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Multicriteria Decision Analysis for Stock Selection: A Comparative Study of ELECTRE III with Veto, TOPSIS, and PROMETHEE Methods

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Abstract

This paper explores the use of three multicriteria decision analysis (MCDA) methods—ELECTRE III with veto, TOPSIS, and PROMETHEE—in ranking stocks within a sector. Each method evaluates stocks based on fundamental, performance, and technical criteria to identify top performers. ELECTRE III with veto emphasizes robustness, TOPSIS focuses on balanced performance, and PROMETHEE customizes rankings based on specific preferences. The analysis finds common high-ranking stocks like Apple, Universal Display, and Microsoft across all methods, while each method also uniquely highlights different stocks. The paper demonstrates how these MCDA methods provide comprehensive insights for informed stock investment decisions.

Keywords: *Stock Selection**,** ELECTRE III, Veto**,** TOPSIS**,** PROMETHEE*

1. Introduction

Artificial intelligence (AI) refers to the capacity of computers or software to perform tasks that usually require human intelligence. As a key branch of computer science, AI focuses on the development and research of intelligent machines, with extensive applications in various sectors such as business, government, academia, and more. It provides a contemporary approach to decision analysis and decision-making.

One significant AI algorithm used in decision-making is multi-criteria decision analysis (MCDA). MCDA evaluates multiple factors simultaneously when making decisions, applicable to everyday situations and specialized fields like business, government, and healthcare. Decision-making often involves competing criteria; for instance, when purchasing a car, factors such as cost, quality, comfort, safety, and fuel efficiency need to be balanced. Typically, the least expensive cars might not offer the highest quality or comfort.

In the realm of portfolio management, the goal is to minimize risk while maximizing profit, which involves considering a range of factors. In everyday life, individuals often make decisions based on intuition and are generally satisfied with the outcomes (Rew L., 1988). However, in high-stakes scenarios, it is crucial to properly frame the problem and evaluate multiple criteria (Franco L. A. and Montibeller G., 2010). These decisions are complex, involving multiple considerations and frequently affecting various stakeholders, thus requiring a thorough and nuanced decision-making process.

Making better selections requires careful consideration of several variables and a well-structured approach to difficult situations. Since the early 1960s, when the contemporary multi-criteria decision analysis discipline was founded, there has been a significant advancement in this field with numerous different strategies and techniques, many of which were carried out by specialized decision-making software (Grace S. et al., 2016; Justin A. 2018), have been developed for use in a variety of fields, including business, politics, the environment and energy (Angeliki K. et al. 2016). The Artificial Intelligence Multi-criteria Decision Analysis algorithm will assist in solving the problem of selecting the right stock with the lowest risk and highest return.

2. Literature Review

In the paper titled "Incorporating FAT and privacy aware AI modeling approaches into business decision-making frameworks," an artificial intelligence system built to function within the fairness, accountability, and transparency (FAT) criteria framework is applied in a privacy-constrained dataset to demonstrate the compatibility of these criteria to demonstrate that AI can be trusted in decision making. These criteria were chosen because they are trending in the requirements of the operation of a business decision-making algorithm. (Zhdanov D. et al. 2022).

The majority of modern company advances are centered on electronic business, or "e-business," which uses the internet to expand internationally and improve its competitiveness. However, even with all of the internet's benefits, a sizable portion of e-businesses fail. To meet this challenge, effective analysis is therefore necessary for effective business decision-making. Buyukozkan G. (2004) presented a fuzzy logic that relies on multicriteria assessment as a superior algorithm to improve the effectiveness of decision-making in enterprises under uncertain conditions to address this difficulty.

Kartal H. et al. (2016) designed a hybrid mechanism that combines machine learning algorithms with multi-criteria decision-making (MCDM) techniques to efficiently perform multi-attribute inventory analysis. The hybrid initially implemented ABC analysis applying simple-addictive weighing, analytical hierarchy process, and VIKOR to find the class of individual inventory items. Then naïve Bayes, Bayesian network, artificial neural network (ANN), and support vector machine (SVM) algorithms are applied to predict classes of initially found items. A comparison of the algorithms indicates that SVM produced the best result. The analysis also shows that Bayesian networks, SVMs, and ANNs can efficiently analyze unbalanced data of Pareto distribution. This indicates that machine learning can efficiently manage business decisions based on inventory classification.

Mamoudan M. M. et al. (2021) looked at factors that affect insurance companies and analyzed the relationships between these factors to increase the profit margins of the insurance market. They applied two methods to find out how the charge of insurance companies is affected by some variables: first, they used data analysis with the help of diagrams to examine how these variables affect each other; second, they applied a multi-criteria decision-making technique called the Best-Worst method. These methods were applied to the data of an insurance company, and the results indicate the variable that can have the greatest effect on cost. This information can help insurance companies provide appropriate macro-fiscal policies and pricing.

Establishing the proper location of the logistic center is important for the proper estimation of the cost and profit of that center. Ozman M. and Aydogan E. A. (2020) proposed a three-stage methodology framework for determining the location of the logistic center based on Kayseri's logistics. First, the criteria are derived from the expert literature review. Next, the criteria are weighed by applying the linear Best-Worst method. Analysis based on distance from average solution method using different distance measures is applied to rank the locating. Sensitivity analysis is employed to determine the location.

A multi-criteria decision-making model for the digitalization of industrial plants was developed as a result of the intense competition among these companies, which makes it necessary for them to improve their operations to stay competitive and turn a profit within a short period. The model uses AHP and Fuzzy Logic in conjunction with a classified hierarchy of digital technologies to demonstrate the benefits of choosing compatible technologies (Maretto L. et al 2022).

To help businesses choose the best web services to perform various tasks online, Bagga et al. (2019) applied and compared five popular multi-criteria decision analysis methods for 50 and 100 web services. The 50 and 100 web services were ranked based on numerous Quality of service (QoS) parameters. Due to the abundance of fraudulent and sometimes dummy web services available on the internet, it is imperative to adopt the right measures to select the required web services, avoid fraudulent web services, and also help businesses save time. To identify the optimal multi-criteria decision maker (MCDM) with the least deviation in their rank, Spearman's Rank Correlation Coefficient was also interpolated for a variety of pairs of MCDM.

Ceballos B. et al. (2016) empirically compared results from the rankings generated by several multi-criteria decision-making methods with the aid of the Spearman correlation coefficient index. They put TOPSIS, and VIKOR in three different settings, and MOORA into practice. This was done by the application of decision matrices with diverse alternatives and criteria. The rankings done by MOORA and TOPSIS gave results that are closely comparable while rankings created by different settings of VIKOR caused differences. This outcome will assist firms in making productive decisions to optimize profit.

Businesses worldwide are grappling with the challenge of swiftly and effectively analyzing inventories to make well-informed decisions. In 2016, Kartal H. et al. introduced a hybrid methodology that merges a machine learning algorithm with multi-criteria decision-making (MCDM) techniques, successfully executing a multi-attribute inventory analysis. Their approach involved applying ABC analysis alongside three distinct MCDM algorithms: the analytical hierarchy process, simple additive weighting, and VIKOR. This strategy enabled accurate classification of individual inventory items. For predicting the classes of previously tagged stock items, they employed naïve Bayes, Bayesian network, artificial neural network (ANN), and support vector machine (SVM) methods. The findings revealed that while all methods efficiently analyzed the inventory, SVMs delivered the most accurate results, showcasing the performance measures of each approach.

3. Methodology

Figure 3.1 shows some Multi-criteria Decision Analysis methods and they differ from each other e.g. in the way preferences are expressed and how the preferences are utilized when new solutions. In this project, three multicriteria decision analysis algorithms were applied to a sector of stock and their results were compared, the three Multi-criteria Decision Analysis methods are ELECTREEI with veto, TOPSIS, and PROMETHEE.

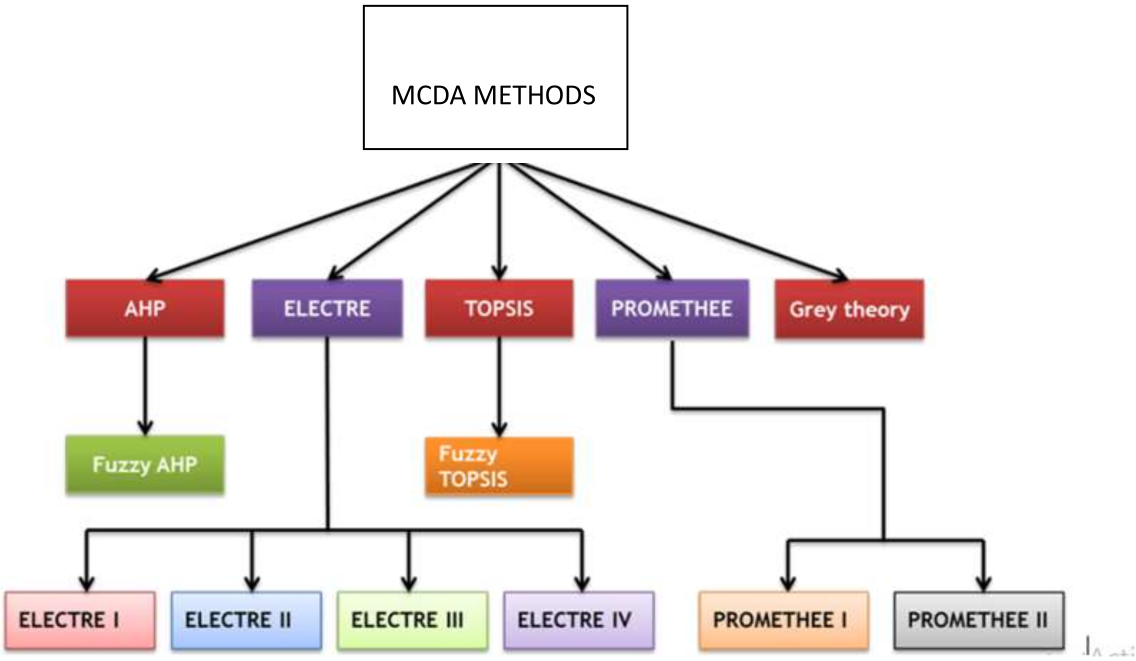

Figure 3.1 Some MCDA Methods

The sector of stocks and data sources is collected from investing.com and Yahoo finance decision-makers. The criteria are calculated based on historical data provided by both decision makers with a risk metric to eliminate stock with bad programmes. The stock dataset in which the multi-criteria decision analysis is applied is shown in Table 3.1.

Table 3.1 Stock Dataset

Symbol	Name	Market Cap	P/E Ratio	Revenue	Average Vol. (3m)	EPS	Beta	YTD	1 Year	3 Years	Weekly	Monthly
TXN	Texas Instruments	1.046900e+11	20.16	1.559000e+10	4850000.0	5.51	1.22	17.39	-2.90	78.89	4	4
OTEX	Open Text	1.110000e+10	40.51	2.880000e+09	499120.0	1.02	0.48	25.43	13.71	35.62	4	4
AMAT	Applied Materials	3.971000e+10	11.86	1.577000e+10	9230000.0	3.57	1.63	29.23	-12.91	79.05	4	3
UBNT	Ubiquiti	9.220000e+09	29.86	1.140000e+09	449380.0	4.44	1.34	30.95	51.18	225.04	2	4
AMSWA	American Software	4.432200e+08	73.81	1.117900e+08	66460.0	0.19	0.69	36.17	-6.13	42.16	4	4
TTEC	TTEC	2.070000e+09	41.87	1.530000e+09	84980.0	1.08	0.68	57.51	20.81	63.46	4	4
AVGO	Broadcom	1.102900e+11	33.95	2.131000e+10	2790000.0	8.19	0.91	7.86	4.99	74.77	2	4
AAPL	Apple	9.124400e+11	17.01	2.584900e+11	29290000.0	11.67	1.23	25.83	6.42	108.71	4	4
QCOM	Qualcomm	8.680000e+10	39.71	2.123000e+10	21120000.0	1.81	1.61	24.78	20.79	31.77	3	4
XLNX	Xilinx	2.829000e+10	32.81	3.060000e+09	4360000.0	3.41	1.22	30.29	61.67	138.65	2	4
ESLT	Elbit Systems	6.770000e+09	32.17	4.710000e+09	12680.0	4.85	0.83	38.38	30.99	70.87	4	4
TER	Teradyne	7.930000e+09	20.14	2.110000e+09	2160000.0	2.27	1.55	45.92	16.81	134.70	4	4
CSCO	Cisco	2.409200e+11	20.47	5.132000e+10	20060000.0	2.74	1.19	29.59	28.37	94.97	4	4
SSNC	SS&Cs	1.472000e+10	117.98	4.140000e+09	1360000.0	0.49	1.29	28.77	6.49	98.06	2	4
CDW	CDW Corp	1.534000e+10	23.78	1.659000e+10	684910.0	4.38	1.05	29.56	24.58	155.31	4	4
MSFT	Microsoft	1.000000e+12	30.14	1.222100e+11	23690000.0	4.48	1.23	32.35	31.96	168.48	4	4
MANT	ManTech	2.570000e+09	30.85	1.990000e+09	125000.0	2.08	0.94	23.35	18.13	77.52	4	4
GRMN	Garmin	1.532000e+10	21.80	3.400000e+09	1070000.0	3.71	0.98	27.62	31.53	90.05	4	4
ADI	Analog Devices	4.070000e+10	26.19	6.240000e+09	2780000.0	4.20	1.40	27.95	8.73	93.38	4	4
JKHY	Jack Henry&Associates	1.059000e+10	37.55	1.580000e+09	385560.0	3.66	0.94	8.20	4.39	63.66	2	3
BRKR	Bruker	7.410000e+09	40.46	1.930000e+09	811410.0	1.17	1.27	58.25	55.53	93.23	4	4
OLED	Universal Display	8.680000e+09	105.25	3.351800e+08	732430.0	1.75	1.51	96.59	109.15	164.87	4	4

3.1 ELECTREEI with veto

ELECTRE methods share similarities in conceptual descriptions but differ based on the specific decision problems they address. Notably, ELECTRE I has been demonstrated to be particularly effective for selection problems.

3.2 TOPSIS

TOPSIS, or the Technique for Order Preference by Similarity to the Ideal Solution, is a straightforward multi-criteria decision analysis (MCDA) method. It operates on the principle of identifying both ideal and anti-ideal solutions and then measuring the distance of each alternative from these solutions. The goal is to select alternatives that have the greatest distance from the worst ideal solution in a geometric sense. Because ideal and anti-ideal solutions follow a monotonously decreasing function, their computation is relatively simple. This method allows for the ranking of alternatives, with the top-ranking ones being selected based on their distance metrics.

3.3 PROMETHEE

One of the creators of PROMETHEE, Professor Bertrand Mareschal, maintains a full list of references to his website that as of April 2017 numbered approximately 1,500 references, rendering the method to be quite popular. Input data is similar to TOPSIS and VIKOR, but the modeler is optionally required to feed the algorithm with a couple of more variables, depending on his preference function choice.

4. Results Analysis

The criteria chosen are applied with respect to the following criterion important weights, they are: high Market cap, low P/E ratio, high Revenue, Medium Average Vol (3m), high EPS, low beta, high YTD, high 1-Year return, high 3-Year return, high Weekly performance and high Monthly performance, as shown in Figure 4.1

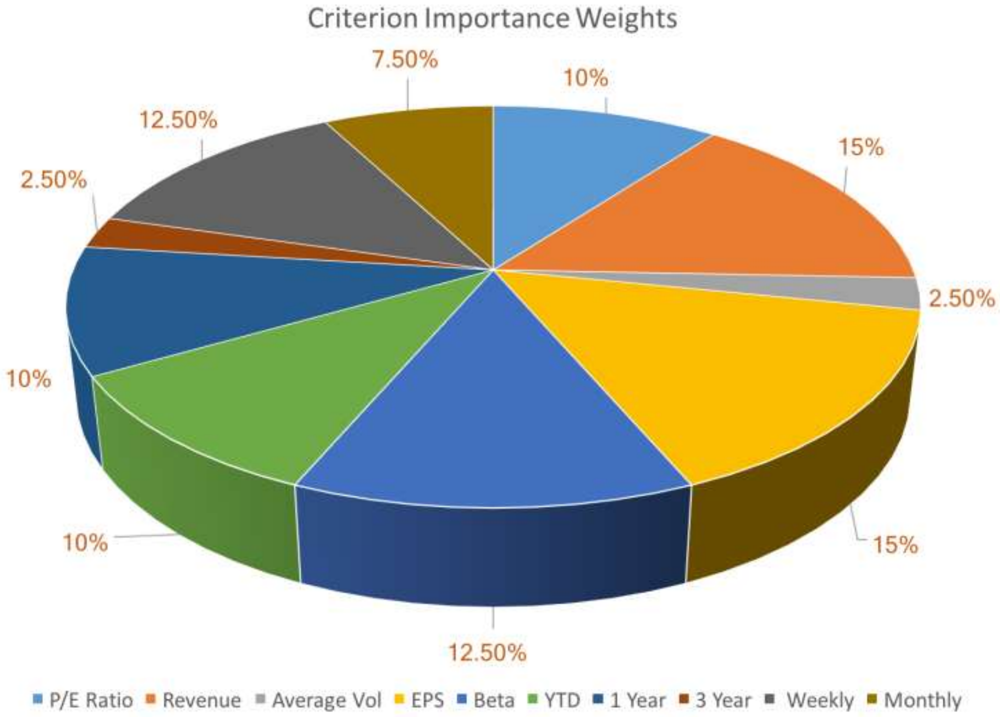

Figure 4.1 Criterion Importance Weights

Market capitalization, or market cap, refers to the total value of a company's outstanding shares of stock, calculated by multiplying the stock's current price by the total number of shares. The price-to-earnings ratio (P/E ratio) is a valuation tool that compares a company's share price to its earnings per share (EPS), also known as the price multiple or earnings multiple.

Revenue, also known as the top line, represents the total income a company generates from its sales of goods and services. This amount is listed at the top of the income statement and shows the gross sales before any expenses are deducted. Earnings per share (EPS) is a crucial indicator of profitability, calculated by dividing the net income by the number of outstanding shares.

Average volume (Avg Vol) indicates the daily average trading volume over the past three months. The beta coefficient assesses a stock's volatility, or systematic risk, compared to the overall market's unsystematic risk. Statistically, beta is represented as the slope of the regression line that plots an individual stock's returns against market returns.

Year to date (YTD) encompasses the period from the beginning of the current calendar or fiscal year to the present date. YTD data is valuable for analyzing business trends and comparing performance metrics, frequently used for evaluating investment returns, earnings, and net pay.Fundamental and technical analysis are then carried out on the criteria with the Multi-criteria Decision Analysis methods and calculations are carried out with respect to the LSTM classifier within 0 to 5 strengths. All criteria are then normalized with a standard deviation threshold of 0.8 and stocks greater than the threshold were eliminated an explicit analysis on the criterion based on the three Multi-criteria Decision Analysis methods produced similar results as shown in Figure 4.2

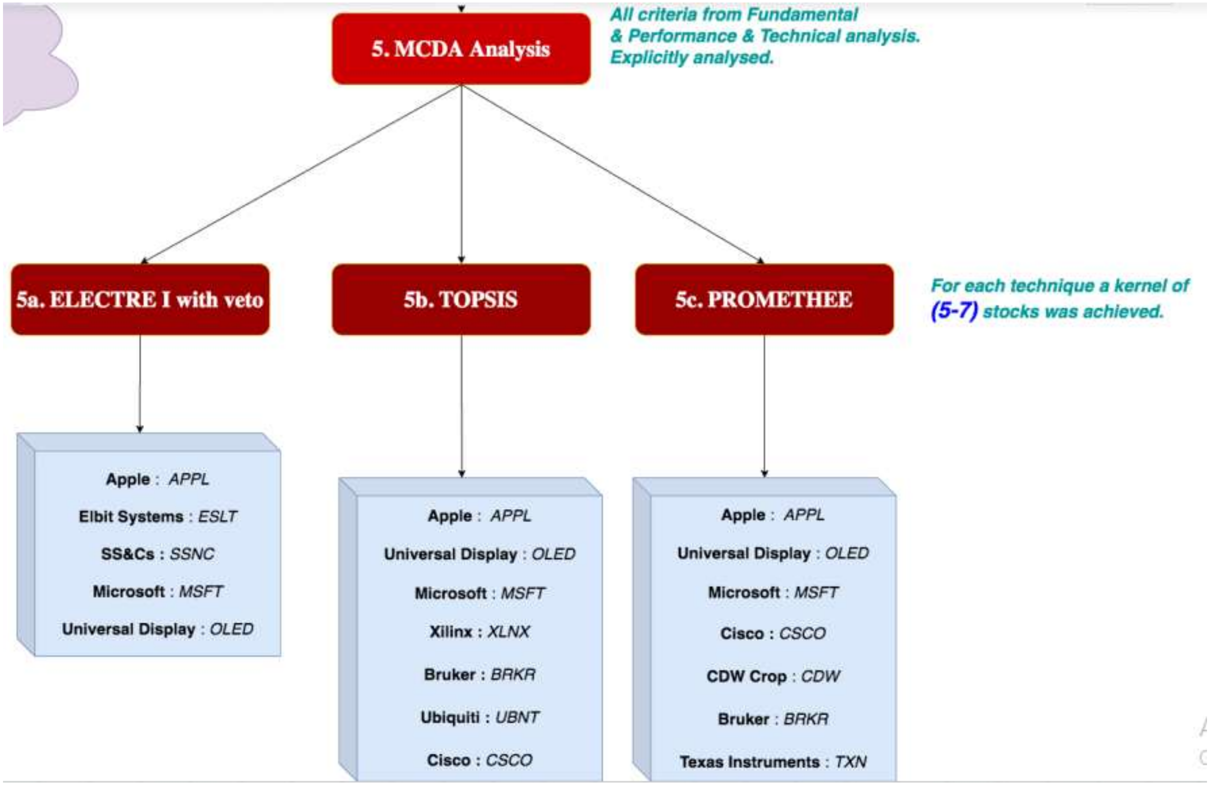

Figure 4.2 Result Analysis

Figure 4.2 shows the results of applying three multicriteria decision analysis (MCDA) methods—ELECTRE III with veto, TOPSIS, and PROMETHEE—on a stock sector. Each method analyzed various criteria from fundamental, performance, and technical perspectives to identify a set of 5-7 stocks that are deemed optimal according to each method. Here is a detailed explanation of the results:

4.1 ELECTRE III with Veto

Stocks Identified:

- Apple (APPL)
- Elbit Systems (ESLT)
- SS&C Technologies (SSNC)
- Microsoft (MSFT)
- Universal Display (OLED)

Explanation: ELECTRE III with veto is a robust method that evaluates alternatives by considering both their strengths and weaknesses. The veto threshold plays a crucial role in this method by excluding alternatives that fail to meet certain critical criteria. As a result, the selected stocks here are those that have generally strong performances across various metrics and do not critically fail in any single area. This method highlights stocks that are strong candidates for investment by avoiding those with significant downsides in any criteria.

4.2 TOPSIS

Stocks Identified:

- Apple (APPL)
- Universal Display (OLED)
- Microsoft (MSFT)
- Xilinx (XLNX)
- Bruker (BRKR)
- Ubiquiti (UBNT)
- Cisco (CSCO)

Explanation: TOPSIS ranks alternatives based on their proximity to an ideal solution and their distance from a nadir (worst) solution. The stocks identified by TOPSIS are those that exhibit a balance of strong performance across multiple criteria. This method ensures that the selected stocks are closest to the optimal performance while being farthest from the worst, suggesting a well-rounded and stable set of stocks for investment.

4.3 PROMETHEE

Stocks Identified:

- Apple (APPL)
- Universal Display (OLED)
- Microsoft (MSFT)
- Cisco (CSCO)
- CDW Corporation (CDW)
- Bruker (BRKR)
- Texas Instruments (TXN)

Explanation: PROMETHEE is a flexible outranking method that uses preference functions to evaluate alternatives. It allows for a more nuanced comparison based on the decision-maker's specific preferences and criteria importance. The stocks chosen by PROMETHEE are those that align well with the predefined preferences and perform strongly in key areas of interest. This method provides a tailored selection of stocks that cater to specific investment goals and criteria.

4.4 Comparison and Insights

- **Common Stocks:** Apple (APPL), Universal Display (OLED), and Microsoft (MSFT) appear in all three lists, indicating their robust performance across different MCDA methods and suggesting them as strong investment candidates.
- **Method-Specific Selections:** Each method has identified unique stocks as well, highlighting the different strengths and sensitivities of the methods. For example, Elbit Systems (ESLT) and SS&C Technologies (SSNC) are unique to ELECTRE III, while Xilinx (XLNX) and Ubiquiti (UBNT) are specific to TOPSIS, and CDW Corporation (CDW) and Texas Instruments (TXN) are exclusive to PROMETHEE.
- **Diversity in Results:** The diversity in the results reflects the different evaluation approaches of each method, providing a comprehensive overview of the stock sector. This multifaceted analysis allows for a more informed and balanced investment decision.

By leveraging the unique strengths of each MCDA method, decision-makers can gain deeper insights into the performance and potential of various stocks, ensuring a well-rounded and strategic investment portfolio.

Conclusion

In conclusion, the stock dataset was successfully and efficiently ranked by AI utilizing the MCDA. This suggests that AI algorithms are important for making commercial decisions. Businesses can gain from precise forecasts, more intelligent decision-making, and more overall efficiency by utilizing AI technologies. Organizations may reduce human biases and make better informed decisions based on objective data when AI algorithms are integrated into the decision-making process. Businesses who take advantage of these developments will have a major competitive advantage in the dynamic and always changing global economy as AI technologies continue to progress.

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