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A MULTI-CRITERIA BASED STOCK SELECTION FRAMEWORK IN EMERGING MARKET

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Abstract: *The present study aims to compare the stock performances of the Fast Moving Consumer Goods (FMCG) and Consumer Durables (CD) firms at the Bombay Stock Exchange (BSE), India. It is evident from the extant literature that investment in the stock market depends on two broad objectives such as maximization of return while minimization of risk. Besides, investment decisions are also influenced by the behavioral nature of the investors. To this end, the current work considers the earning prospect (average market return, return on net worth, earning per share, and yield), market-centric risk (beta), market perception (price to book value, shares traded), momentum (turnover) and benchmarked performance (alpha) to set the criteria for comparison. The study period considers seven consecutive financial years to discern the performance. For the comparative analysis, a combined multi-criteria decision-making (MCDM) framework of Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) (used to determine criteria weights) and Evaluation Based on Distance from Average Solution (EDAS) (for ranking) methods has been utilized. Borda Count Method (BC), Copeland Method, and Simple Additive Weighting (SAW) have been used to aggregate the year-wise rankings. The calculated weights show consistency to the modern portfolio theory as average return, beta, and return on net worth obtain higher weightage than others. It is observed that there are variations in the year-wise comparative ranking, while on aggregation, FMCG firms dominate the top positions. The analysis reveals that Avanti Feeds Ltd., Hindustan Unilever Ltd., Procter & Gamble Hygiene & Health Care Ltd., Britannia Industries Ltd., and Nestle India Ltd. are the top five performers, while Godfrey Phillips India Ltd., E I D-Parry (India) Ltd., United*

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Breweries Ltd., Rajesh Exports Ltd., and Radico Khaitan Ltd. hold the bottom five positions during the same period. The results also indicate that, more or less, the firms having higher market capitalizations have performed well. The results obtained using the EDAS method and other popular MCDM models, such as multi-attributive border approximation area comparison (MABAC) and the Complex Proportional Assessment (COPRAS), show a significant correlation. Further, the outcome of the sensitivity analysis confirms the stability of the performance-based ranking results.

***Key words**: Stock performance, Portfolio selection, Logarithmic Percentage Change-driven Objective Weighting (LOPCOW), Evaluation Based on Distance from Average Solution (EDAS), Borda Count*

1. Introduction

Investment decision-making is a multi-factors-based complex activity. The investors consider several aspects such as financial goals, present condition prior to investment, objectives of investment, and selection of financial instruments vis-à-vis intended outcome (Asad et al., 2018). Essentially, financial investment intends to generate wealth to achieve financial security and independence and fulfill the desired financial goals (Goyal et al., 2021; Gupta et al., 2019a). The underlying objective is to formulate a portfolio of financial instruments to optimize the overall return at an affordable risk (Ren et al., 2017). Among all financial instruments, the equity stock market has been an attractive option for investment over the last several decades (Gupta et al., 2019b).

The portfolio selection is a complex issue that gets influenced by many aspects encompassing investors' characteristics, backgrounds and their decisions, performance, and characteristics of the stocks, entry and exit timing, market behavior, and macro-economic influences (Biswas et al., 2019; Bhattacharya et al., 2022). The vastly expanded strand of literature on security analysis and portfolio selection has the genesis in two celebrated contributions, such as security analysis for value investing (Graham et al., 1934) and the mean-variance framework (modern portfolio theory) of Markowitz (1952). According to their work, investment decisions entail maximization of the mean (return) while minimizing the variance (risk). In subsequent years, the stated school of thoughts has been enriched and expanded with many notable contributions, for instances capital asset price model (CAPM), market efficiency and conditions for capital market equilibrium (Sharpe, 1964; Lintner, 1965; Mossin, 1966; Fama, 1970; Black, 1993), effect of organizational characteristics on stock returns (Stattman, 1980; Banz, 1981; Reinganum, 1981; Basu, 1983; Rosenberg et al., 1985; Bhandari, 1988; Chan et al., 1991), three factor model for asset pricing and stock selection (Fama and French, 1992, 1993), momentum and contranian effect on stock performance (Jegadeesh and Titman, 1993, Grinblatt et al., 1995, Cooper et al., 2004), four factor model for asset pricing (Carhart, 1997), estimation of volatility and its effect on stock performance (Chong and Phillips, 2012; Hsu and Li, 2013), integration of fundamental and technical indicators for assessment of stock performance for portfolio selection (Peachavanish, 2016), multi-factor based portfolio selection (Fama and French, 2017, 2018) among others.

The modern portfolio theory (MPT) and CAPM depend on the theoretical foundations of the expected utility theory (Morgenstern and Von Neumann, 1953), which state that investors make rational decisions using the available information fully and also on the notions of bounded rationality (Barnard and Simon, 1947). Further, the market is also treated as an efficient one wherein the market price determines the intrinsic values of the firms. However, in real-life scenarios, investment decisions are not always grounded on rationality or bounded rationality, and the investment market is not necessarily efficient. The MPT and CAPM do not consider the behavioral manifestations, such as emotions, social orientations, and cognitive dissonance of the investors, which notably affect the final decisions (Ogunlusi and Obademi, 2021; Huang et al., 2011). Keeping into consideration the impact of behavioral factors on investment decision-making, a new school of thought ("Behavioral Finance Theory or BFT") has emerged and evolved with the proposal of the prospect theory (PT) by Tversky and Kahneman (1979). In the subsequent years, the extant literature has been contributed by the cumulative prospect theory, aka CPT (Tversky and Kahneman, 1992), modified CPT with uncertain information (Schmidt et al., 2008; Schmidt and Zank, 2009). All these theories entail the impact of abnormal phenomena on investment decisions. The PT and CPT are based on the value function that explains the investment decisions regarding potential gains and losses with respect to the reference point. The other strand of the BFT points out that the investors safeguard the risk or potential loss over the gain (disposition effect) while contradicting the fundamental propositions of the expected utility theory (Shefrin and Statman, 1985; Levy, 1992). From a linked perspective, the researchers (Loomes and Sugden, 1982; Bell, 1985) also highlighted the disappointment of the investors if the outcome is below par with expectations. Investors prefer to have better gains at an affordable risk (Gul, 1991), leading to their choices for a low risk-free rate with a higher equity gain (Li et al., 2021).

From the theories of the investment decision making it is understood that investors do select the portfolio from multiple perspectives such as market performance indicators like return, risk, price to book value and earnings, and volatility along with fundamental performance and technical analysis (Patil and Bagodi, 2021). Hence, the investment decisions stand on multiple criteria or features which are conflicting to each other and complex in nature (Aouni et al., 2019).

In this paper we aim to carry out a comparative analysis of selected FMCG and CD stocks listed in BSE, India over a period of seven consecutive financial years (FY 2013-14 to FY 2019-20). FMCG products are the consumer packaged goods that are regularly consumed by the common households in their daily life. The FMCG sector is characterized by a number of interesting features such as a higher level of consumption, wider range for products and prices available to a large consumer base (both urban and rural segments), lower entry and exit conditions for the firms leading to stiff intra-industry competitions among several domestic and multinational firms and presence of substantial number of unorganized players (Dhingra et al., 2018). On the other side, CD products (white, brown and consumer electronics items) are also used in the kitchens for utility purpose, as electronic gadgets for daily entertainment purpose, for home furnishing and as leisure items. The sector is featured by rapid developments of technology, presence of organized and/or unorganized domestic players and multinationals and intense competitions on brands. With the rise in the disposable income and increasing urbanizations, the sector has been witnessing a notable growth over the last few decades and there has been an increasing familiarity among common households belonging to rural area also (Sarangi, 2019). Hence, FMCG and CD sectors have been drawing growing attentions from the Indian investors and fetching a substantial inflow from abroad too (IBEF, 2022a, 2022b). The present paper attempts to answer the following research questions:

RQ1. How can a multi-criteria based model be formulated to compare the market performance of a set of selected FMCG and CD stocks?

RQ2. To what extent do the stocks differ from each other in terms of their market performance?

We construct the rest of the paper in the following manner. In section 2, a brief summary of the recently published research work is presented. Section 3 sketches out the data and methodology used in this paper while in section 4, the major findings are highlighted. Section 5 exhibits the discussions on the result and includes the implications of the work. At the end, section 6 makes the concluding remarks while mentioning some of the future research scope.

2. Related Work

The extant literature is vastly contributed with the research work on stock selection approaches and frameworks. In this section, we shall present a summary of some related work published recently. For this purpose, we organize the literature review section in two parts. The first part summarizes the work applying statistical analysis and predictive and machine learning (ML) algorithms are discussed. The second part highlights some of the work that used MCDM models for stock selection.

2.1. Stock selection using statistical analysis and predictive and ML algorithms

The extant literature shows ubiquitous applications of statistical models and ML algorithms for predicting stock performances and portfolio selection.

For instance, Dai and Zhou (2019) considered equal-weight linear models and machine learning frameworks to identify the criteria for stock selection and put forth an efficient portfolio. Wu et al. (2019) presented a cross-sectional forecasting model for the stocks listed in the Shanghai Composite Index. They advocated selling lower decile stocks while buying upper decile stocks to formulate the portfolio. Tan et al. (2019) proposed a nonlinear predictive analytics framework such as random forest and examined its efficacy in stock selection. Two types of features such as technical/fundamental and momentum were considered to compare the Chinese stocks and observed lesser efficiency of the market in the stock market. Yang et al. (2019) suggested a hybrid stock selection method incorporating stock prediction and effectively capturing the future features of complex stock markets. The result implies that the proposed model can be an efficient tool for profit generation portfolios by outperforming a series of benchmark models by incorporating stock prediction into stock selection.

Asadi and Mohammadi (2020) proposed a semi-variance model for analyzing information development with cross-sectional return for selecting portfolios in a fuzzy environment. The study used 14 financial parameters collected from financial statements of 40 companies listed on the Tehran Stock Exchange. The analysis concluded that the proposed method was more suitable than other methods as it provided better results for performance analysis, efficiency, and company selection which helps in selecting a portfolio in a fuzzy multipurpose model. Chen et. al (2020) proposed a solution to the portfolio selection problem with high order moments. The study aimed to extend the Mean-Variance model to the Mean-Variance Skewness Kurtosis model. Daily trading data of the 50 Shanghai Stock Exchange Index was taken from the period of January 04, 2010 to February 20, 2017 to verify the effectiveness and robustness of the proposed model. The out-of-the-sample performance of the suggested model showed significantly better results than the classic mean-variance model. The proposed hybrid approach also included three machine learning algorithms for constructing a portfolio to invest in.

Alfonso and Ramirez (2020) suggested a combinational approach with a neural network to guarantee better results in stock forecasting. The study used 6 different Chinese Stock Indexes and 36 technical indicators as inputs in a non-linear model. The results showed that the suggested model can be a feasible one for stock forecasting. Wu (2020) suggested an investment strategy based on the K-Clustering model using Machine Learning. The monthly data of 5175 stocks from the US Stock market from the period of August 2009 to August 2016 along with their technical indicators like- MA, KDJ & MACD was used for the study. These stocks were divided into several clusters and the stock closest to the center of the best cluster was chosen for the construction of the portfolio. The results showed that the investment in the portfolio created using the model had the highest excess return during the bull market and the same showed a decline in synch with S&P 500 index during the bear market.

Arif and Sohail (2020) attempted to incorporate additional dimensions to risk in the Markowitz Mean-Variance framework. They suggested incorporating Skewness, Kurtosis, and Coherent risk measure (CVaR) for obtaining an optimal portfolio with the PGP approach. The model used stock selected from the KSE-100 Index during the period of 2009-to 2018 and analyzed their Mean-Variance, Mean-Variance Skewness, Mean-Variance Skewness Kurtosis, and Mean CVaR Skewness Kurtosis. The analysis concluded that the return of the portfolio constructed using higher-order co-moments and a more sophisticated risk measuring tool gave a higher return over the benchmark portfolio. Somathilake (2020) explored the factors that influence the Investment Decisions of Individual Investors. The data used for the study were collected from 150 individual investors who were actively participating in Columbia Stock Exchange during the year 2020 using a standard questionnaire created using the Likert Scale. The factors like- accounting information, neutral information, and recommendations were considered Independent Variables for the study. The data collected were analyzed using correlation and regression. The results showed neutral information and advocated recommendations influences individual investment decision more than accounting information available which concludes that investors are not so rational while making investment decisions. Ogbebor and Alalade (2020) examined the factors considered by the individual investors while selecting stock and how they affect the stock prices. The study was made taking into consideration individual investors including Stock Brokers, Investment Bankers, and Equity Investors, and the stock prices of the companies listed on the Nigerian Stock Exchange. The responses of 250 investors collected through a questionnaire were analyzed using Regression (Correlation & ANOVA). The study showed that the independent variables such as investment, earnings, dividends, bills (three months Treasury bill rates), inflation rate, board characteristics, public (public image), product and history, product line, and long history of existence jointly along with the personal preference of Individual Investors significantly affect the stock price behavior of the companies listed in Nigerian Stock Exchange.

Zhou and Yin (2020) proposed a multi-factor stock selection model based on Kernel Principal Component Analysis. The study adopted a tree-like method that took factors like fundamental, technical, macro, investor sentiment, and analyst prediction, and these factors are further sub-classified to create a new method of processing a large amount of high dimensional nonlinear factors quickly and accurately. The paper takes all stocks of the Shanghai and Shenzhen 300 Index in 2016 as the benchmark for the stock pool and analyses data from 2010 to 2016 in multi-dimensional space. The data was arranged, processed, identified, and extracted by the characteristic of factors by Kernel Regression. The robustness of the model was verified using the bootstrap method. The result concluded that a combination of Kernel Principal Component Analysis and Multifactor Stocks Selection model could beat the market with high profitability and also can effectively overcome the problem of random stock selection.

Huang et al. (2021) applied three machine learning models such as Feed-forward Neural Network (FNN), Random Forest (RF) and Adaptive Neural Fuzzy Inference System (ANFIS) to predict stock performance based on fundamental performance. Bernal et al. (2021) aimed to present a multiple criterion hierarchical process (MCHP) approach for the first stage of portfolio selection, the evaluation of stock. 21 financial indicators (financial ratios, volatility, and Beta of shares) from 121 companies listed on the Mexican Stock Exchange were used to propose a structure hierarchical analysis of three levels. The multi-criteria ranking of stocks based on selected financial indicators was done using the Multiple Criteria Hierarchical Process which evaluated each macro criterion by directly interacting with immediate descending sub-criteria forming the hierarchical structure. Lastly, a preferential model is generated to understand how a company performs against another company at the given time and how that impacts the problem of portfolio selection. The study concluded that subgroups of indicators for market influence were ranked highly as they are considered the most important decision criteria in stock evaluation compared to other indicators. It also observed that some companies showed a better ranking when the company’s performance values were considered in the stock evaluation. De Nard et al. (2021) blends the traditional factor model of covariance matrix estimation with modern large -dimensional asymptotic theory. The study proposes a new AFM1-DCC-NL model and allowing time-varying conditional heteroscedasticity on historical data. Further, they also suggested a new forecasting covariance matrix where the dynamic estimator is used and the holding period of portfolio exceeds the frequency of the observed returns. The suggested techniques aimed at helping portfolio manager develop better-performing investment strategies along with contributing to academics to develop more powerful predictive tests.

Nazneena et al. (2021) studied comparative analysis of methods of constructing an optimal portfolio and thereby creating an optimum portfolio for the investment of the funds based on CNX Nifty and the indices of the relative sub-group. Daily data for the period of November 09, 2020 to February 05, 2021 of 5 sectors were considered for the study. Sharpe single index model is used to construct the portfolio. The study compares the risk and return of an individual sector with the risk and return associated with the market and creates an optimal portfolio.

Cheng et al. (2021) have applied data mining techniques and decision tree analysis to explore the relationship between financial ratios, corporate governance, and stock return to form a basis for making stock selection decisions. The study also employs another algorithm, the Apriori in association rules to supplement the explanation of mutual influence between various variables. 10 years of complete data of Sports and Leisure companies listed in Taiwan from 2005 to 2014 were used to construct the investment decision model. The annual rate of return as the dependent variable and 19 independent variables like- stock price, years on market, DS&F Holding, EPS, R&D expense, ROE, ROA, etc of the sample companies were studied as the case study formulating the proposed model. The study established an effective investment decision model and also provides a reference basis for stock-picking.

Dou et al. (2021) used Support Vector Model (SVM) for multi-factor stock selection. The study uses quarterly financial information such as profitability, income quality, debt-paying ability, etc of all the constituent stocks of the CSI 300 Index from 2013 to 2017 along with the risk indicators and investor sentiment indicators to make the model more comprehensive and effective. Further, Principal Component Analysis (PCA) is used for reducing the dimension and establishing the model before testing it empirically. The stock selection is done according to the sample values generated by the prediction of the model and it was concluded that its reliability was higher when compared to other research. Bermejo et al. (2021) proposed a factor-based long-term investing approach that evaluates the performance of the combined portfolios using the factors such as value, profitability, and momentum. The factor investment methodologies were applied to a balanced panel of 17,400 observations of 1830 different European companies distributed among 29 countries and 19 economic sectors from 1991 to 2019. The results showed that risk-adjusted returns can be improved by combining the factors into a single portfolio and the top-performing mixed portfolios are made from the combination of two different factors (profitability and momentum). The study also shows how the investor can combine value, profitability, and momentum factors in top quintile value portfolios to increasingly improve the risk-adjusted returns of those portfolios.

Mortazian (2021) investigated the changes in stocks' liquidity and return volatility after their movement from the Main Market to Alternative Investment Market (AIM). The study is made on the companies that moved from the Main Market to AIM between January 1996 to December 2013 on London Stock Exchange. The results showed that the stock that moved to AIM had a lower level of treading activity, higher transaction cost, and less stock return volatility in comparison to the stock that stayed. Further, it was also observed that the increase in illiquidity and decrease in volatility are sustained for four years after the movement. Jin et al. (2021) created an investment portfolio using the Markowitz model and Index Model. The study used the historical daily returns on 10 stocks from different sectors for 20 years (2001-2021) to design the best portfolio for different risk preferences with the best possible rate of return. The daily data were aggregated into the monthly observation to reduce the non-Gaussian effects. The results of the Markowitz Model & Index Model were presented in tabular and graphical form which concluded, that the Index model, compared to the Markowitz model, is more practical in the real situation of the market. As the Index Model involves a simpler calculation of co-variance which decreases the demand for the number of estimators. Hence, investors may largely use the Index model to help themselves find optimal portfolios.

Chaya et al. (2021) validated the Fama French Factor Model by studying the effect of systematic risk, size, and valuation of stock return. The study is made on the daily stock prices on the Lebanese Stock Market from the period of 2011 to 2018. It was concluded that market risk and valuation are significant in explaining the average stock market variation whereas the size factor appears to be very insignificantly small. It was also seen that the stock market exhibited a negative market risk premium due to US T-Bills and a high level of other factors inter-correlated during the period of study. Nugroho and Tjong (2021) aimed to determine the optimal stock as a basis for decisions in investment in company shares using Single Index Model. 19 stocks were selected from the purposive sampling from the IDX30 index listed on the Indonesia Stock Exchange from 2015 to 2019. Zhang et al. (2021) forecasts the closing of 10 stocks for the next 100 days through the Time Series, considering multiple constraints such as maximum return and minimum risk and thereby selecting an Optimal Portfolio Strategy. The study uses the Long-Term and Short-Term Memory (LSTM) is used with a good prediction effect along with the MAPE index to judge the error between the predicted result and the real value. Finally, the effectiveness of the model is verified by analyzing the new portfolio which shows that the expected income along with other investment benefits is positive.

Shahidin et al. (2021) proposed a mathematical method of Variance Covariance to determine the stocks for the creation of portfolios by following the risk preference of the investors and evaluating the Value at Risk (VaR) of multiple stock portfolios. Geometric Brownian Motion was also used to forecast share prices for future investment. The study was conducted on five different sectors from October 2017 to April 2018. The study of the VaR of each stock portfolio concludes that Industrial products and Trading are more suitable for Risk-Averse and Service sectors for Risk Premium Investors. Gubu et al. (2021) suggest a robust way of portfolio selection by grouping the stocks into clusters based on the different sectors. Sharpe ratio is used to select representatives from each cluster and a portfolio is constructed that optimized the use of FCMD and S- estimation. The proposed method was employed in the stock listed on the Indonesia Stock Exchange for the period starting from August 2017 to July 2018. The study showed that the portfolio created using clustering based on the business sector of stocks combined with FMCD estimation, outperformed the other possible combinations.

Mustafa et al. (2022) proposed a new generalized auto regression conditional heteroscedasticity (GARCH) econometric model with fuzzy numbers to forecast stock prices and observed significant accuracy in the results. Vo-Van et al. (2022) suggested a new approach for short-term stock trend prediction using the Bayesian classifier. The proposed stock selection method aimed at maximizing the probability of correct identification of peaks and troughs, thereby limiting risk and ensuring relatively higher profit. The study uses a new approach to computing the stock variation from the closing value of the last two days of the stock listed on the Vietnamese Stock Exchange. The Time Series data is transformed into Tabular Data and then the prediction is done using a Bayesian classifier. The results showed that the proposed two-step ahead prediction model is feasible and is better suited for short-term profits. In a recent work, Solares et al. (2022) demonstrated a combined forecasting, selection and optimization framework related to investment in equity market. The authors applied artificial neural network, fundamental analysis, differential evolution and evolutionary algorithms like genetic algorithm for the stocks listed at the S&P's 500 index. Further, the authors compared the performances (in terms of the features like risk adjusted returns, actual return etc.) with respect to the benchmark market indices and observed that the proposed portfolio outperforms the benchmark. On a different note, Devine and Siddiqui (2022) formulated an equilibrium constraint based model (grounded on the concept of oligopoly) to explain the stock performance in the context of electricity market. The authors considered two categories of firms such as market leaders and followers.

2.2. Stock selection using MCDM algorithms

MCDM algorithms have also been extensively used for comparing stock performances for portfolio selection problems. For example, Tey et al. (2019) used single valued neutrosophic fuzzy based AHP model to compare the financial performance of a sample of five public companies listed in Kuala Lumpur Stock Exchange (KLSE). The authors considered 15 fundamental financial ratios as criteria. In the same direction, Witayakiattilerd (2019) considered price to earnings and book value, and return ratios to compare the stock performance of the property & construction industry in Thailand.

Sang et al. (2019) designed an MCDM stock selection model which deals simultaneously with possibilities and probabilities under an interval type-2 fuzzy environment. The model is applied to financial data and its corresponding probabilities on 7 selected real estate companies in China from 2000 to2017. The study considered the subjective uncertainty of the investors and objective uncertainty of information insufficiency in decision making. Entropy weight was also computed based on the theory of information entropy, through which investors were able to assess potential stocks more scientifically and objectively. The interval type-2 fuzzy positive-ideal and the negative-ideal solution are used as the points of reference and the relative closeness is used to select an ideal alternative by ranking.

Rahiminezhad et al. (2020) aimed to identify the main criteria for selecting and assessing portfolios and to develop a Fuzzy Analytic Network Process to improve the process of stock selection in a portfolio. The study is made on stocks listed on Tehran Stock Exchange and 23 portfolio selection criteria were identified from previous literature. A Likert-type questionnaire was developed using the identified criteria and was analyzed after it was filled by experts. The findings suggested that the classical model of portfolio selection developed by Markowitz is not adequate as it takes only yield and risk into consideration whereas the present study showed that stock selection for portfolio creation involves multiple factors so MCDM techniques should be used. FANP was used and helped in ranking 10 different TSE portfolios which helped investors in selecting the best portfolio.

Nguyen et al. (2020) proposed an integrated method based on Analytical Hierarchy Process (AHP), Grey Relational Analysis (GRA), Technique for Order Performance by Similarity to Ideal Situation (TOPSIS), and Multi-Objective Optimization Ratio Analysis (MOORA) to evaluate the financial performance of the agriculture companies listed on Vietnamese Stock Exchange. The 20 financial ratios of 13 agricultural companies were analyzed from 2013-to 2019. AHP was used to determine the weights of the financial ratios and the stocks of the selected companies were ranked using GRA, TOPSIS, and MOORA. The results showed that the stock HSL was the top stock with the highest ranking and GRA, TOPSIS, and MOORA rankings are highly correlated. The study also suggested that the proposed model along with

COPRAS, KEMIRA & EDAS could be implemented to evaluate the financial performance of other industries like- oil & gas, textile, etc.

Tang et al. (2020) established a novel q-rung orthopair fuzzy (qROF) based MCDM model. A practical case about risk evaluation of stock investment was analyzed to check the practicality and viability of the proposed methods. The results were contrasted with Liang and Liu's method which concluded that the proposed method can handle a wide range of fuzzy information. Vuković et al. (2020) applied five MCDM models on the ground of the modern portfolio theory for a period of three years while considering stock return and beta, average traded volume, price to book value and equity and sales ratios and turnover ratios.

Peng et al. (2021) introduced an innovative solution of Z-numbers and ELECTRE I to deal with the issues of information reliability and criterion non-compensation of the stock selection process. The study uses Z-number as a tool for describing the information and identifying its reliability, next it defines the outranking degree of Z-numbers based on fuzzy and probability. Lastly, outranking aggregation and exploitation procedures are presented based on ELECTRE I to handle the non-compensation among stock evaluation criteria. The study concluded that the developed Z- number and ELECTRE I can qualitatively and flexibly deal with uncertain and unreliable information dealing with stock investment and can also effectively manage non-compensation among criteria.

Tatlari et al. (2021) proposed a solution combining the Data Envelopment Analysis (DEA) and Multi-Criteria Decision Making (MCDM) approach to retrieve the financial information for solving the problem of stock selection. The solution of designing an optimal portfolio using the suggested model is worked out in two stages. In the first stage, the DEA approach was used to calculate the cost-effectiveness and profit, while in the second stage companies were classified using the MCDM approach. The study was made using financial information of the Petrochemical Companies listed on the Tehran Stock Exchange for the period from 2015 to 2019.

Suroso et al. (2021) applied the Preference Ranking Organisation Method of Enrichment Evaluation (PROMETHEE) model to select the optimal stock of sustainable certification and risk criteria. The model is applied to the annual data from 2016 to 2018 of 11 palm oil companies listed on the Indonesia Stock Exchange. The study is made by integrating aspects of the RSPO sustainability certificate and risk criteria proxied by beta. The results of the study show the three best stock alternatives from the sample studied and conclude that the above said criteria can be used by the investors as a preference along with the company's internal criteria.

Jankova et al. (2021) proposed to apply a higher degree of Fuzzy Logic (Type- II) as a tool for investment decision making in Exchange Traded Funds (ETFs) in the US Stock Market. The model uses the return, risk, dividend, and a total expense ratio of 10 ETFs of the real state sector. The study showed that the Type-2 fuzzy logic is preferable to use than type- I, as it gives more realistic and accurate results as it uses a 3- dimensional set of functions and includes the footprint of uncertainty.

Jain et al. (2021) investigated the major behavioral stock selection criteria of Individual Equity Investors in India by focusing on the factors influencing the decisions of the retail investors' stock selection. The study is conducted on the primary data collected from a questionnaire and the response of 168 traders at the National Stock Exchange was selected as the sample for study during the last quarter of 2019. The sample was analyzed using the Fuzzy Analytic Hierarchy Process (AHP) approach. The results highlighted that behavioral Factors, Trading Opportunities, and Accounting information are the three most influential criteria for stock selection. Factors like- affordable price, recent price movement, the sensitivity of the company, trend of major indices, and evaluation by well-known experts are the five most important sub-criteria.

Arasu et al. (2021) aimed to identify and compare the appropriate variables for stock selection by testing three different sets of input and output variables using Data Envelopment Analysis (DEA). The first set consists of fundamental variables, the second set comprises technical variables and the third set includes both fundamental and technical variables. 69 companies were selected from National Stock Exchange and their financial ratios, Momentum variables were classified as input & output for the study. The results show that the average returns of the effective stocks, identified using the three sets of variables gives higher return than the market return. Further, it can also be concluded that a portfolio created using just the momentum variables gives a higher return than the other two. Narang et al. (2021) proposed a hybrid multi-criteria decision-making method consisting of group fuzzy COPRAS and fuzzy BCM. Fuzzy BCM is used for the relative weights of the criteria derived from the group decision-making process and then to rank the alternatives, these criteria weights are integrated with the fuzzy COPRAS method. The study aims at increasing the practicability of soft computing in the selection of stocks for creating a portfolio with a better return. Both the methods are applied in a real case study where 5 stocks were selected based on the criteria - Long Term Beta, Revenue, and ROE for the period of January 2009 to December 2019. An exponential Moving Average was used to convert the multi-dimensional data into a single numerical value. The portfolio constructed based on the proposed ranking gave a better return.

Narang et al. (2022) proposed a new integrated F-CoCoSo-H model based on the two-stage framework aiming to solve the problem of Investment decision-making. The study also suggests some modifications to the main structure like – the heronian mean operator is combined with the traditional Combined Compromise Solution method to calculate the relative optimal weights of specific decision criteria, which is calculated using the base-criterion method. The proposed model eliminates the efficacy of anomalous data and also makes complex decisions more flexible. The model is validated with the help of 15 stocks selected based on Revenue and ROE as beneficial criteria and DER & P/E as non-beneficial criteria. The study was made taking 11 years of historical data and different portfolios were constructed using Particle Swarm Optimization. The study validates the prominence and stability of the proposed model. Thakur et al. (2022) applied a mixed approach of artificial intelligence models and Dempster-Shafer (DS) theory for generating stock returns based on fuzzy rules and optimization of the portfolio by the Ant Colony Optimization (ACO) algorithm under a mean-variance framework. Gong et al. (2022) presented a dynamic fuzzy portfolio for the investors of different risk tolerance levels and observed a superior performance of the portfolio in the long-run. Ecer et al. (2022) focused on the cryptocurrency market to figure out a comparative evaluation. The authors compared a set of 15 popular cryptocurrencies (based on market capitalization) subject to the influence of 16 features. The analysis was carried out using a combination of Evaluation Based on Distance from Average Solution (EDAS), Multi-Attributive Ideal Real Comparative Analysis (MAIRCA) and Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) framework in a group decision-making set up with user opinions expressed in terms of intuitionistic fuzzy information. The authors noted that reliability, ease of use and stability are the dominant features to declare Ethereum, Tether, and Bitcoin as the most preferred options.

2.3. Findings from the literature review and research gap

We have noticed that a sizeable amount of research carried out in past regarding the selection of the portfolio of equity stocks. Table 1 provides a summary of the review of the past work as described in section 2.1 and 2.2. It is evident that the past research has extended the fundamental work on mean-variance framework while considering the other higher order moments, technical indicators, fundamental performance indicators and momentum variables. The extant literature shows umpteen evidences of using predictive models, machine learning algorithms, classical and extended optimization methods and MCDM frameworks. From the theoretical perspectives, past work have used MPT, CAPM framework, expected utility theory, PT and MPT. There has been a numerous work that considered BFT and its propositions to explore the behaviors of the investors and their impact on the stock selection process. Still, the interesting fact is that the volume of work in the stated field has been increasing over the years which is an indication of an ever increasing importance of research on stock selection.

Further, the extant literature shows a scantiness of comprehensive evaluation (considering the earning prospect, market centric risk, market perception, momentum and benchmarked performance to set the criteria for comparison) of the market performance of the stocks using MCDM models. We also observe that there is a scantiness of work that considered performance evaluation of stocks over a longitudinal period using MCDM models and subsequently aggregating the results to arrive at the conclusion.

Table 1. Summary of literature review

Theme	Theoretical Framework	Methods used	References
Classification and prediction of stock performance for portfolio selection	Modern portfolio theory is followed. Fundamental and/or technical indicators are considered. The analysis have been carried out using objective information.	Linear statistical models; non-linear predictive models; ML algorithms	Dai and Zhou (2019); Wu et al. (2019); Tan et al. (2019); Yang et al. (2019); Asadi and Mohammadi (2020); Chen et. al (2020); Alfonso and Ramirez (2020); Wu (2020); Arif and Sohail (2020); Zhou and Yin (2020); Huang et al. (2021); Bernal et al. (2021); De Nard et al. (2021); Nazneena et al. (2021); Cheng et al. (2021); Dou et al. (2021); Bermejo et al. (2021); Mortazian (2021); Jin et al. (2021); Chaya et al. (2021); Nugroho and Tjong (2021); Zhang et al. (2021); Shahidin et al. (2021); Gubu et al. (2021); Vo-Van et al. (2022); Solares et al. (2022);

Theme	Theoretical Framework	Methods used	References
			Mustafa et al. (2022)
Investment decision-making for stock selection	Behavioural aspects of the investors and performance indicators are considered. The analysis was carried out using subjective information.	Qualitative and statistical analysis	Ogbebor and Alalade (2020); Somathilake (2020)
Evaluation of stock performance for portfolio selection	Fundamental and market based multiple indicators are used. Mostly, objective information has been used. In some cases, subjective information has also been used.	MCDM models like Analytic Hierarchy Process, Analytic Network Process, Grey Relational Analysis (GRA), Technique for Order Performance by Similarity to Ideal Situation (TOPSIS), Multi-Objective Optimization Ratio Analysis (MOORA), COPRAS, KEMIRA, EDAS, ELECTRE I, Data Envelopment Analysis, Preference Ranking Organisation Method of Enrichment Evaluation (PROMETHEE) and CoCoSo with crisp, fuzzy, interval type-2 fuzzy, neutrosophic fuzzy, qRung orthopair fuzzy, Z-numbers	Tey et al. (2019); Witayakiattilerd (2019); Sang et al. (2019); Rahiminezhad et al. (2020); Nguyen et al. (2020); Tang et al. (2020); Vuković et al. (2020); Peng et al. (2021); Tatlari et al. (2021); Suroso et al. (2021); Jankova et al. (2021); Jankova et al. (2021); Jain et al. (2021); Arasu et al. (2021); Narang et al. (2021); Narang et al. (2022); Thakur et al. (2022); Gong et al. (2022); Ecer et al. (2022)

2.4. Main Contributions of the work

The present paper fills the gap in the literature and contributes to the growing volume of literature on stock selection as follows

a) The present paper presents a comprehensive mix of market performance indicators in tune with the MPT, expected utility theory, PT, intrinsic value of the firms and fundamental performance of the stocks for the comparative analysis using MCDM model.

b) It is seen that assessment of stock performance related to FMCG and CD sectors in Indian context vis-à-vis investment decision making is quite rare in the extant literature. Hence, the present paper sheds a new direction in this regard. In this context, the present work provides a year to year comparative analysis over seven consecutive financial years to arrive at the overall performance based ranking of the stocks.

c) The current work provides a new hybrid MCDM framework combining the most recently developed algorithm for calculating the criteria weights with objective information such as LOPCOW (Ecer and Pamucar, 2022) and a widely used ranking model such as EDAS (Keshavarz Ghorabaee et al., 2015) for portfolio selection problems.

d) Finally, the present research utilizes three types of ranking aggregation methods such as Borda method, Copeland method and Simple Additive Weighting (SAW) in connection with the year wise ranking of the stocks using LOPCOW-EDAS framework to arrive at the final selection of stocks.

3. Materials and Methods

In this paper, we aim to compare the market performances of the stocks of the selected FMCG and CD firms listed in BSE, India. In what follows are the brief description of the methodology including the sample selection, criteria description and procedural steps of the methods used. The flow of the steps is depicted in figure 1.

3.1. Sample

The present paper considers the study period from April 01, 2013 to March 31, 2020 (i.e., from FY 2013-14 to FY 2019-20). At the first stage, we consider the FMCG and CD stocks which have been listed in BSE, India during this period and discard the others. Further, we find out the average market capitalization values using geometric mean (GM) for all the stocks (screened at the first stage) over the study period. GM is preferred here to reduce the effect of the outliers (if any) and is applicable as there are no missing and/or zero values for the market capitalization. Finally, we select top 25 FMCG and 05 CD stocks (based on the average market capitalization value) to form our sample for comparative analysis. The size of our sample (i.e., 30) satisfies the minimum requirement for a standard sample size as recommended by many researchers (for example, Roscoe, 1975; Luanglath and Rewtrakunphaiboon, 2013; Louangrath, 2014; Luanglath, 2014; Agresti and Kateri, 2021) vis-à-vis the central limit theorem, n-hat and n-omega methods. In effect, the sample selected for the present study comprises of more than 30 percent of elements of FMCG and CD sectors (i.e., 25 out of total 72 stocks from FMCG and 5 out of total 10 stocks from CD sectors respectively). The constituent stocks of the sample used in the present study is listed in table 2. These 30 stocks are the alternatives or decision making units (DMU) under comparison subject to a set of criteria as described in the subsequent section.

Table 2. List of DMUs (i.e., stocks) under comparison

S/L	DMU	Category
A1	Avanti Feeds Ltd.	FMCG
A2	Bajaj Consumer Care Ltd.	FMCG
A3	Bombay Burmah Trdg. Corpn. Ltd.	FMCG
A4	Britannia Industries Ltd.	FMCG
A5	C C L Products (India) Ltd.	FMCG
A6	Colgate-Palmolive (India) Ltd.	FMCG
A7	Dabur India Ltd.	FMCG
A8	E I D-Parry (India) Ltd.	FMCG

S/L	DMU	Category
A9	Emami Ltd.	FMCG
A10	Future Consumer Ltd.	FMCG
A11	Gillette India Ltd.	FMCG
A12	Godfrey Phillips India Ltd.	FMCG
A13	Godrej Consumer Products Ltd.	FMCG
A14	Hatsun Agro Products Ltd.	FMCG
A15	Hindustan Unilever Ltd.	FMCG
A16	I T C Ltd.	FMCG
A17	Jyothy Labs Ltd.	FMCG
A18	K R B L Ltd.	FMCG
A19	Marico Ltd.	FMCG
A20	Nestle India Ltd.	FMCG
A21	Procter & Gamble Hygiene & Health Care Ltd.	FMCG
A22	Radico Khaitan Ltd.	FMCG
A23	Tata Consumer Products Ltd.	FMCG
A24	United Breweries Ltd.	FMCG
A25	Zydus Wellness Ltd.	FMCG
A26	Rajesh Exports Ltd.	CD
A27	Symphony Ltd.	CD
A28	Titan Company Ltd.	CD
A29	Voltas Ltd.	CD
A30	Whirlpool Of India Ltd.	CD

3.2. Criteria Description

To compare the stock performance nine criteria are selected in this paper. The selection of the criteria is based on the literature review. In this section we briefly describe the criteria and their relevance to stock selection strategy.

Average Rate of Return (AROR) (C1)

In this paper, for a given financial year the monthly closing prices of the stocks are considered. The rate of return or simply return (ROR) for the i^{th} stock ($i = 1, 2, \ldots, 30$) for the t^{th} month is calculated as (Gupta et al., 2022)

$$R_{it} = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Where, P_t is the closing price of the t^{th} month.

To calculate the AROR for for the i^{th} stock for a given financial year we take the average of the monthly ROR. The AROR represents the average return generated by the stock in a particular financial year. From the perspectives of the MPT and expected utility theory, an investor wants to maximize the gain. Hence, higher is value of AROR more is the attractiveness for investment.

Return on Net Worth (RONW) (C2)

The return of equity (ROE) or RONW is defined as

$$\mathrm{RONW} = \frac{\text{Net Income}}{\text{Shareholders}'\text{Equity}} \tag{2}$$

RONW indicates the utilization of the shareholders' invested amount in generating the net return through business operations. Hence, from an investor's perspective a higher value of RONW indicates a better earning prospect through efficient fundamental performance of the company. Therefore, an investor wants to see a higher value of RONW before selection of the stock.

Earnings per Share (EPS) (C3)

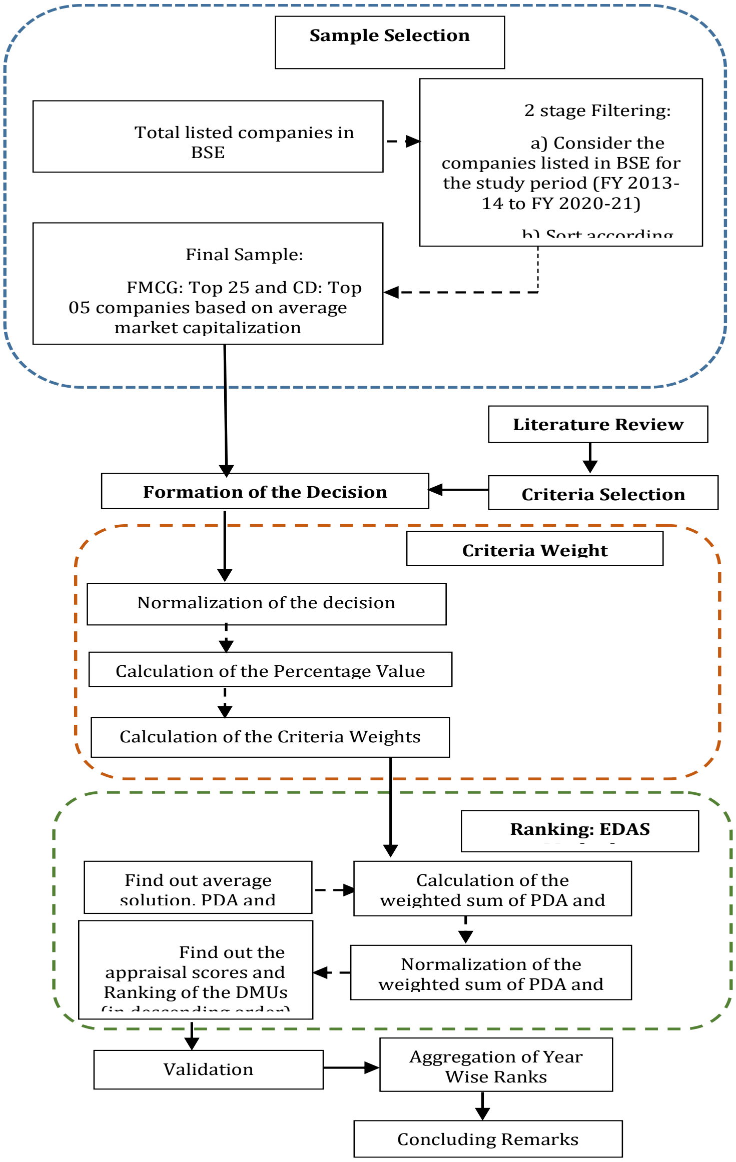

Figure 1. Research Framework

EPS is defined as the net profit divided by the number of outstanding common shares. It is an indication of the intrinsic value of the firm in terms of profit made per share. A higher value of EPS allures the investors as they find the possibility of higher earnings given the share price (Indrayono, 2019). Hence, from MPT and expected utility theory perspective, the investors want maximum value of EPS.

Price to Book Value (P/B) (C4)

The P/B ratio is given as the stock price divided by the book value per share. A higher value of P/B ratio is the reflection of the efficient fundamental performance of the firms to maximizing the wealth of the shareholders in terms of higher stock price (Indrayono, 2019). Hence, from the investors' perspective a higher value of P/B is recommended.

Turnover (C5)

It is an indicator of the liquidity of the stocks and is measured as a ratio of number of shares traded and average number of common shares outstanding in a given period. A higher value of turnover is an indication of momentum and therefore, from the investors' point of view more is the better.

Shares traded (C6)

It signifies the total number of shares of a specific equity stock being traded during a given period. Though this variable is not an absolute measures influencing the investment decision making, however, a higher value provides a positive signal to the investors about the continuation of the upward trend and future prospect. Hence, a period with higher trading volume is marked as a period of investors' trust and agreement and positive sentiment with belief of future earnings and cash flow (Baker and Wurgler, 2006; Hong and Stein, 2007; Chiah and Zhong, 2020). In other words, higher is the volume better is the prospect of the stock to the investors.

Yield (C7)

Yield is a measurement of the amount of cash flow to the investors given the investment in the stock. A higher value of yield signifies a higher growth potential of the company. Stock market yield positive influences the investors' sentiment (An et al., 2018).

Alpha (C8)

The value of the alpha signifies the ability of the stock to beat the market (Karmakar et al., 2018). In other words, alpha is the estimated risk-adjusted performance representing the average return of the portfolio in excess of that is predicted by the CAPM (Abu-Alkheil et al., 2020). Therefore, a higher value is an indicator of better total performance.

Beta (C9)

The systematic or undiversifiable risk is measured in terms of the Beta values. The value is determined through the following equation

$$R_{it} = \alpha + \beta_i R_{mt} + e_{it} \tag{3}$$

Where, R_{mt} is the market return at time t and α and β_i are the intercept and slope respectively. Using the ordinary least square method, the beta value is calculated as

$$\beta_i = \frac{Co\,\mathrm{var}(R_{it}, R_{mt})}{Var(R_{mt})} \tag{4}$$

A lower value of beta is an indication of lower risk (Gupta et al., 2022). From the perspectives of BFT, an investor wants to minimize the risk to an affordable level given the optimal value of the return. Hence, a lower value of beta is recommended. Table 3 provides a summary of all criteria used in this paper for comparing the stocks.

Table 3. List of criteria

S/L	Criteria	Effect Direction	UOM
C1	Average Stock Return (AROR)	Max	Value
C2	Return on Net Worth (RONW)	Max	%
C3	EPS	Max	Rs.
C4	P/B	Max	Times
C5	Turnover	Max	Rs. Million
C6	Shares Traded	Max	Nos.
C7	Yield	Max	%
C8	Alpha	Max	Value
C9	Beta	Min	Value

3.3. Data

In the present paper we have a total of 30 DMUs and 9 criteria for constructing the decision matrices for seven consecutive financial years (i.e., FY 2013-14 to FY 2019-20). The period FY 2020-21 and FY 2021-22 have not been considered as these periods are significantly affected by the recent Covid-19. Therefore, in our paper a comparatively less interrupted period has been considered. The data have been collected from the BSE website and CMIE Prowess IQ database (version 1.96). The decision matrices are given in Appendix A.

3.4. Criteria Weight Calculation: LOPCOW Method

The LOPCOW method is an objective measure to calculate the criteria weights that provides the following benefits (Ecer and Pamucar, 2022)

- A comparatively lesser unevenness in the distribution of the criteria weights
- Capability to work properly with the negative performance values of the DMUs under the criteria influence which is of particular use in this paper as most often returns are negative.
- Can deal with a large number of criteria and alternatives

Let, $X = \left[x_{ij} \right]_{m \times n}$ denotes the decision-matrix where, m is the number of DMUs (i.e., stocks under comparison; m=30) and n is the number of criteria ($n = 8$). The computational steps can be elaborated following Ecer and Pamucar (2022)

Step 1. Construction of the normalized decision matrix

We obtain the normalized decision matrix through application of linear max-min type scheme as follows. Let, $R=\left[r_{ij}\right]_{m\times n}$ is the normalized decision matrix whose elements are found as under

$$r_{ij}=\frac{x_{ij}-x_{\min}^{j}}{x_{\max}^{j}-x_{\min}^{j}} \text{ (when } j\in j^{+}\text{, desired direction: maximizing)} \tag{5}$$

$$r_{ij}=\frac{x_{\max}^{j}-x_{ij}}{x_{\max}^{j}-x_{\min}^{j}} \text{ (when } j\in j^{-}\text{, desired direction: minimizing)} \tag{6}$$

Step 2. Find the Percentage Value (PV) for each criterion

The PV for each criterion is given by

$$P_j=\left|\ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^{2}}{m}}}{\sigma}\right).100\right| \tag{7}$$

σ denotes the standard deviation. As the mean square value is expressed as a proportion of the standard deviation this step helps to reduce the narrow the gaps among the criteria weights.

Step 3. Calculation of the criteria weights

The weight for the j^{th} criterion is given by

$$w_j=\frac{P_{ij}}{\sum_{j=1}^{n} P_{ij}} \tag{8}$$

Where, $\sum_{j=1}^{n} w_j=1$ (i.e., sum of the weights of all criteria = 1)

3.5. EDAS Method

To compare the DMUs, the EDAS method derives two distances such as PDA (positive distance from the average) and NDA (negative distance from the average) while satisfying the effects of the criteria (Keshavarz Ghorabaee et al., 2015). EDAS extends a number of advantages over the other MCDM models (Pramanik et al., 2021) such as

- stability in the outcome
- reliability of the result even under the presence of a large number of DMUs and criteria
- capability to withstand variations in the values in the decision matrix
- no presence of rank reversal phenomenon

As a result of its benefits, EDAS method has been extensively applied in various real-life complex problems and extended over the years. For instance, Stanujkic et al. (2017) extended the classical EDAS model with the use of interval grey numbers for practical applications. Ecer (2018) put forth an integrated fuzzy AHP and EDAS framework for providing logistics solution to select the best third party service provider in terms of cost, quality of service and efficiency. Darko and Liang (2020) defined new extensions of Hamacher aggregation operators for q-Rung orthopair fuzzy numbers and applied to modify the EDAS method for mobile payment selection problem. In the Turkish market, Demirdağ et al. (2021) applied EDAS based methodology for comparing innovative practices of the hotels and subsequently finding out the success factors. For a competitive bidding purpose Naik et al. (2021) applied EDAS method in assessing prior qualifications of the contractors in the construction industry. Jiang et al. (2022) utilized EDAS method in conjunction with the CPT for selection of appropriate site for construction of shopping mall. In the context of investment decision-making, in a very recent work Biswas et al. (2022c) applied EDAS method for determining the dividend payment capabilities of Indian FMCG and consumer durables organizations.

The extant literature shows a noteworthy growth in the volume of work utilizing EDAS method. In this paper we consider the EDAS method for evaluation of the stock performance which is subject to significant variations in the performance values of the stocks vis-à-vis the criteria. Further, we have considered 30 stocks (i.e., DMUs) for comparison purpose with respect to nine criteria over seven financial years. Hence, the dataset is considerably large. In addition, there may be variations in the performance based ranking leading to false aggregation if rank reversal happens. To this end, EDAS method provides a number of advantages. We deal with objective information for comparison purpose. Therefore, we have not considered any fuzzy based analysis. However, that may be an extension of the present work. The computational steps are demonstrated below.

Step 1. Formation of the decision matrix

The decision matrix is expressed as

$$X = \left[x_{ij} \right]_{m \times n} = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{9}$$

Where m and n are having usual meaning as given above

Step 2. Find out the average solution

The average solution is found as

$$\overline{x_j} = \frac{\sum_{i=1}^{m} x_{ij}}{m}; \; j = 1, 2, \ldots n \tag{10}$$

Step 3. Obtain the distances such as PDA and NDA

The PDA and NDA are obtained as follows
PDA:

$$d_{ij}^{+} = \left.\begin{array}{l} \dfrac{Max(0,(x_{ij}-\overline{x}_j))}{\overline{x}_j};\forall j \in j^{+} (\max imizing) \\ \dfrac{Max(0,(\overline{x}_j-x_{ij}))}{\overline{x}_j};\forall j \in j^{-} (\min imizing) \end{array}\right\} \tag{11}$$

NDA:

$$d_{ij}^{-} = \left.\begin{array}{l} \dfrac{Max(0,(\overline{x}_j-x_{ij}))}{\overline{x}_j};\forall j \in j^{+} (\max imizing) \\ \dfrac{Max(0,(x_{ij}-\overline{x}_j))}{\overline{x}_j};\forall j \in j^{-} (\min imizing) \end{array}\right\} \tag{12}$$

Step 4. Find out the weighted sum of PDA (SP) and NDA values (SN) for all the DMUs

The weighted sums are calculated as

$$S_i^{+} = \sum_{j=1}^{n} w_j d_{ij}^{+} \tag{13}$$

$$S_i^{-} = \sum_{j=1}^{n} w_j d_{ij}^{-} \tag{14}$$

Here, w_j is the weight of the j^{th} criterion.

Step 5. Find out the normalized weighted sum of PDA (NSP) and NDA values (NSN)

For weighted sum of PDAs:

$$NS_i^{+} = \frac{S_i^{+}}{\underset{i}{Max}(S_i^{+})} \tag{15}$$

For weighted sum of NDAs:

$$NS_i^{-} = 1 - \frac{S_i^{-}}{\underset{i}{Max}(S_i^{-})} \tag{16}$$

Step 6. Calculate the appraisal scores (AS) of the DMUs

The appraisal score of the i^{th} DMU is computed as

$$S_{ai} = \frac{1}{2}(NS_i^{+} + NS_i^{-}) \tag{17}$$

Here, $0 \le S_{ai} \le 1$

Step 7. Ranking of the alternatives

The DMUs are ranked as per their appraisal scores in descending order.

3.6. Aggregation of the MCDM results

MCDM methods are useful in explaining the tradeoffs of the influences of the criteria to select the best course of actions and/or optimizing the benefits over the cost in various real-life scenarios (Biswas, 2020a). However, achieving a consensus in a typical group decision making and/or in a situation wherein multiple decision making premises are considered is a critical factor to obtain reliable solutions (Biswas et al., 2021a; Biswas, 2020b). Hence, selection of appropriate aggregation methods assumes mentionable importance. In what follows are the two popular approaches available in the literature.

Borda Count (BC)

BC is a widely used preference based aggregation method (Borda, 1784). The procedural steps are given below (Ecer, 2021)

Step 1. Obtain the ranking of the DMUs based on different opinion makers or method.

Step 2. Assign a point to the DMU under focus which is equal to the number of options succeeding that DMU. Therefore, the best option (DMU) shall receive (m-1) points, the second best shall get (m-2) points and so on.

Step 3. Calculate the sum of the points obtained by each DMU

Step 4. Rank the DMUs based on the total points in descending order.

Copeland Method (CM)

The CM is the extended and modified version of the BC method. The CM starts after the BC. The procedural steps are given as (Ecer, 2021)

Step 1. Find out the win score for each DMU with respect to other options

Step 2. Find out the loss score which is obtained by subtracting of the score obtained by the DMU in the first stage from majority wins' score

Step 3. Derive the final score as the difference between the win and loss scores.

Step 4. Rank the DMUs in terms of their corresponding overall scores in descending order.

In addition, the present paper also utilizes the simple additive weighting (SAW) method (Simanaviciene and Ustinovichius, 2010) to arrive at the aggregated final ranking. SAW method works on determining the significance of the alternatives subject to the influence of the criteria based on a robust and simple method (Karamaşa et al., 2021). Hence, it is quite applicable for aggregation of rakings.

For calculation and analysis purpose, MS Office (2016) and SPSS (version 25) software tools on a computer with Intel(R) Core(TM) i3-1005G1 CPU @ 1.20GHz 1.19 GHz, 8GB RAM have been used.

4. Results

This section exhibits the key findings of the present research. In what follows are the step by step results. First, we find out the criteria weights for all the FYs using the procedural steps of LOPCOW method as described in section 3.4. The normalized decision matrices are given in the Appendix B. Using the normalized decision matrices, we apply the expressions (7) and (8) to calculate the criteria weights for the financial years. Tables 4-10 provide the results of the criteria weights. Table 11 provides a comparative preferential orders of the criteria based on their weights.

Table 4. Criteria weights (FY 2013-14)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean Square	0.321	0.111	0.066	0.092	0.094	0.056	0.203	0.193	0.438
SD	0.171	0.215	0.219	0.227	0.264	0.209	0.246	0.190	0.279
PV	120.031	43.530	15.858	29.240	15.006	12.079	60.399	83.881	86.171
Wj	0.258	0.093	0.034	0.063	0.032	0.026	0.130	0.180	0.185

Table 5. Criteria weights (FY 2014-15)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean Square	0.553	0.152	0.100	0.105	0.036	0.038	0.156	0.129	0.510
SD	0.189	0.201	0.257	0.226	0.183	0.189	0.234	0.196	0.283
PV	137.272	66.147	20.801	35.810	3.490	3.794	52.204	60.569	92.640
Wj	0.290	0.140	0.044	0.076	0.007	0.008	0.110	0.128	0.196

Table 6. Criteria weights (FY 2015-16)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean Square	0.319	0.208	0.094	0.171	0.042	0.045	0.190	0.120	0.511
SD	0.185	0.208	0.223	0.254	0.187	0.195	0.255	0.196	0.281
PV	111.818	78.581	32.054	48.971	9.458	8.193	53.803	57.035	93.459
Wj	0.227	0.159	0.065	0.099	0.019	0.017	0.109	0.116	0.189

Table 7. Criteria weights (FY 2016-17)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean Square	0.299	0.263	0.087	0.166	0.102	0.067	0.112	0.169	0.527
SD	0.203	0.217	0.225	0.242	0.262	0.232	0.236	0.233	0.245
PV	99.055	85.890	27.060	52.243	19.632	10.882	35.042	56.722	108.690
Wj	0.200	0.173	0.055	0.106	0.040	0.022	0.071	0.115	0.220

Table 8. Criteria weights (FY 2017-18)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean Square	0.233	0.256	0.119	0.140	0.075	0.077	0.094	0.169	0.527
SD	0.213	0.191	0.262	0.250	0.229	0.250	0.225	0.233	0.245
PV	81.908	97.481	27.713	40.373	17.874	10.323	31.179	56.722	108.690
Wj	0.173	0.206	0.059	0.086	0.038	0.022	0.066	0.120	0.230

Table 9. Criteria weights (FY 2018-19)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean Square	0.618	0.179	0.074	0.119	0.048	0.050	0.084	0.107	0.504
SD	0.211	0.186	0.208	0.252	0.208	0.206	0.201	0.206	0.236
PV	131.813	82.102	27.117	31.172	5.047	8.221	36.809	46.348	109.996
Wj	0.275	0.172	0.057	0.065	0.011	0.017	0.077	0.097	0.230

Table 10. Criteria weights (FY 2019-20)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean Square	0.506	0.172	0.067	0.091	0.055	0.042	0.136	0.393	0.455
SD	0.198	0.206	0.202	0.249	0.213	0.197	0.265	0.235	0.263
PV	127.815	69.763	24.609	18.886	9.515	3.566	33.276	98.009	94.171
Wj	0.267	0.146	0.051	0.039	0.020	0.007	0.069	0.204	0.196

Table 11. Comparative preferential orders of the criteria (year wise)

Criteria	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20
C1	1	1	1	2	3	1	1
C2	5	3	3	3	2	3	4
C3	7	7	7	7	7	7	6
C4	6	6	6	5	5	6	7
C5	8	9	8	8	8	9	8
C6	9	8	9	9	9	8	9
C7	4	5	5	6	6	5	5
C8	3	4	4	4	4	4	2
C9	2	2	2	1	1	2	3

From the table 11, it is seen that the ranking orders are maintaining considerable consistency in their relative importance over the years. From figure 2 also it is concluded that there are no abrupt variations in the preferential order of the criteria based on their calculated weights. Further, we apply the dominance theory (Brauers and Zavadskas, 2011) and find that

$$C_1 \succ C_9 \succ C_2 \succ C_8 \succ C_7 \succ C_4 \succ C_3 \succ C_5 \succ C_6$$

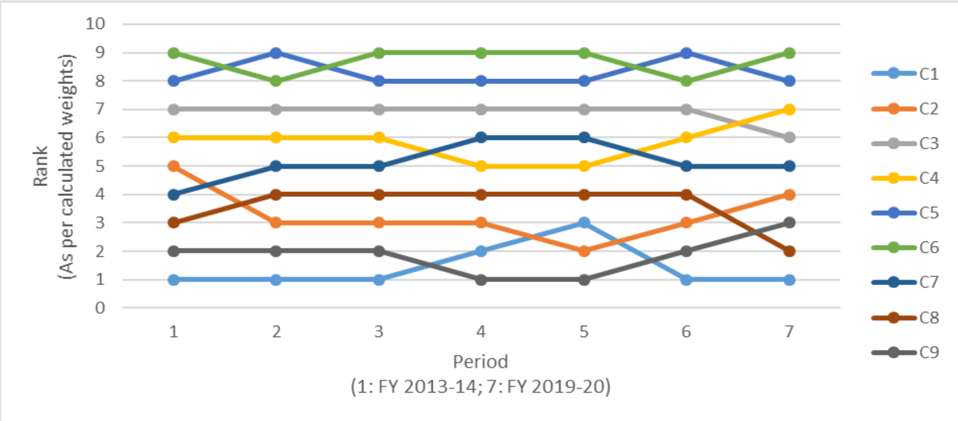

Figure 2. Year wise preferential order of the criteria based on calculated weights

It is observed that based on the calculated weights the average return, Beta and RONW hold top 3 priorities. The result is justified as the primary motive behind any investment is to maximize the return while minimizing the risk. Now we move to use the calculated criteria weights to rank the stocks by applying the procedural steps of the EDAS method as explained in section 3.5 (see the expressions (10) to (17)). Tables 12 provides the appraisal scores and the ranking of the DMUs for the FY 2013-14. In the similar way, the ranking is done for all other FYs (i.e., FY 2014-15 to FY 2019-20) which are given in Appendix C.

Table 12. Ranking of the DMUs (i.e., stocks) using EDAS method (FY 2013-14)

DMU	SP	SN	NSP	NSN	AS	Rank
A1	3.159	0.095	1.000	0.973	0.986	1
A2	0.216	0.450	0.069	0.870	0.469	21
A3	0.212	0.950	0.067	0.725	0.396	25
A4	0.756	0.109	0.239	0.968	0.604	7
A5	0.058	3.453	0.018	0.000	0.009	30

A6	0.561	0.165	0.178	0.952	0.565	8
A7	0.409	0.126	0.130	0.963	0.547	9
A8	0.000	1.002	0.000	0.710	0.355	27
A9	0.125	0.915	0.039	0.735	0.387	26
A10	0.112	2.229	0.036	0.355	0.195	29
A11	0.072	0.564	0.023	0.837	0.430	24
A12	0.254	0.152	0.080	0.956	0.518	14
A13	0.156	0.224	0.049	0.935	0.492	16
A14	1.937	0.091	0.613	0.974	0.793	2
A15	0.917	0.084	0.290	0.976	0.633	5
A16	0.352	0.071	0.111	0.979	0.545	10
A17	0.255	0.157	0.081	0.955	0.518	15
A18	1.318	0.303	0.417	0.912	0.665	4
A19	0.194	0.400	0.061	0.884	0.473	20
A20	0.405	0.217	0.128	0.937	0.533	12
A21	0.334	0.098	0.106	0.971	0.539	11
A22	0.074	0.384	0.023	0.889	0.456	22
A23	0.411	0.237	0.130	0.931	0.531	13
A24	0.138	0.295	0.044	0.914	0.479	19
A25	0.050	0.133	0.016	0.962	0.489	18
A26	0.013	1.169	0.004	0.662	0.333	28
A27	1.497	0.056	0.474	0.984	0.729	3
A28	0.215	0.294	0.068	0.915	0.492	17
A29	1.199	0.486	0.380	0.859	0.619	6
A30	0.045	0.533	0.014	0.846	0.430	23

We find that there has been a mentionable variation in the ranking order of the DMUs over the different financial years. To obtain the final ranking of the DMUs we proceed for aggregation of the results using the methods described in section 3.6. Tables 13 provides the aggregated ranking obtained by using the BC method.

Table 13. Aggregation of year wise ranks of the DMUs (BC Method)

DMU	Borda Count	Final Rank_ BORDA	DMU	Borda Count	Final Rank_ BORDA
A1	198	1	A16	106	14
A2	135	8	A17	108	12
A3	72	23	A18	138	7
A4	148	4	A19	110	11
A5	85	19	A20	144	5
A6	138	6	A21	155	3
A7	93	16	A22	67	26
A8	38	29	A23	69	24
A9	104	15	A24	49	28
A10	90	18	A25	81	20
A11	106	13	A26	59	27
A12	37	30	A27	124	9
A13	73	22	A28	91	17
A14	121	10	A29	68	25
A15	160	2	A30	78	21

In the present study we use the aggregated ranks of the DMUs (i.e., stocks) derived by using BC method. However, to validate the result of the BC method we find the aggregated ranks by using CM and SAW methods also. Tables 14-15 provide the aggregated ranking obtained by using the CM and SAW models.

Table 14. Aggregation of year wise ranks of the DMUs (CM Method)

DMU	Wins	Losses	Final Score	Final Rank	DMU	Wins	Losses	Final Score	Final Rank
A1	198	2847	-2649	1	A16	106	2939	-2833	14
A2	135	2910	-2775	8	A17	108	2937	-2829	12
A3	72	2973	-2901	23	A18	138	2907	-2769	7
A4	148	2897	-2749	4	A19	110	2935	-2825	11
A5	85	2960	-2875	19	A20	144	2901	-2757	5
A6	138	2907	-2769	6	A21	155	2890	-2735	3
A7	93	2952	-2859	16	A22	67	2978	-2911	26
A8	38	3007	-2969	29	A23	69	2976	-2907	24
A9	104	2941	-2837	15	A24	49	2996	-2947	28
A10	90	2955	-2865	18	A25	81	2964	-2883	20
A11	106	2939	-2833	13	A26	59	2986	-2927	27
A12	37	3008	-2971	30	A27	124	2921	-2797	9
A13	73	2972	-2899	22	A28	91	2954	-2863	17
A14	121	2924	-2803	10	A29	68	2977	-2909	25
A15	160	2885	-2725	2	A30	78	2967	-2889	21

Table 15. Aggregation of year wise ranks of the DMUs (SAW method)

DMU	Final Score	Rank	DMU	Final Score	Rank
A1	0.9642	1	A16	0.4888	13
A2	0.5474	8	A17	0.4921	12
A3	0.3706	24	A18	0.5761	5
A4	0.5964	4	A19	0.4836	14
A5	0.3960	20	A20	0.5629	6
A6	0.5542	7	A21	0.6325	3
A7	0.4254	18	A22	0.3677	25
A8	0.2538	29	A23	0.2982	27
A9	0.4929	11	A24	0.2944	28
A10	0.4388	17	A25	0.3785	23
A11	0.4746	15	A26	0.3171	26
A12	0.1723	30	A27	0.4972	10
A13	0.3939	21	A28	0.4451	16
A14	0.5360	9	A29	0.3839	22
A15	0.6711	2	A30	0.4172	19

Figure 3 shows a comparative analysis pictorially and table 16 exhibits the statistical test (Spearman's rank correlation) for examining the consistency among the aggregated ranking results as provided by BC, CM and SAW methods. From figure 3 and table 15 it is evident that all there is a significant consistency among all these methods. The summary of year wise ranking including the final ranking of the stocks using the EDAS method is given in table 17.

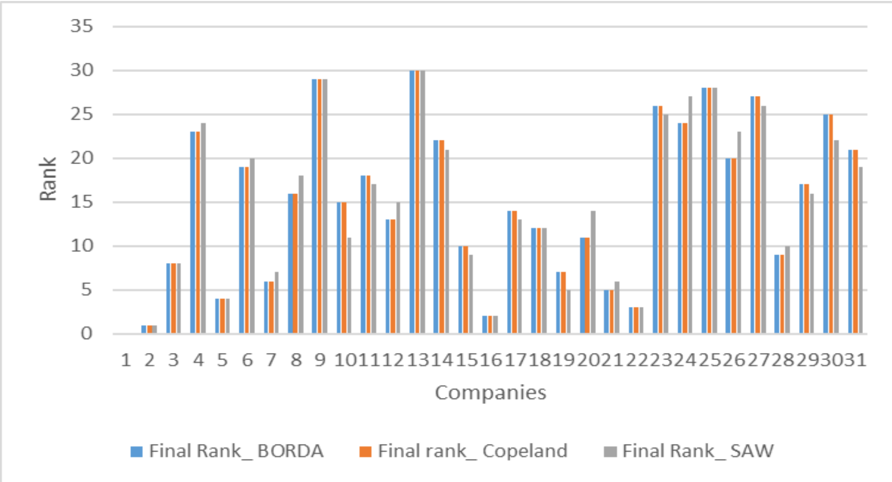

Figure 3. Comparison of results (BC, CM and SAW methods)

Table 16. Spearman's rank correlation among the results of BC, CM and SAW method

		Final_Rank_Copeland	Final_Rank_SAW
Final_Rank_ BORDA	Spearman's rho	1.000**	0.982**
	Sig. (2-tailed)	.	0.000
Final_Rank_ SAW	Spearman's rho	0.982**	0.982**
	Sig. (2-tailed)	0.000	0.000

** Correlation is significant at the 0.01 level (2-tailed).

Table 17. Summary of the rankings of the DMUs (i.e., stocks)

Company	Rank							
	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	Final
A1	1	1	1	1	1	1	6	1
A2	21	6	6	8	9	4	21	8
A3	25	10	10	13	28	28	24	23
A4	7	4	23	6	6	5	11	4
A5	30	13	22	7	26	18	9	19
A6	8	5	2	10	10	19	18	6
A7	9	16	15	16	11	25	25	16
A8	27	27	25	25	29	11	28	29
A9	26	9	14	17	21	2	17	15
A10	29	19	28	18	12	13	1	18
A11	24	12	13	20	4	9	22	13
A12	14	30	29	30	30	30	10	30
A13	16	23	26	19	27	6	20	22
A14	2	21	24	5	8	15	14	10
A15	5	3	16	2	3	16	5	2
A16	10	15	18	15	19	23	4	14
A17	15	24	20	14	18	3	8	12
A18	4	11	27	4	17	7	2	7
A19	20	18	3	12	14	17	16	11
A20	12	7	5	11	7	21	3	5
A21	11	8	9	3	2	10	12	3
A22	22	29	21	24	13	27	7	26
A23	13	28	7	28	23	12	30	24
A24	19	25	8	29	25	29	26	28
A25	18	17	4	21	16	24	29	20

Company	Rank							
	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	Final
A26	28	20	30	26	20	14	13	27
A27	3	2	12	27	15	8	19	9
A28	17	22	11	23	5	26	15	17
A29	6	26	19	22	24	22	23	25
A30	23	14	17	9	22	20	27	21

We observe that Avanti Feeds Ltd. (A1), Hindustan Unilever Ltd. (A15), Procter & Gamble Hygiene & Health Care Ltd. (A21), Britannia Industries Ltd. (A4), and Nestle India Ltd. (A20) are the top five performers based on their stock performance during FY 2013-14 to FY 2019-20 while Godfrey Phillips India Ltd. (A12), E I D-Parry (India) Ltd. (A8), United Breweries Ltd. (A24), Rajesh Exports Ltd. (A26), and Radico Khaitan Ltd. (A22) hold the bottom five positions during the same period.

We also test the correlations among the year wise ranks and the final rank obtained by using the EDAS method (see table 18) and observe that the rankings are consistent.

Table 18. Spearman's rank correlation among year wise ranks and the final rank (EDAS method)

		FY 13-14	FY 14-15	FY 15-16	FY 16-17	FY 17-18	FY 18-19	FY 19-20
FINAL	Spearman's rho	.568**	.815**	.390*	.788**	.799**	.504**	.456*
	Sig. (2-tailed)	0.001	0.000	0.033	0.000	0.000	0.005	0.011

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

4.1. Validation

The results of MCDM models are vulnerable to the changes in the fundamental considerations related to formulation of the decision matrix, variations in the criteria weights and entry and removal of the criteria and changes in the dimensions and features among others (Pamucar et al., 2021; Pamucar et al., 2022). Therefore, it is essential to validate the result. In this paper we follow the approaches available in the extant literature (for instance, Biswas et al., 2022a, 2022b, 2021b) and compare the result obtained by using the EDAS method with the outcomes of two other methods such as MABAC (Pamučar and Ćirović, 2015) and COPRAS method (Zavadskas et al., 2007). We rank the stocks for all the years and derive the final aggregated rank for both these methods separately. Then the ranking results of EDAS, MABAC and COPRAS are compared and statistical correlations are tested. Table 19 provides the values of the rank correlation coefficients that reflect that the ranking results are consistent. Hence, we contend that EDAS method provides reasonably valid result.

Table 19. Spearman's rank correlation among the final ranks (EDAS, MABAC and COPRAS)

		MABAC_FINAL	COPRAS FINAL
EDAS_FINAL	Spearman's rho	.849**	0.992**
	Sig. (2-tailed)	0.000	0.000

** Correlation is significant at the 0.01 level (2-tailed).

4.2. Sensitivity Analysis

For any MCDM based analysis it is important to examine the changes in the overall ranking subject to variations in the given conditions such as changes in the alternatives, variations in the criteria weights and so on. The sensitivity analysis is carried out to the stability in the result (Pamucar et al., 2021, 2022). To this end, in the present paper we follow the work of Pamucar et al. (2021). The sensitivity analysis is carried out for all years. We have observed that the ranking results are stable in nature with respect to changes in the criteria weights. In what follows is the sample demonstration of the sensitivity analysis for FY 2019-20.

For FY 2019-20, C1 is the criterion with highest weight. We reduce the weight of the criterion C1 by 5% at each experimental case and subsequently, proportionately increase the weights of all other criteria to make the sum of criteria weights equal to one. In this way, we generate 10 experimental cases (see table 20)

Table 20. Criteria weights in different experimental cases (FY 2019-20)

Cases	C1	C2	C3	C4	C5	C6	C7	C8	C9
Original	0.2665	0.1455	0.0513	0.0394	0.0198	0.0074	0.0694	0.2044	0.1963
Exp 1	0.2532	0.1471	0.0530	0.0410	0.0215	0.0091	0.0710	0.2060	0.1980
Exp 2	0.2405	0.1487	0.0546	0.0426	0.0231	0.0107	0.0726	0.2076	0.1996
Exp 3	0.2285	0.1502	0.0561	0.0441	0.0246	0.0122	0.0741	0.2091	0.2011
Exp 4	0.2171	0.1516	0.0575	0.0456	0.0260	0.0136	0.0756	0.2105	0.2025
Exp 5	0.2062	0.1530	0.0588	0.0469	0.0274	0.0150	0.0769	0.2119	0.2039
Exp 6	0.1959	0.1543	0.0601	0.0482	0.0287	0.0163	0.0782	0.2132	0.2052
Exp 7	0.1861	0.1555	0.0614	0.0494	0.0299	0.0175	0.0794	0.2144	0.2064
Exp 8	0.1768	0.1567	0.0625	0.0506	0.0311	0.0186	0.0806	0.2156	0.2076
Exp 9	0.1680	0.1578	0.0636	0.0517	0.0322	0.0198	0.0817	0.2167	0.2087
Exp 10	0.1596	0.1588	0.0647	0.0527	0.0332	0.0208	0.0827	0.2177	0.2097

Now, we use these criteria weights to rank the DMUs. Once we get the ranks, the distribution of the ranks of the DMUs is plotted (see figure 4) which indicates that the ranking distributions do not change substantially with respect to the changes in the criteria weights. Hence, it may be concluded that the sensitivity analysis supports the stability in the result for FY 2019-20. In the similar way, we conduct the sensitivity analysis for all other FYs and observe the stability in the result. Therefore, for our problem, EDAS provides a stable and reliable outcome.

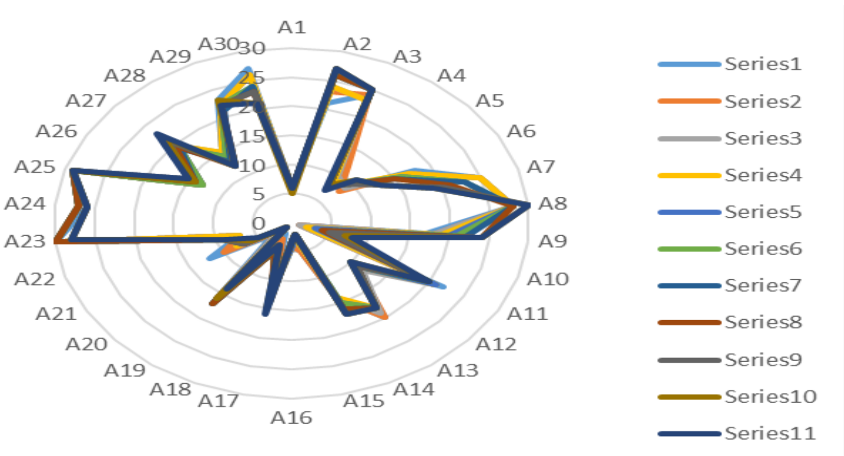

Figure 4. Result of the sensitivity analysis (FY 2019-20)

5. Discussion

We observe that based on the calculated weights the average return, Beta and RONW hold top 3 priorities. Further, turnover (C5) and shares traded (C6) are in the bottom bracket. The result is justified as the primary motive behind any investment is to maximize the return while minimizing the risk. The result is in line with findings of the past work (for example, Chen et al., 2020; Wu et al., 2020).

The final aggregated ranking of the DMUs (i.e., FMCG and CD stocks) reveals some interesting observations. It is a common notion that a company which is having higher market capitalization is expected to have a better stock performance at the market place. But, in our case we notice that not all top FMCG and CD stocks (as per average market capitalization) are found to be the top performers. This finding suggests that market capitalization does not necessarily contributed by the stock performance always. This finding is consistent with the observations of Marito and Sjarif (2020) wherein the authors found a negative influence of market capitalization on the stock return. In fact, the market capitalization is influenced by the fundamental financial performance, competitive strategy, product performance, sales and promotion etc. Further, stock performance is subject to the influence of several factors like market sentiment and news, company performance, dividend payment, changes in macroeconomic factors (for instance, changes in the export-import policy, foreign exchange rate, raw material availability, oil price, climate conditions, social and geopolitical environmental conditions and many others) and their impact on business operations and expected earnings, behavioural bias of the investors among others. Though, in our study we have not considered the behavioural aspects, but still the findings reflect against the common notion and is in sync with the previous work (for instance, Indrayono, 2021; Marito and Sjarif, 2020). However, it may be noted that more or less the firms having higher market capitalizations have performed well. This is more visible for the bottom performers at the stock level. One interesting subject is ITC limited, the top most company in terms of market capitalization but ranked 14 on aggregate based on the stock performance. ITC has a multi-product portfolio with related and unrelated diversifications which helped them to capture the market but as far as the stock performance is concerned, it shows below par performance in most of the financial years under the study period.

We also notice that FY 2014-15, FY 2016-17 and FY 2017-18 show higher correlation with the final ranking while the other FYs are having low correlation with the aggregated ranking. From the technical point of view, the present study shows that a reasonably reliable solution is provided by the combined LOPCOW-EDAS method. In view of the above findings and observations, the present paper shall be of interest to readers, policy makers and investors.

6. Conclusion

The primary objective of the current work is to compare a selected group of stocks belonging to Indian FMCG and CD sectors. The sample has been decided on the basis of the average market capitalization over the study period (FY 2013-14 to FY 2019-20). Accordingly, 30 stocks (25 from FMCG and 5 from CD) have been compared with respect to their performance at BSE during the study period. For comparative analysis 9 criteria such as AROR, RONW, EPS, P/B, Turnover, Shares Traded, Yield, Alpha and Beta have been considered. The selection of criteria has been done in line with the past research while taking into consideration the theoretical cornerstones of MPT, CAPM, expected utility theory and BFT in addition to intrinsic value of the firms.

For comparative analysis, we have utilized a combined LOPCOW-EDAS framework. For aggregation of the year wise ranks, widely used methods like BC, CM and SAW have been used. We note that average return, Beta and RONW obtain higher weights than others. The analysis reveals that Avanti Feeds Ltd. (A1), Hindustan Unilever Ltd. (A15), Procter & Gamble Hygiene & Health Care Ltd. (A21), Britannia Industries Ltd. (A4), and Nestle India Ltd. (A20) are the top five performers based on their stock performance during FY 2013-14 to FY 2019-20 while Godfrey Phillips India Ltd. (A12), E I D-Parry (India) Ltd. (A8), United Breweries Ltd. (A24), Rajesh Exports Ltd. (A26), and Radico Khaitan Ltd. (A22) hold the bottom five positions during the same period. Based on the results we contend that market capitalization does not necessarily contributed by the stock performance always. Moreover, the performance of the stocks over the FYs show significant variations.

The present paper presents a comprehensive mix of market performance indicators in tune with the MPT, expected utility theory, PT, intrinsic value of the firms and fundamental performance of the stocks for the comparative analysis using MCDM model. A year to year comparative analysis over seven consecutive financial years to arrive at the overall performance based ranking of the stocks is carried out. In this sense, the ongoing work is topical. In addition, the current work provides an unique combination of LOPCOW-EDAS and BC methods which may be used in solving various contextual real-life problems.

However, the present study is too limited in some aspects and invokes the following future research. First, the major limitation of this paper is that we have not considered the opinions of the investors and carried out the comparison grounded on the fundamental assumptions of the BFT. Therefore, a future study may attempt to combine objective information based and subjective opinion based comparison of the stock performance. Secondly, a deep down study may be carried out to discern the reasons of the year to year variations in the ranking. In this regard as a third scope, one future study may be carried out to explore the causal relationship of fundamental performance, financial stability, dividend payment, innovativeness, growth prospect and economic sustainability with the stock performance for a comprehensive portfolio selection. Fourth, a granular analysis may be thought which shall consider the low beta and higher market capitalization organization and shall attempt to find out their performance. Fifth, from the technical point of view, the LOPCOW model may be modified in future with imprecise information. Nevertheless, we do hope that the current study shall be of interest to readers, policy makers and investors.

Supplementary Materials: Along with this paper Appendices A to D are provided for dataset and supporting calculations.

Authors' contributions Conceptualization: SB, DP, GB, NJ; Data collection and formatting: NJ; Formal analysis: SB; Validation: SB, GB, DP; Writing original draft: SB, NJ; Review and editing the final draft: DP, GB; Supervision: GB

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