Multi-Criteria Decision-Making Techniques for Ranking NSE Sectorial Indices: A Comparative Analysis with Feature Weighting

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Abstract: Data analysis plays a crucial role in financial and managerial applications, impacting a range of IT and business operations. This research focuses on the use of Multi-Criteria Decision Making (MCDM) techniques to rank Sectorial Indices of the National Stock Exchange (NSE) based on various criteria. Traditional approaches often involve high computational complexity, prompting the exploration of more efficient alternatives.

In this study, we apply MCDM techniques, including Simple Additive Weighting Method (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Complex Proportional Assessment (COPRAS), Additive Ratio Assessment (ARAS), and Evaluation based on Distance from Average Solution (EDAS), to rank NSE Sectorial Indices. To enhance the performance of these techniques, feature weighting is incorporated, demonstrating superior accuracy and scalability compared to state-of-the-art approaches.

Keywords: *Multi-Criteria Decision-Making (MCDM), National Stock Exchange (NSE), SAW, TOPSIS, ARAS, COPRAS, EDAS, MCDM Approaches.*

I. Introduction

Financial decision-making in investment requires a comprehensive analysis of market data. This study employs datasets obtained in CSV format from the National Stock Exchange (NSE) to analyze and rank the relative performance of various sectors within the NSE over the period from 01-April-2018 to 31-March-2023. The primary objective is to enhance the decision-making process in investment by applying multi-criteria analysis methods.

Sectorial indices of NSE data are ranked using the five MCDM approaches: SAW, TOPSIS, COPRAS, ARAS, and EDAS. The feature weights for each criterion are calculated using the CRITIC method, providing a foundation for enhanced accuracy in the ranking process. These weights are applied into each MCDM method to improve the decision-making process. Additionally, Pearson rank correlation coefficient is applied to evaluate the performance of each MCDM approaches.

The research aims to emphasize the necessity of adopting a multi-criteria analysis approach to evaluate the effectiveness of investments. By considering various criteria, this approach contributes to a more informed and robust decision-making process aligning with investment goals.

II. Related Work

MCDM approaches have a wide variety of real-world applications across different fields. There are numerous previous research papers on different MCDM approaches which are used to solve decision-making problems in different fields. In order to choose the best company from the group of companies, the writers research MCDM methodologies. Kung et al. [1] have suggested the optimal investment strategy based on the analysis of data from financial reports and the use of the fuzzy MCDM method.

Previous research has explored the application of MCDM techniques in financial analysis, particularly in the context of investment decision-making. Studies have highlighted the significance of considering multiple criteria to evaluate the performance of investment alternatives and enhance decision-making processes in financial domains [2] [3].

Investigations into sectorial analysis within financial markets have been undertaken to understand the dynamics of various sectors. Researchers have delved into methods for comparing and ranking sectorial performance, providing insights into the relative strengths and weaknesses of different market segments [4]. Liu Zongsheng [5] has presented a Financial Management Assessment Model based on Analytical Hierarchical Process. The assessment factors include three different parts i.e., elemental work, personal management and structural establishment. The model appreciates the correct financial management assessment.

Türegün N. [6] compared the entropy-based TOPSIS and VIKOR techniques to analyze the stock performance outcome and presented a model as suggestion to the tourism companies for evaluating financial performance outcome. Gupta et al. [7] have presented an MCDM model to rank the performance of sectors in the Indian stock market. To identify the best performing sectors for investments, build a hybrid ranking technique that performs a relative ranking of the NSE sectorial indices. Gupta et al. [8] have reviewed a three-stage model (Perceptual Map-Data Envelopment Analysis-COPRAS) that integrates market performance with the fundamental complement in an MCDM framework to provide a comprehensive approach to understanding the performance of the stocks.

Literature has explored the importance of feature weighting in financial decision-making models. The consideration of feature weights in MCDM approaches has been acknowledged as a crucial factor in accurately reflecting the significance of different criteria in investment evaluations [9] [10]. Kanwar et al. [11] Computed the correlation based feature weight and ranking the alternatives to identify top-k alternative based on MCDM approcah i.e., weighted TOPSIS.

The CRITIC method has gained attention in the literature for its effectiveness in determining criterion weights in MCDM applications. Studies have demonstrated its application in various domains, emphasizing its ability to provide reliable and consistent weights for different criteria [12]. Researchers have conducted comparative analyses of different MCDM techniques in the context of financial markets. Investigations into the performance of methods such as SAW, TOPSIS, COPRAS, MOORA, and EDAS, both individually and in combination, have contributed to the understanding of their efficacy in ranking financial assets and aiding investment decision-making [13].

By building upon and synthesizing insights from these related works, the current research aims to extend the understanding of multi-criteria decision-making in financial contexts, specifically focusing on the ranking of NSE sectorial indices over the period of 01-April-2018 to 31-March-2023.

Methodology

Criteria weighting in multi-criteria decision-making methods has a substantial impact on the final result of decision making and ranking options that engage in the model. It improves the accuracy and efficiency of methods by assigning a particular weight. To ranking the Sectorial Indices of NSE data proposed an approach i.e., "Hybrid Ranking" using five different MCDM approaches: SAW, TOPSIS, COPRAS, ARAS, and EDAS.

First, the feature weights are calculated for every criterion using CRITIC method. These weights are assigned to each criterion while applying MCDM approaches: SAW, TOPSIS, ARAS, COPRAS and EDAS. Applied the Pearson correlation coefficient method between final results of above used methods and then find the final ranking of alternatives.

Criteria Importance Trough Intercriteria Correlation (CRITIC)

The CRITIC technique of weight calculation method is developed by Diakoulaki et. al. in 1995 [14]. It is used to determine the criteria's objective weights. The CRITIC approach uses correlation analysis to identify differences among criteria and assists in determining the precise weights assigned to each criterion.

Steps followed by the CRITIC method [15]:

1. Create the decision matrix.
2. Normalize the decision matrix using below equation:

$$x_{ij} = \frac{x_{ij} - min(x_{ij})}{(x_{ij}) - min(x_{ij})}, \text{ i=1,..,m and j = 1,.., n.}$$

3. Calculate the weight of the j[th] criterion (W_j) and where C_j is the quantity information contained in j[th] criterion.

$$C_j = \sigma_j \sum_{j=1}^{n} (1 - r_{ij})$$

$$W_j = \frac{C_j}{\sum_{j=1}^{n} C_j}, \text{ Where } \sigma_j \text{ is the standard deviation.}$$

Simple Additive Weighting Method (SAW)

The simple additive weighting method is also known as the "summing up method", which is a multi-criteria decision-making method. The results of the multiplication between the rating and the weight of each attribute are added up to determine the overall score for an option. The Simple Additive Weighting method needs a normalized decision matrix that is comparable to all existing alternatives [16]. The steps used by SAW method are as follows:

1. Create decision matrix.
2. Normalize the decision matrix.
3. Calculate the weighted alternative value,

$$V_i = \sum_{j=1}^{n} W_i r_{ij}$$

   Where, w_i is weight, r_{ij} is the normalized value.
4. Arrange the alternatives in descending order.

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS was developed by Hwang and Yoon in 1981. It is an MCDM approach to identify an alternative solution that is closest to the positive ideal solution and farthest to the negative ideal solution [17]. The following steps of TOPSIS:

1. Create decision matrix.
2. Normalize the decision matrix.
3. Determine the weighted decision matrix.
4. Identify the positive ideal solution and negative ideal solution.
5. Compute the Euclidian Distance from positive ideal solution and negative ideal solution.
6. Compute relative closeness coefficient and rank the alternatives based on relative closeness.

Additive Ratio Assessment (ARAS)

The ARAS method is first proposed by Zavadskas and Turkis aiming at eliminating the influence of different measurement units and the different optimization directions in MADM [18]. There are following steps in ARAS method:

1. Create decision matrix.
2. Normalize the decision matrix.
3. Define the weighted normalized matrix.
4. Calculate the optimal value (S_i) and the utility degree (Q_i).

$$S_i = \sum_{j=1}^{n} x_{ij}, \text{ i=0, 1, 2, …, m.}$$

$$S_0 = \sum_{j=1}^{n} S_i$$

$$Q_i = \frac{S_i}{S_0}, \text{ i= 1, 2, …, m}$$

7. Determine the final ranking.

Complex Proportional Assessment (COPRAS)

Complex Proportional Assessment (COPRAS) is a multi-criteria decision-making method developed by Zavadskas, Sarka, and Kaklauskas in 1994 to determine the rank of alternatives. This is commonly utilized in engineering field complications for project appraisal and selection. The fundamental goal of the COPRAS technique is to rank each alternative by considering the particular weights of each criterion [19]. The following steps of COPRAS method:

1. Create decision matrix.
2. Normalize the decision matrix.
3. Compute the weighted normalized matrix.
4. Calculate the sum of maximum weighted value and minimum weighted value.
5. Compute the relative significance of all the alternatives.

$$Q_i = S_{+i} + \frac{S_{-min-} min(x_{ij})}{S_{-i}\sum_{i=1}^{m}(\frac{S_{-min}}{S_{-i}})}$$

6. Calculate the quantitative utility (Ui).

$$U_i = [\frac{Q_i}{Q_{max}}]*100$$

7. Rank the alternative based on quantitative utility.

Evaluation based on Distance from Average Solution (EDAS)

EDAS stands for Evaluation based on Distance from Average Solution; it was presented by Keshavarz Ghorabaee et al. [20] in the year of 2015. EDAS method is related to the distance from average solution, first measure the PDA and NDA that is positive distance from average and negative distance from average respectively. This metric can demonstrate the variations between each alternative and the average solution. Higher values of PDA (Positive Distance Average) and lower values of NDA (Negative Distance Average) are used to evaluate the alternatives. There are following steps:

1. Construct the decision matrix.
2. Compute the average solution.
3. Compute the positive distance from average (PDA) and negative distance from average (NDA).
   For Beneficial criterion:

$$PDA_{ij} = \frac{max(0,(X_{ij} - AV_j))}{AV_j},$$

$$NDA_{ij} = \frac{max(0,(AV_j - X_{ij}))}{AV_j}$$

   For Non-Beneficial criterion:

$$PDA_{ij} = \frac{max(0,(AV_j - X_{ij}))}{AV_j},$$

$$NDA_{ij} = \frac{max(0,(X_{ij} - AV_j))}{AV_j}$$

4. Calculate the weighted sum of PDA and NDA for each alternative.

$$SP_i = \sum_{j=1}^{m} w_j PDA_{ij}$$

$$SN_i = \sum_{j=1}^{m} w_j NDA_{ij}$$

   Where w_j is the weight.

5. Normalize the value of SP and SN.

$$NSP_i = \frac{SP_i}{max_i(SP_i)}$$

$$NSN_i = \frac{SN_i}{max_i(SN_i)}$$

6. Compute the appraisal score (AS) for each alternative and rank the alternative based on appraisal score.

$$AS_i = \frac{1}{2}(NSP_i + NSN_i)$$

Data Collection

The data for research was collected from the NSE database in CSV format (Data Source: “https://www.nseindia.com”), including the period from 01-April-2018 to 31-March-2023. Sixteen sectorial indices were considered for analysis. Two key data points, the Total Return Index and the closing price at the end of the day, were downloaded for each sector. Additionally, includes various indicators for NSE data analysis i.e., standard deviation, Beta, price-to-book (P/B), price-to-earning (P/E), and dividend yield (Div. Yield) and standard-deviation. These indicators provide a comprehensive view of the performance and risk profile of each sector. First calculate the daily return and daily return mean from the closing price value. Beta, price-to-earning (P/E), price-to-book (P/B) and standard deviation are calculated from the daily return.

To assess the risk and volatility of each sector, daily returns were calculated from the closing prices. Subsequently, Beta values were computed, measuring the volatility of each sector in relation to the Nifty 50 index. Standard deviation, derived from the mean value of daily returns, provided insights into the risk associated with each sector. This approach enhances the accuracy of the subsequent MCDM analysis by combining market dynamics and risk factors.

The P/E ratio, a critical financial metric, was utilized to evaluate the valuation of each sector's stock. A high P/E ratio may indicate overvaluation, while a low ratio may suggest undervaluation or robust performance. This analysis aids in understanding market sentiment and identifying potential investment opportunities or risks.

A company's market value and book value are compared using the P/B ratio. A lower P/B ratio typically denotes an undervalued stock. The yearly dividend to share price ratio of a firm is known as the dividend yield. Table 1 show the initially used data that includes sixteen sectorial indices with different criterion.

Table 1. Decision Matrix

Sectorial Indices (A1 to A16)	Total Return Index	P/E	P/B	Div Yield	STD Dev	Beta
Nifty Auto	12291.10	79.58	4.35	1.23	0.70	1.05
Nifty Bank	42343.75	33.11	2.79	0.45	0.73	1.23
Nifty Consumer Durables	22053.31	61.30	11.23	0.45	0.56	0.79
Nifty Energy	29965.73	13.55	1.86	2.96	0.64	0.92
Nifty Financial Services_25_50	18178.91	23.53	3.44	0.92	0.69	1.19
Nifty Financial Services	17490.95	28.75	3.71	0.63	0.70	1.20
Nifty FMCG	51329.92	40.87	10.39	1.64	0.48	0.65
Nifty Healthcare	7654.99	36.34	4.45	0.64	0.53	0.57
Nifty IT	28981.82	25.76	7.14	1.87	0.64	0.79
Nifty Media	2381.12	287.45	3.01	0.98	0.86	0.95
Nifty Metal	5678.66	11.46	1.62	3.99	0.87	1.15
Nifty Oil & Gas	8533.80	12.96	1.93	3.24	0.66	0.95
Nifty Pharma	13210.98	36.79	4.29	0.68	0.58	0.59
Nifty Private Bank	19237.49	29.41	3.00	0.46	0.75	1.25
Nifty PSU Bank	3384.45	19.85	0.82	0.43	0.95	1.19
Nifty Realty	13210.98	217.49	2.51	0.41	0.84	1.11

Results and Discussion

Table 2. CRITIC Result

Total	Total Return Index	P/E	P/B	Div Yield	STD Dev	Beta
1	0.16	0.15	0.18	0.18	0.15	0.18

We acquire the rankings from each MCDM method. Table 3 shows that there is overlap in the ranks across the different indices. Weights are provided for each condition in Table 2. The CRITIC technique is used to determine the weights needed for additional computations. The decision matrix and weights are used to rank the five MCDM techniques. Table 3 shows the rank of sectorial indices for each MCDM approaches. In all MCDM approaches, it can be inferred that the indices with the highest rankings are Nifty FMCG, Nifty Media, Nifty IT, Nifty Consumer Durables, and Nifty Metal.

We have solved the diverging ranking issues using Pearson's rank correlation coefficient method, even if the rankings from the various MCDM approaches have been acquired. Ascertain the highest-ranking sectors as our suggestion, then provide a hybrid rank to each sector. An overview of the Pearson's rank correlation coefficient between the five MCDM approaches' ranks can be found in Table 4. Refer A1 to A16 as alternatives (sectorial indices) accordingly Table 1.

Table 3. MCDM Approaches Ranking

Sectorial Indices	SAW	TOPSIS	ARAS	COPRAS	EDAS
A1	9	10	9	10	4
A2	8	8	8	5	2
A3	4	3	5	11	6
A4	7	7	7	1	7
A5	11	11	11	7	15
A6	12	12	12	9	11
A7	1	1	1	3	1
A8	15	15	15	16	14
A9	3	4	4	6	5
A10	2	2	2	13	8
A11	6	5	6	2	3
A12	10	9	10	4	10
A13	14	14	14	15	12
A14	13	13	13	8	13
A15	16	16	16	14	16
A16	5	6	3	12	9

Table 4. Rank Correlation Result

	SAW	TOPSIS	ARAS	COPRAS	EDAS
SAW	1.000				
TOPSIS	0.979	1.000			
ARAS	0.995	0.981	1.000		
COPRAS	0.567	0.535	0.507	1.000	
EDAS	0.819	0.769	0.795	0.634	1.000

Table 5. Correlation ranking

	SAW	TOPSIS	ARAS	COPRAS	EDAS
Weights	0.216	0.211	0.212	0.161	0.199
Rank	1	3	2	5	4

Table 4 shows the Pearson's rank correlation coefficient result that indicates the relationship between five MCDM approaches i.e., SAW, TOPSIS, COPRAS, ARAS, and EDAS. It can observe that SAW, TOPSIS and ARAS gives the best outcome. Table 5 shows the weights and rank of each MCDM methods that is calculated from the correlation table.

After obtaining weights of each MCDM approach, as show in Table 5, we incorporate a hybrid MCDM ranking approach using ensemble method i.e., "Majority Voting" to obtain the optimal result. Values are assigned to options based on their ranking in majority voting, where the top ranked option is assigned the highest value. We calculate the weighted score, first multiplying the option value into with weights for each alternative then summing of all the criterion value and find the final rank of each alternative.

Table 6. Final Ranking

Sectorial Indices	SAW	TOPSIS	ARAS	COPRAS	EDAS	Weighted Score	Final Rank
A1	9(12)	10(11)	9(12)	10(11)	4(17)	12.611	9
A2	8(13)	8(13)	8(13)	5(16)	2(19)	14.664	7
A3	4(17)	3(18)	5(16)	11(9)	6(15)	15.296	5
A4	7(14)	7(14)	7(14)	1(20)	7(14)	14.952	6
A5	11(9)	11(9)	11(9)	7(14)	15(5)	9	11
A6	12(8)	12(8)	12(8)	9(12)	11(9)	8.835	12
A7	1(20)	1(20)	1(20)	3(18)	1(20)	19.658	1
A8	15(5)	15(5)	15(5)	16(4)	14(6)	5.033	15
A9	3(18)	4(17)	4(17)	6(15)	5(16)	16.678	2
A10	2(19)	2(19)	2(19)	13(7)	8(13)	15.855	4
A11	6(15)	5(16)	6(15)	2(19)	3(18)	16.437	3
A12	10(11)	9(12)	10(11)	4(17)	10(11)	12.166	10
A13	14(6)	14(6)	14(6)	15(5)	12(8)	6.231	14
A14	13(7)	13(7)	13(7)	8(13)	13(7)	7.959	13
A15	16(4)	16(4)	16(4)	14(6)	16(4)	4.318	16
A16	5(16)	6(15)	3(18)	12(8)	9(12)	14.113	8

Conclusion and Future work

This research has successfully applied MCDM approaches, namely SAW, TOPSIS, COPRAS, MOORA, and EDAS, to rank sectorial indices of the NSE. By calculating criterion weights using the CRITIC method and applying the Pearson rank correlation coefficient between these MCDM approaches, a comprehensive understanding of the relative performance of NSE sectors has been achieved. The incorporation of criterion weights has improved the accuracy and reliability of the rankings, providing valuable insights for investment decision-making.

In future, there is potential for extending this approach to handle larger datasets. The scalability and applicability of the methodology can be explored to identify and rank sectors on a broader scale, potentially encompassing additional indices and economic variables. Furthermore, future research endeavors could involve the integration of MCDM approaches with machine learning techniques. Developing a model that combines the strengths of MCDM and machine learning could offer more efficient forecasting of economic decisions. By leveraging the predictive capabilities of machine learning, the model could enhance the ability to anticipate market trends and make informed investment decisions.

References

[1] J. Y. C. T. N. &. K. C. M. Kung, "A fuzzy MCDM method to select the best company based on financial report analysis," in IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2011), 2011.

[2] R. W. Saaty, The analytic hierarchy process—what it is and how it is used, 1987.

[3] S. Opricovic, Multicriteria optimization of civil engineering systems, 1998.

[4] A. H. R. J. X. Y. &. Z. X. Ang, "High idiosyncratic volatility and low returns: International and further US evidence," Journal of Financial Economics, pp. 1-23, 2009.

[5] L. Zongsheng, "Application of analytical hierarchy process technology in financial management assessment," in The 2nd International Conference on Computer and Automation Engineering (ICCAE), Singapore, 2010.

[6] N. Türegün, "Financial performance evaluation by multi-criteria decision-making techniques.," in Heliyon, 8(5), e09361, 2022.

[7] D. P. A. &. D. T. K. Gupta, "A multi-criteria decision making approach to rank the sectoral stock indices of national stock exchange of India based on their performances," National Accounting Review, pp. 272-292, 2021.

[8] S. B. G. B. M. &. B. S. Gupta, "Portfolio Selection using DEA-COPRAS at risk-return interface based on NSE (India)," International Journal of Innovative Technology and Exploring Engineering (IJITEE), pp. 4078-4086, 2019.

[9] P. X. X. S. H. a. C. C. Wang, A linguistic large group decision making method based on the cloud model, IEEE Transactions on Fuzzy Systems, 2018.

[10] I. M. C. a. F. T. Kaya, A comprehensive review of fuzzy multi criteria decision making methodologies for energy policy making, 2019.

[11] P. M. R. &. T. B. Kanwar, "Correlation Based Muti-Criteria Feature Weighting for Identification of

Top-k Investors and Companies," in In 2019 9th International Conference on Advances in Computing and Communication (ICACC), 2019.

[12] D. G. M. a. L. P. Diakoulaki, Determining objective weights in multiple criteria problems: The critic method, Computers & Operations Research, 1995.

[13] S. &. R. T. Chakraborty, "Bank-based versus market-based financial systems: A growth-theoretic analysis," Journal of Monetary Economics, pp. 329-350, 2006.

[14] D. G. M. a. L. P. Diakoulaki, "Determining objective weights in multiple criteria problems: The critic method.," Computers & Operations Research, pp. 763-770, 1995.

[15] E. A. &. I. A. T. Adalı, "CRITIC and MAUT methods for the contract manufacturer selection problem," European Journal of Multidisciplinary Studies, pp. 88-96, 2017.

[16] A. &. S. R. Cahyapratama, "Application of Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW) methods in singer selection process.," in In 2018 International Conference on Information and Communications Technology (ICOIACT), 2018.

[17] M. a. A. K. J. Panda, "TOPSIS in multi-criteria decision making: a survey," in International Conference on Data Science and Business Analytics (ICDSBA), 2018.

[18] N. a. Z. X. Liu, "An overview of ARAS method: Theory development, application extension, and future challenge," nternational Journal of Intelligent Systems, pp. 3524-3565, 2021.

[19] A. J. S. S. R. &. F. K. Patel, "Comparative study of MCDM techniques COPRAS and TOPSIS for selection of electric motorcycles," in Proceedings of the 2020 IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA), Bangkok, Thailand , 2020.

[20] M. Z. E. K. O. L. &. T. Z. Keshavarz Ghorabaee, "Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS)," pp. 435-451, 2015.