19 distinct techniques. It was concluded that the model's parameters must be appropriately defined to minimize inconsistencies and enhance the predictions. Five large-cap, open-ended, direct, suspended sales mutual funds were analyzed in a second study. First, fuzzy Analytic Hierarchy Process (AHP) was used to compare a list of criteria to choose the most important. Then the Pythagorean fuzzy grey relational analysis approach was applied to determine the weights and ranks of the shortlisted criteria. Finally, the Multi-Attributive Border Approximation Area Comparison (MABAC) technique was used to rank the portfolios with criteria such as information, Sharpe, Sortino ratios, etc. [19].

Paul et al. [20] adopted a hybrid method based on a two-stage framework. A novel decision-making technique was proposed to deal with the stock selection subject by combining the Heronian mean operator with the traditional compromise solution method. Then based on the specified decision criteria, the relative optimal weights were calculated using the base-criteria method. Complex Consensus Solution-Hybrid (CoCoSo-H) was used to increase the flexibility of complex decisions by eliminating the efficacy of anomalous data. The cross-efficiency scores were evaluated by integrating several critical financial information into a regret cross-efficiency evaluation model. The mean-variance-skewness framework was incorporated with cross-efficiency to develop a multi-objective portfolio selection model based on regret theory. Since data are inherently uncertain, evaluating ROE and analyzing return on assets (ROA) can also be considered fuzzy variables [21]. Vásquez et al. [22] presented the AHP-TOPSIS technique to make decisions concerning the stock market by assessing risk, liquidity, and profitability criteria. From April 2012 to April 2017, the model was used to select a portfolio of stocks with high and medium marketability. According to the computational results, investing in equity portfolios requires the integration of traditional and multicriteria investment criteria to find an appropriate balance between profitability and risk. A consensus process was considered in the second type of interval fuzzy environment as part of an integrated method for solving the portfolio allocation problem [23].

Mohammed [24] believed that MCDM in a fuzzy environment can be applied to selecting and prioritizing projects in portfolio management. It is critical to measure the criteria weights through the fuzzy TOPSIS technique to achieve the desired performance levels, allows for adjusting the ranking of other options. Peng et al. [25] developed a method for managing stock selection problems based on information reliability and non-compensation criteria. For stock evaluation information, Z-numbers were introduced first. Then fuzzy and probability data were used to define the outranking degree of Z-numbers. Based on the Elimination and Choice Translating Reality (ELECTRE) method, some outranking aggregation and exploitation procedures were presented. A Z-number ELECTRE tool was proposed by integrating the above studies. Finally, a selection problem of stock investment objects was solved. Nguyen et al. [26] determined objective weights for financial ratios using the Criteria Importance Through Intercriteria Correlation (CRITIC) method. Based on the expert assessments, the cause-effect relationship was obtained using Decision-Making Trial and Evaluation Laboratory (DEMATEL). The ranking process was performed by applying TOPSIS.

Narang et al. [27] proposed a novel hybrid MCDM technique consisting of the fuzzy Complex Proportional Assessment of Alternatives (COPRAS) and the Base-Criterion Method (BCM). The relative optimal weights of specified criteria were first extracted from the group decision-making process employing a novel base-criterion method using fuzzy triangular numbers. In an uncertain and ambiguous environment, the fuzzy set theory and COPRAS were used to rank the alternatives. Based on market performance, Gupta et al. [28] used DEA to calculate the efficiency of the stocks based on their risk-return interface after formulating a possible portfolio using a perceptual map. The fundamental performance of operating an MCDA tool was further probed based on the COPRAS technique. MCDM was used to rank stocks based on stock performance in the order of preference of inclusion in a portfolio using a hybrid method, which includes grey relational analysis, AHP, and TOPSIS [29].

2.2 DEA

Companies have widely used DEA to assess their efficiency based on financial ratios. When financial ratios are used in conjunction with DEA, the results can serve as early warnings about inefficiencies for the companies. DEA can convert the financial ratios into a single efficiency score to be evaluated and compared [30].

Rasoulzadeh et al. [31] combined the DEA tool with returns of intuitionistic fuzzy numbers. Additionally, all constraints of the Markowitz model were fully covered by this model to obtain the best portfolio. The model was run using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). Fuzzy DEA was involved in a portfolio selection problem with undesirable fuzzy inputs and outputs. Several realistic constraints were considered, including a budget, buy-in thresholds, no short-selling, and cardinality constraints. The genetic algorithm was employed to solve the proposed problem [32]. Chang et al. [33] developed a nested dynamic network DEA approach to measure a portfolio's multi-period efficiency. In today's highly volatile investment environment, Markov chain Monte Carlo Bayesian algorithms have been used to forecast future performance. Amin and Hajjami [34] dealt with the role of alternative optimal solutions for cross-efficiency evaluation in portfolio selection. Results showed that the proposed approach improved the outcomes. Chen et al. [35] discussed the fuzzy portfolio selection challenge in a multi-objective framework by assimilating the mean-semivariance model and the DEA cross-efficiency. Besides considering the bounds on holdings and cardinality constraints, the presented model was used to formulate the cross-efficiency model within the framework of the Sharpe ratio. Chen et al. [36] discussed several risk measures as part of the fuzzy portfolio efficiency evaluation problem. Three types of DEA-based fuzzy portfolio estimation models in various risk measures were presented to evaluate portfolio efficiency. Results demonstrated that they approximated the real effective portfolio frontier with adequate sample size using the envelop frontier models.

The review of the research background shows that studies have used either an MCDM tool or a DEA technique in the topic under investigation. Therefore, in this study, the data of the problem were examined by combining MCDM and DEA tools.

3 Proposed Algorithm

The proposed 3-phase algorithm for selecting the proper stock portfolio is shown in Figure 1.

As shown in Figure 1, data should be collected in step 1 in the first phase. In step 2, the inventory turnover ratio was calculated. In step 3, the firms that do not reach the required quorum were excluded from the analysis. In step 4 in the second phase, financial ratios were calculated for the data. In step 5, the data were normalized. In step 6, the firms that do not have the required efficiency were removed using DEA. Then in step 7 in the third phase, the beneficial and non-beneficial data were converted. In step 8, the AHP technique was performed. In step 9, the final ranking was determined. A more detailed description of the above steps is presented in the sub-sections below.

3.1 Phase 1

After identifying the firms and collecting their financial data in step 1, the inventory turnover ratio was calculated using the following formula:

$$\text{Inventory turnover} = \frac{\text{Cost of goods sold}}{\text{Average inventories}} \tag{1}$$

Efficiency ratios, also called activity ratios, provide insight into how well a company manages operations and sales. This metric aims to demonstrate how efficiently the company uses its resources to generate income [37].

As an efficiency ratio, inventory turnover was used. According to previous studies, the higher the inventory turnover ratio, the greater the company's profitability [38]. Based on this, the companies for which the mentioned index is less than 2 were excluded from further investigations. At the last step of this phase, firms that do not have the minimum necessary efficiency in inventory turnover ratio were excluded from further analyses.

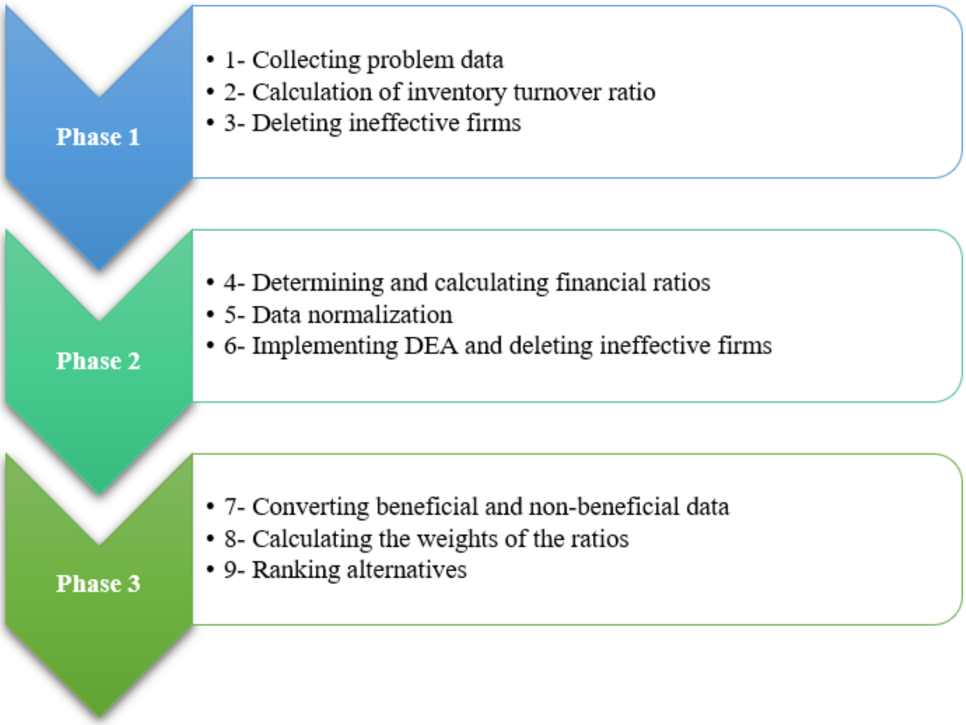

Figure 1. The proposed algorithm

3.2 Phase 2

The primary goal of phase 2 is to remove other ineffective data from the analysis using a well-known method, DEA. In the first step of this phase, some of the most important financial ratios were considered for the firms under investigation. Typically, investors use financial ratios to measure a company's performance and make investment decisions [39]. In the previous studies, these ratios are commonly considered as inputs and outputs of DEA [40]. In this study, the following ratios were employed:

$$\text{Current ratio} = \frac{\text{Current assets}}{\text{Current liabilities}} \tag{2}$$

$$\text{Quick ratio} = \frac{(\text{Current assets} - \text{Inventory})}{\text{Current liabilities}} \tag{3}$$

$$\text{Cash ratio} = \frac{\text{Cash}}{\text{Current assets}} \tag{4}$$

$$\text{Debt ratio} = \frac{\text{Total liabilities}}{\text{Total assets}} \tag{5}$$

$$\text{Debt equity} = \frac{\text{Total debt}}{\text{Equity}} \tag{6}$$

$$\text{Gross profit margin} = \frac{\text{Gross profit}}{\text{Net Sales}} \tag{7}$$

$$\text{Net profit margin} = \frac{\text{Net profits}}{\text{Net sales}} \tag{8}$$

$$\text{ROE} = \frac{\text{Net income}}{\text{Total equity}} \tag{9}$$

$$\text{ROA} = \frac{\text{Net income}}{\text{Total assets}} \tag{10}$$

In the next step, the ratios obtained for the firms were normalized using the following equation:

$$\mathrm{n_{ij}} = \frac{\mathrm{a_{ij}} - \min \mathrm{a_{ij}}}{\max \mathrm{a_{ij}} - \min \mathrm{a_{ij}}} \tag{11}$$

In the last step of phase 2, the firms' efficiency was calculated below.

Consider n decision-making units (DMUs), denoted by DMU_j, where $j = 1, \ldots, n$, each of which consumes x_{ij} of input i to produce y_{rj} of output r [41].

$$\begin{aligned}
&\max z_j = \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} + w \\
&\text{s.t.} \\
&\qquad \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} + w \quad j = 1, 2, \ldots, n, \\
&\sum_{r=1}^{s} u_r \geq 1 \\
&\sum_{i=1}^{m} v_i \geq 1 \\
&\quad i = 1, 2, \ldots, m \quad r = 1, 2, \ldots, s \quad v_i, u_r \geq 0.
\end{aligned} \tag{12}$$

where, u_r^k and v_i^k are output and input weights corresponding to DMU_k.

At the end of phase 2, the firms that do not provide a certain level of efficiency (less than 1) were excluded from further investigations.

3.3 Phase 3

In step 7, the remaining data were converted to R_{ij} [42]:

$$R_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}, \tag{13}$$

For non-beneficial ones (debt ratios):

$$R_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}}. \tag{14}$$

In step 8, the ratio weights were calculated by applying the AHP method.

In the final step, the firms were ranked based on their weighted sum of ratios.

4 Findings

In the first step of phase 1, 195 manufacturing firms existing in the Tehran Stock Exchange were considered as a numerical example. In step 2, using Eq. (1), the inventory turnover ratio was calculated for all the firms and those with a ratio of less than 2 were removed. Table 1 shows a portion of this step output.

Considering Table 1, firms 1, 2, 4, 193, and 195 were eliminated from further investigation. At the end of phase 1, 68 firms with an inventory turnover ratio of less than 2 were eliminated, and 127 cases entered phase 2 for further investigation.

Table 1. A portion of outputs in the 1st step

Firms	Inventory Turnover
1	0.049
2	1.191
3	3.223
4	1.361
5	12.625
...	...
191	4.810
192	2.436
193	0.983
194	12.994
195	1.051

Table 2. A portion of outputs in the 6th step

Firms	Efficiency
0.691	1
1	2
0.579	3
1	4
0.090	5
...	...
0.769	123
0.704	124
1	125
0.876	126
1	127

In the first step of phase 2, the most important financial ratios obtained from the research background were calculated using Eqs. (2)-(10). In the next step, the received data were normalized using Eq. (11). In the last step of phase 2, using Eq. (12), the additive efficiency for the remaining firms was computed, a part of which is shown in Table 2.

As expressed before, firms with an efficiency of less than 1 were excluded from further analysis at the end of this phase. Considering Table 2, for example, firms 1, 3, 5, 123, 124, and 126 were eliminated from further investigation. Accordingly, 78 other firms were excluded from further analysis, and 49 cases qualified for the final phase.

To perform pairwise comparisons in the first step of phase 3, the problem data were converted using Eqs. (13)-(14). Then, in the next step, based on the opinions of three experts in the field of financial engineering, the importance (weight) of each of the financial ratios were obtained using Eqs. (2)-(10), which is shown in Table 3.

Table 3. A portion of outputs in the 1st step

Ratio	Weight
Current ratio	0.24
Quick ratio	0.07
Cash ratio	0.02
Debt ratio	0.22
Debt equity	0.02
Gross profit margin	0.04
Net profit margin	0.03
ROA	0.24
ROE	0.12

Finally, the final ranking was determined by calculating the weighted sum of ratios. These step results are shown in Table 4 and Figure 2.

Table 4. Key parameters of our model

Firms	Ratio	Firm	Ratio	Firm	Ratio	Firm	Ratio	Firm	Ratio
1	0.323	11	0.264	21	0.804	31	0.392	41	0.573
2	0.574	12	0.526	22	0.895	32	0.447	42	0.691
3	0.322	13	0.663	23	0.605	33	0.360	43	0.437
4	0.549	14	0.595	24	0.545	34	0.597	44	0.428
5	0.016	15	0.734	25	0.775	35	0.542	45	0.498
6	0.633	16	0.631	26	0.756	36	0.462	46	0.691
7	0.480	17	0.613	27	0.587	37	0.514	47	0.534
8	0.370	18	0.414	28	0.441	**38**	**0.996**	48	0.782
9	0.526	19	0.691	29	0.490	39	0.761	49	0.481
10	0.449	20	0.706	30	0.449	40	0.355	-	-

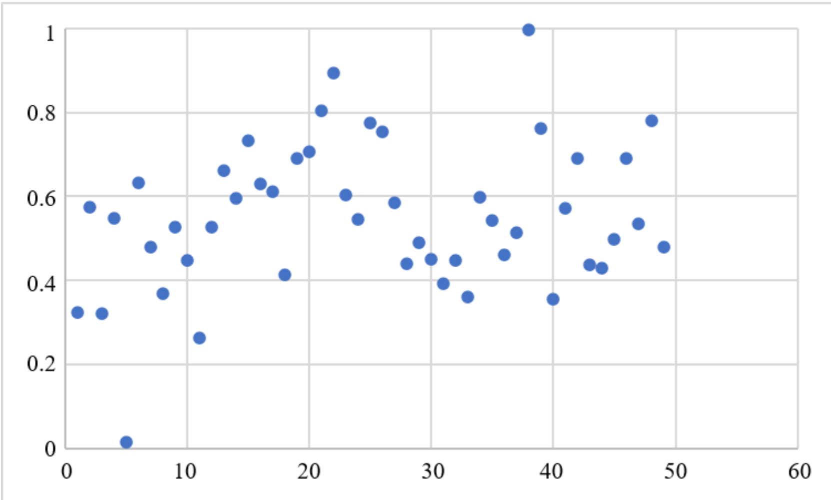

Figure 2. Firms' weighted sum of ratios

5 Discussions and Conclusion

Managers, shareholders, and investors need to evaluate companies' financial performance to identify their strengths, weaknesses and competitive advantages. An integrated assessment index based on all the dimensions was created using the MCDM tool. Therefore, several studies have exploited the capabilities and solutions that the MCDM method offers in financial performance evaluation [43]. Ignoring the importance of making sound decisions based on accurate and relevant financial performance measurements is impossible. Multidimensional and contradictory criteria can only be measured with the MCDM method to achieve the best and most satisfactory results in financial performance analysis [44]. On the other hand, it is common to use the DEA method to evaluate companies' performance from a financial perspective [45]. Financial ratios are commonly used as inputs and outputs in AHP applications for assessing firms' efficiency [46].

Dealing with massive amounts of data and information is usually challenging for decision-makers. Therefore, support tools are needed to make decision-making more accessible and understandable. Based on this, a three-phase approach was used in this study to reduce the data and perform a more detailed analysis. In the first phase, low-efficiency firms were eliminated using the inventory turnover ratio. In the next phase, using the AHP method, the cases with an efficiency of less than 1 were excluded from further investigation. In the final phase, the companies ranking was determined by specifying the ratio weights. The output of this study helps decision-makers consider the top firms in the next stage of decision-making for stock portfolio optimization.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare they have no conflicts of interest to report regarding the present study.

References

[1] Z. Shams Esfandabadi and M. Ranjbari, "Exploring carsharing diffusion challenges through systems thinking and causal loop diagrams," *Systems*, vol. 11, no. 2, p. 93, 2023. https://doi.org/10.3390/systems11020093

[2] P. Qiu, A. Sorourkhah, N. Kausar, T. Cagin, and S. A. Edalatpanah, "Simplifying the complexity in the problem of choosing the best private-sector partner," *Systems*, vol. 11, no. 2, p. 80, 2023. https://doi.org/10.3390/systems11020080

[3] P. Li, S. A. Edalatpanah, A. Sorourkhah, S. Yaman, and N. Kausar, "An integrated fuzzy structured methodology for performance evaluation of high schools in a group decision-making problem," *Systems*, vol. 11, no. 3, p. 159, 2023. https://doi.org/10.3390/systems11030159

[4] F. Taghvaei and R. Safa, "Efficient energy consumption in smart buildings using personalized NILM-based recommender system," *Big Data Comput. Visions*, vol. 1, no. 3, pp. 161–169, 2021. https://doi.org/10.22105/bdcv.2022.325031.1039

[5] K. Zhang, Y. Xie, S. A. Noorkhah, M. Imeni, and S. K. Das, "Neutrosophic management evaluation of insurance companies by a hybrid TODIM-BSC method: A case study in private insurance companies," *Manag. Decis.*, vol. 61, no. 2, pp. 363–381, 2023. https://doi.org/10.1108/MD-01-2022-0120

[6] D. Jing, M. Imeni, S. A. Edalatpanah, A. Alburaikan, and H. A. E. W. Khalifa, "Optimal selection of stock portfolios using multi-criteria decision-making methods," *Mathematics*, vol. 11, no. 2, p. 415, 2023. https://doi.org/10.3390/math11020415

[7] G. S. M. Thakur, R. Bhattacharyya, and S. Sarkar, "Stock portfolio selection using Dempster–Shafer evidence theory," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 30, no. 2, pp. 223–235, 2018. https://doi.org/10.1016/j.jksuci.2016.07.001

[8] S. Gupta, G. Bandyopadhyay, S. Biswas, and A. Mitra, "An integrated framework for classification and selection of stocks for portfolio construction: Evidence from NSE, India," *Decis. Mak. Appl. Manag. Eng.*, vol. 6, no. 1, pp. 774–803, 2023. https://doi.org/10.31181/dmame0318062021g

[9] M. S. Largani, M. Zamani, M. Imeni, and M. Kaviani, "Determine the effects of fundamental variables and mass behaviors in changes of stock price (evidence from Iran Stock Exchange)," *Asian J. Financ. Account.*, vol. 5, no. 1, p. 274, 2013. https://doi.org/10.5296/ajfa.v5i1.3333

[10] Q. Wu, X. Liu, J. Qin, L. Zhou, A. Mardani, and M. Deveci, "An integrated generalized TODIM model for portfolio selection based on financial performance of firms," *Knowledge-Based Syst.*, vol. 249, p. 108794, 2022. https://doi.org/10.1016/j.knosys.2022.108794

[11] M. S. M. M. Emamat, M. Amiri, M. R. Mehregan, and M. T. Taghavifard, "A novel hybrid simplified group BWM and multicriteria sorting approach for stock portfolio selection," *Expert Syst. Appl.*, vol. 215, p. 119332, 2023. https://doi.org/10.1016/j.eswa.2022.119332

[12] M. S. M. M. Emamat, C. M. M. Mota, M. R. Mehregan, M. R. Sadeghi Moghadam, and P. Nemery, "Using ELECTRE-TRI and FlowSort methods in a stock portfolio selection context," *Financ. Innov.*, vol. 8, no. 1, p. 11, 2022. https://doi.org/10.1186/s40854-021-00318-1

[13] M. Jawad, M. Naz, and H. Muqaddus, "A multicriteria decision-making approach for portfolio selection by using an automatic spherical fuzzy AHP algorithm," *J. Oper. Res. Soc.*, vol. 75, no. 1, pp. 85–98, 2024. https://doi.org/10.1080/01605682.2023.2174905

[14] M. Sikalo, A. Arnaut-Berilo, and A. Delalic, "A combined AHP-PROMETHEE approach for portfolio performance comparison," *Int. J. Financial Stud.*, vol. 11, no. 1, p. 46, 2023. https://doi.org/10.3390/ijfs11010046

[15] M. Ensafi, W. Thabet, K. Afsari, and E. Yang, "Challenges and gaps with user-led decision-making for prioritizing maintenance work orders," *J. Build. Eng.*, vol. 66, p. 105840, 2023. https://doi.org/10.1016/j.jobe.2023.105840

[16] A. Sorourkhah, S. Babaie-Kafaki, A. Azar, and M. S. Nikabadi, "A fuzzy-weighted approach to the problem of selecting the right strategy using the robustness analysis (Case study: Iran Automotive Industry)," *Fuzzy Inf. Eng.*, vol. 11, no. 1, pp. 39–53, 2019. https://doi.org/10.1080/16168658.2021.1886811

[17] M. Abbas, M. W. Asghar, and Y. Guo, "Decision-making analysis of minimizing the death rate due to covid-19 by using q-rung orthopair fuzzy soft bonferroni mean operator," *J. Fuzzy Ext. Appl.*, vol. 3, no. 3, pp. 231–248, 2022. https://doi.org/10.22105/jfea.2022.335045.1214

[18] S. F. Saberhoseini, S. A. Edalatpanah, and A. Sorourkhah, "Choosing the best private-sector partner according to the risk factors in neutrosophic environment," *Big Data Comput. Visions*, vol. 2, no. 2, pp. 61–68, 2022. https://doi.org/10.22105/bdcv.2022.334005.1075

[19] T. K. Paul, M. Pal, and C. Jana, "Portfolio selection as a multicriteria group decision making in Pythagorean fuzzy environment with GRA and FAHP framework," *Int. J. Intell. Syst.*, vol. 37, no. 1, pp. 478–515, 2022. https://doi.org/10.1002/int.22635

[20] M. Narang, M. C. Joshi, K. Bisht, and A. Pal, "Stock portfolio selection using a new decision-making approach

based on the integration of fuzzy CoCoSo with Heronian mean operator," *Decis. Mak. Appl. Manag. Eng.*, vol. 5, no. 1, pp. 90–112, 2022. https://doi.org/10.31181/dmame0310022022n

[21] X. Gong, C. Yu, L. Min, and Z. Ge, "Regret theory-based fuzzy multi-objective portfolio selection model involving DEA cross-efficiency and higher moments," *Appl. Soft Comput.*, vol. 100, p. 106958, 2021. https://doi.org/10.1016/j.asoc.2020.106958

[22] J. A. Vásquez, J. W. Escobar, and D. F. Manotas, "AHP–TOPSIS methodology for stock portfolio investments," *Risks*, vol. 10, no. 1, p. 4, 2022. https://doi.org/10.3390/risks10010004

[23] Q. Wu, X. Liu, J. Qin, and L. Zhou, "Multi-criteria group decision-making for portfolio allocation with consensus reaching process under interval type-2 fuzzy environment," *Inf. Sci.*, vol. 570, pp. 668–688, 2021. https://doi.org/10.1016/j.ins.2021.04.096

[24] H. J. Mohammed, "The optimal project selection in portfolio management using fuzzy multicriteria decision-making methodology," *J. Sustain. Financ. Invest.*, vol. 13, no. 1, pp. 125–141, 2021. https://doi.org/10.1080/20430795.2021.1886551

[25] H. G. Peng, Z. Xiao, J. Q. Wang, and J. Li, "Stock selection multicriteria decision-making method based on elimination and choice translating reality I with Z-numbers," *Int. J. Intell. Syst.*, vol. 36, no. 11, pp. 6440–6470, 2021. https://doi.org/10.1002/int.22556

[26] P. H. Nguyen, J. F. Tsai, Y. C. Hu, and G. V. Ajay Kumar, "A hybrid method of MCDM for evaluating financial performance of vietnamese commercial banks under COVID-19 impacts," in *Shifting Economic, Financial and Banking Paradigm: New Systems to Encounter COVID-19*, S. A. Abdul Karim, Ed. Springer International Publishing, 2022, pp. 23–45. https://doi.org/10.1007/978-3-030-79610-5_2

[27] M. Narang, M. C. Joshi, and A. K. Pal, "A hybrid fuzzy COPRAS-base-criterion method for multicriteria decision making," *Soft Comput.*, vol. 25, pp. 8391–8399, 2021. https://doi.org/10.1007/s00500-021-05762-w

[28] S. Gupta, G. Bandyopadhyay, M. Bhattacharjee, and S. Biswas, "Portfolio selection using DEA-COPRAS at risk–return interface based on NSE (India)," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 10, pp. 4078–4087, 2019. https://doi.org/10.35940/ijitee.J8858.0881019

[29] S. Ghosh, "Application of a new hybrid MCDM technique combining grey relational analysis with AHP-TOPSIS in ranking of stocks in the Indian IT sector," in *Computational Intelligence in Communications and Business Analytics (CICBA 2021)*, 2021, pp. 133–149. https://doi.org/10.1007/978-981-16-8515-6_1

[30] L. P. Fun, L. W. Siew, and L. W. Hoe, "Optimizing the financial efficiency of logistics companies with data envelopment analysis model," in *Proceedings of the 8th International Conference on Computational Science and Technology: ICCST 2021*, Labuan, Malaysia, 2022, pp. 1–12. https://doi.org/10.1007/978-981-16-8515-6_1

[31] M. Rasoulzadeh, S. A. Edalatpanah, M. Fallah, and S. E. Najafi, "A multi-objective approach based on Markowitz and DEA cross-efficiency models for the intuitionistic fuzzy portfolio selection problem," *Decis. Mak. Appl. Manag. Eng.*, vol. 5, no. 2, pp. 241–259, 2022. https://doi.org/10.31181/dmame0324062022e

[32] W. Chen, S. S. Li, M. K. Mehlawat, L. Jia, and A. Kumar, "Portfolio selection using data envelopment analysis cross-efficiency evaluation with undesirable fuzzy inputs and outputs," *Int. J. Fuzzy Syst.*, vol. 23, pp. 1478–1509, 2021. https://doi.org/10.1007/s40815-020-01045-y

[33] T. S. Chang, K. Tone, and C. H. Wu, "Nested dynamic network data envelopment analysis models with infinitely many decision making units for portfolio evaluation," *Eur. J. Oper. Res.*, vol. 291, no. 2, pp. 766–781, 2021. https://doi.org/10.1016/j.ejor.2020.09.044

[34] G. R. Amin and M. Hajjami, "Improving DEA cross-efficiency optimization in portfolio selection," *Expert Syst. Appl.*, vol. 168, p. 114280, 2021. https://doi.org/10.1016/j.eswa.2020.114280

[35] W. Chen, S. S. Li, J. Zhang, and M. K. Mehlawat, "A comprehensive model for fuzzy multi-objective portfolio selection based on DEA cross-efficiency model," *Soft Comput.*, vol. 24, pp. 2515–2526, 2020. https://doi.org/10.1007/s00500-018-3595-x

[36] W. Chen, Y. Gai, and P. Gupta, "Efficiency evaluation of fuzzy portfolio in different risk measures via DEA," *Ann. Oper. Res.*, vol. 269, pp. 103–127, 2018. https://doi.org/10.1007/s10479-017-2411-9

[37] R. Okunev, "Independent T-Test," in *Analytics for Retail: A Step-by-Step Guide to the Statistics Behind a Successful Retail Business*, 2022, pp. 107–114. https://doi.org/10.1007/978-1-4842-7830-7_5

[38] M. Alnaim and A. Kouaib, "Inventory turnover and firm profitability: A Saudi Arabian investigation," *Processes*, vol. 11, no. 3, p. 716, 2023. https://doi.org/10.3390/pr11030716

[39] E. Harinurdin, "The influence of financial ratio and company reputation on company stock prices financial sector," in *The 5th International Conference on Vocational Education Applied Science and Technology 2022)*, Teluk Betung, Indonesia, 2023, p. 47. https://doi.org/10.3390/proceedings2022083047

[40] P. Seran, U. S. Sucahyo, A. D. R. Atahau, and S. Supramono, "The efficiency of Indonesian pension funds: A two-stage additive network DEA approach," *Int. J. Financial Stud.*, vol. 11, no. 1, p. 28, 2023. https://doi.org/10.3390/ijfs11010028

[41] A. Charnes, W. W. Cooper, and E. Rhodes, "Measuring the efficiency of decision making units," *Eur. J. Oper. Res.*, vol. 2, no. 6, pp. 429–444, 1978. https://doi.org/10.1016/0377-2217(78)90138-8

[42] N. P. Nirmal and M. G. Bhatt, "Selection of automated guided vehicle using single valued neutrosophic entropy based novel multi attribute decision making technique," in *New Trends in Neutrosophic Theory and Applications*, 2016, pp. 105–114.

[43] A. T. Almeida-Filho, D. F. Lima Silva, and L. Ferreira, "Financial modelling with multiple criteria decision making: A systematic literature review," *J. Oper. Res. Soc.*, vol. 72, no. 10, pp. 2161–2179, 2021. https://doi.org/10.1080/01605682.2020.1772021

[44] M. Baydaş, O. E. Elma, and D. Pamuçar, "Exploring the specific capacity of different multi criteria decision making approaches under uncertainty using data from financial markets," *Expert Syst. Appl.*, vol. 197, p. 116755, 2022. https://doi.org/10.1016/j.eswa.2022.116755

[45] F. Z. Montazeri, "An overview of data envelopment analysis models in fuzzy stochastic environments," *J. Fuzzy Ext. Appl.*, vol. 1, no. 4, pp. 272–278, 2020. https://doi.org/10.22105/jfea.2020.258330.1030

[46] A. Ampountolas, "Postcrisis REIT performance using financial ratios: A DEA approach," *Tour. Econ.*, vol. 28, no. 2, pp. 371–393, 2020. https://doi.org/10.1177/1354816620962664