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Evaluation Security Analysis and Portfolio Management using EDAS Method

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Abstract

Portfolio management and security analysis. Security analysis, portfolio management, and financial derivatives are three fields of contemporary investment analysis that are merged. It gives a fair treatment of theories, organizations, markets, academic research, and real-world applications while presenting both basic concepts and sophisticated principles. Instead of investing in a single security, a portfolio refers to a collection of securities. Finding out the potential risk and rewards of holding different combinations of individual securities is the goal of portfolio analysis. Security analysis has a variety of goals. They are the expansion of capital, dependable income, preservation of capital, defense against inflation, and liquidity. It is a method for figuring out an asset's intrinsic worth and researching factors that can affect its price in the future. Security analysis is the study of tradable financial instruments also known as securities. It concentrates on figuring out the fair value of particular securities (i.e., stocks and bonds). These are typically categorized as stocks, debentures, or some combination of the two. When choosing between several investment options, such as real estate, bonds, debentures, equity shares, fixed deposits, gold, jewelry, etc., security analysis can help. Portfolio management is the process of selecting, prioritizing, and managing an organization's activities and programs according to its strategic goals and capacity to carry them out. It's crucial to establish a balance between implementing change efforts and carrying on with business as usual to optimize return on investment. Economic analysis, industry analysis, and basic analysis are the three core subfields of security analysis. Security analysis is important because it enables the investor to examine a stock's options while calculating the expected return and risk. Organizations may install real-time monitoring of servers, endpoints, and network traffic, integrate and integrate a variety of event data from application and network logs, do forensic analysis to better understand attack patterns, and more using security analytics technology. EDAS Evaluation Based on Distance from Average Solution method for Fundamental Weighting, Minimum Variance, and Stable ROE Portfolio Alternative and Volatility, Sharpe Ratio, Excess Return Over Benchmark Evaluation. Fundamental Weighting, Minimum Variance, and Stable ROE Portfolio. Volatility, Sharpe Ratio, Excess Return Over Benchmark. Minimum Variance has the highest rank whereas Stable ROE Portfolio has the lowest rank.

Keywords: The Investment Decision, Directly Return-Related Attributes, EDAS Method.

Introduction

In the coming decades, it will gain a substantial market share in the global market for financial data for financial professionals working in a variety of institutions such as commercial banks, investment banks, brokerage firms, and investment firms. It is also obvious that students who receive funding to operate a Bloomberg terminal will stand out as prospects in the tight labor market of today. Surprisingly, there aren't many tools available to the instructor on how to include the data from the Bloomberg terminal in the finance lesson. This paper fills that gap by demonstrating how an equity-focused security analyst and portfolio management course may create analyst reports using data from a Bloomberg terminal. We note two significant difficulties we encounter: Giving students who are unfamiliar with the terminal's features in-person training sessions and showing them how to produce an analyst report on the terminal are two ways to do this. The amount of stock market participants is rapidly increasing. As a result, investors will need to create tools to manage their portfolios of investments. Investors often find it challenging to distribute their equities effectively. Their return on investment is impacted by improper investment allocation. In contrast, a portfolio with well-distributed investments will have low risk and great returns. So good portfolio management and investment allocation are necessary. On the other hand, the technical analysis [2] technique makes future asset price predictions using historical market data, primarily price, and volume. Technical analysts might employ the relative strength index (RSI), moving averages, and other patterns and trading rules based on changes in price and volume (MA). There are distinct traits for each technical indicator. However, because each indication exhibits a distinct behavior, it is challenging to set their relative parameters of them. As a result, an optimization approach is required to change the parameters of various indicators.

The Investment Decision

To support investment decisions, the features of potential investments and the investor's preferences (preferences) must be appropriately understood and related to one another. Unfortunately, the majority of models for portfolio management focus on the "average" investor rather than a specific (often non-average) investor, replacing the real world with a simplified model world. However, the presumptions used to describe this typical investor are frequently flawed and inaccurate. Consider the mean-variance framework, which is both the classic and the most often-used method of approaching the issue of investment decision-making. The apparent contribution unquestionably substitutes a two-dimensional investing approach for the conventional one-dimensional investing technique that solely considers expected or average returns. Using (co)variance or standard deviation, a previously undefined concept of risk is operationalized through the unpredictability of returns in a portfolio framework. Transforming the actual decision-making situation into mean-variance dimensions is a challenge. However, because the mean-variance paradigm involves significant assumptions about the investor's preferences and/or the representativeness of investment alternatives, applying this two-dimensional reality might prove to be overly limiting in practice. Variance as a risk indicator could stop correlating with an investor's security preferences or preference structure as well as portfolio return distributions. It is not always possible to differentiate between investment options effectively based just on mean and variance information. However, given the limiting nature of the underlying assumptions and the wide range of applications, mean-variance analysis is frequently an obvious choice. By cutting off the multidimensional elements that the investor can see, the mean-variance framework turns into a Procrustes bed. Using (co)variance or standard deviation, a previously unknown concept of risk is operationalized to identify and formalize risk through the unpredictability of returns in a portfolio environment. The challenge, therefore, becomes expressing the real decision-making context in terms of mean-variance dimensions.

Directly Return-Related Attributes

The shared distribution of returns between securities is the most common scholarly presumption. Any probability distribution's location and shape can be used to fully characterize it. The location parameter of the return distribution, the expected return on a security, is a clear candidate for an attribute. The distributional pattern of security has a direct bearing on the risk associated with its return. A distribution's shape can be described using the shape parameters or statistical moments of the distribution. From the standpoint of building a portfolio, payouts on securities that are combined rather than their marginal distributions should be made. Three issues arise when using form parameters or moments as risk factors, each of which is related to a different step in the investment decision-making process. The requirement to account for any correlations between security results at the level of pertinent parameters or moments creates an "information challenge" during the security analysis stage. Due to the need to process and combine pertinent security data to acquire portfolio attributes, a "combination problem" occurs during the portfolio analysis step. The final issue is the "criteria problem": to use probabilistic information in the decision-making process, one needs to take into account the investor's preferences for each of these traits as well as their relative weight. As a result, the intricacy of the risk component makes it seriously troublesome. The vagueness of the issue of perceived risk is another difficulty. Sufficient definitions may be a sign of risk's multifaceted character.

Edas Method

The EDAS score is primarily based on the space from the suggested agreement machine is the installed energy for a manufacturing plant. Experts' critiques and derived numbers do not trust each different concerning solar energy and geothermal electricity. Although solar strength is a renewable power source, its miles the desired electricity supply by professionals due to Access and giant availability characterization (2d in Fuzzy AHP space) however numeric Physically damaging electricity due to the high setup cost (4th area in EDAS). And low performance. EDAS is a powerful approach for multi-standards stock type and dealer choice, and it can be effectively carried out to a few conflicting standards. EDAS is subtle, from average response amazing distance, every from the alternative recommendation solution Terrible distance too Calculates based on the criteria type. (Advantage vs. Price). Third, the proposed method of Evaluation of each opportunity calculates the score and uses the CVPFRS model to assess every opportunity through the Usual Appraisal Value. Later on, A full assessment of alternatives We get the EDAS approach a rating for everything calculates the estimated options and ranks the options in step with decreasing values of the evaluation score. Hydrogen mobility roll-up alternatives EDAS methods for assessment are used This MCDM method helps calculate a smoothness rating and rank every opportunity The ideal is contradictory in nature Hydrogen Mobility Roll-up to choose an alternative. Every method is its strength and obstacles. EDAS approach is proposed for their stock category. The top-notch benefit of EDAS Compared to other methods for class, it has greater correct performance and Fewer math calculations. EDAS in, each of the evaluation of alternatives Appreciate the scale as well a form standard solution Depends on the location of the character replacement, introducing a prolonged EDAS technique for figuring out providers. strong waste for removal in determining the site, EDAS-based totally instinct counseled a fuzzy model. In this study, EDAS was incorporated to analyze boundaries for RE improvement. Application of EDAS technique in MAGDM. Firstly, the Basic definition of projects and distance method is Briefly advocated. Next, amplified EDAS The approach is classical underneath real context Inspired using the EDAS method. EDAS method Solving the MCDM hassle with inverse houses an original and green device to resolve. AVS to prioritize choices uses and strong waste disposal website PDA and NDA EDAS technique for evaluation used prolonged the EDAS version. EDAS technique for MCGDM. Also, EDAS compiles a few algorithms for neutrosophic easy selection making. It is clear that EDAS has obtained a whole lot of attention from pupils, however, given those arguments and motivations, no work extends EDAS to q- Rung. To solve problems related to MCDM EDAS is a brand-new system that Can be used as a framework This is a review of the literature that revealed prime time use of a prolonged EDAS model based totally on the proposed intuitive parametric difference measures. Furthermore, it is an empirical Sanitary disposal approach It helps to fix the selection problem for evaluating opportunity sanitary First-time waste disposal techniques to ensure the stability of results for the proposed approach Evaluation is done between some current techniques to demonstrate the validity of the consequences done. The EDAS method has been extended to the DHHFL framework for 0 carbon operations to allow Indian Smart Cities' carbon footprint to be significantly reduced in size via the manner of 2050. EDAS Completely distance based The ranking technique is the average using parameters Sweet and nadir statistics factors. EDAS is developed among the best and most popular MCDM methods, however, the EDAS method is the best alternative. EDAS Methodology for Supplier Selection. However, to the satisfaction of our expertise, no take look at the MADM problem primarily based on the EDAS approach has been reported within the current academic literature. Therefore, the usage of EDAS in MADM is a thrilling research subject matter to rank and determine the pleasant opportunity below an unmarried-valued neutrosophic clean environment. EDAS (Estimation distance from the mean solution-based) method A new and It is efficient technique is proposed and carried out to solve the stock type problem. Validated the effectiveness of the EDAS method by comparing it with some different MCDM techniques. A fuzzy extension of EDAS is proposed) and applied to the provider selection trouble. Also, developed an intuitive EDAS method and carried out it to stable waste disposal website selection. Proposed a few algorithms for gentle selection-making with neutrosophic units based on the EDAS approach. An EDAS approach is proposed for order allocation thinking about dealer evaluation and context. Some steps of the EDAS technique and mathematics functions of IT2FS are used to assess providers with recognition of environmental standards. The result of this evaluation method is two parameters for every supplier: effective ratings and negative scores. Purchase expenses and glued parameters are used to develop multi-goal linear programming to determine the order amount from each supplier. We use a fuzzy programming method to resolve this multi-objective model.

Result And Discussion

TABLE 1. Security Analysis and Portfolio Management

	Volatility	Sharpe Ratio	Excess Return over Benchmark	Tracking Error
Fundamental Weighting	101.08	95.43	91.3	29.15
Minimum Variance	129.12	92.17	99.18	23.69
Stable ROE Portfolio	124.08	82.58	84.17	29.18
AVj	**118.09**	**90.06**	**91.55**	**27.34**

Table 1 shows the Security Analysis and Portfolio Management using the Analysis method in EDAS. Fundamental Weighting, Minimum Variance, and Stable ROE Portfolio Alternative and Volatility, Sharpe Ratio, Excess Return Over Benchmark Evaluation are seen all Average in Value.

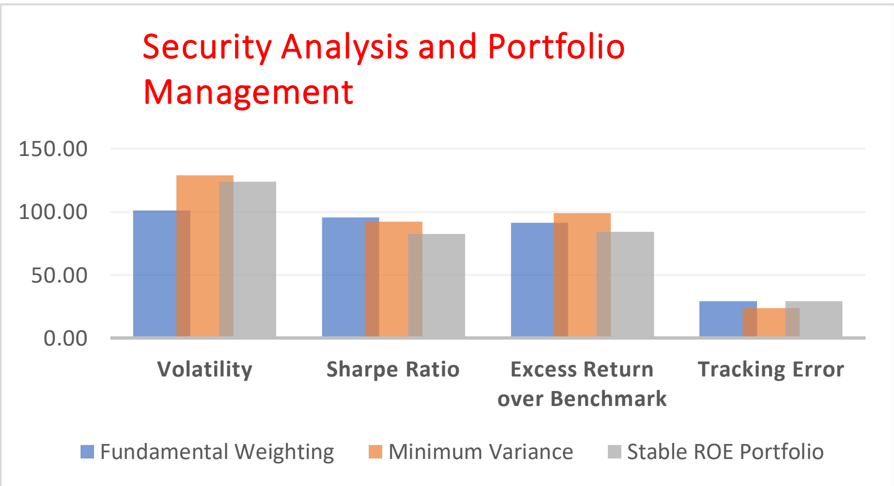

FIGURE 1. Security Analysis and Portfolio Management

Figure 1 shows the Security Analysis and Portfolio Management using the Analysis method in EDAS. Fundamental Weighting, Minimum Variance, and Stable ROE Portfolio Alternative and Volatility, Sharpe Ratio, Excess Return Over Benchmark Evaluation are seen all Average in Value.

TABLE 2. Positive Distance from Average (PDA)

	Positive Distance from Average (PDA)			
Fundamental Weighting	0	0.059627	0	0.066203
Minimum Variance	0.093372	0.023429	0.083342	0
Stable ROE Portfolio	0.050694	0	0	0.067301

Table 2 shows the Positive Distance from the Average (PDA) in a Security Analysis and Portfolio Management using the Analysis method in EDAS. Fundamental Weighting, Minimum Variance, Stable ROE Portfolio, Volatility, Sharpe Ratio, and Excess Return Over Benchmark is seen as all Maximum Value.

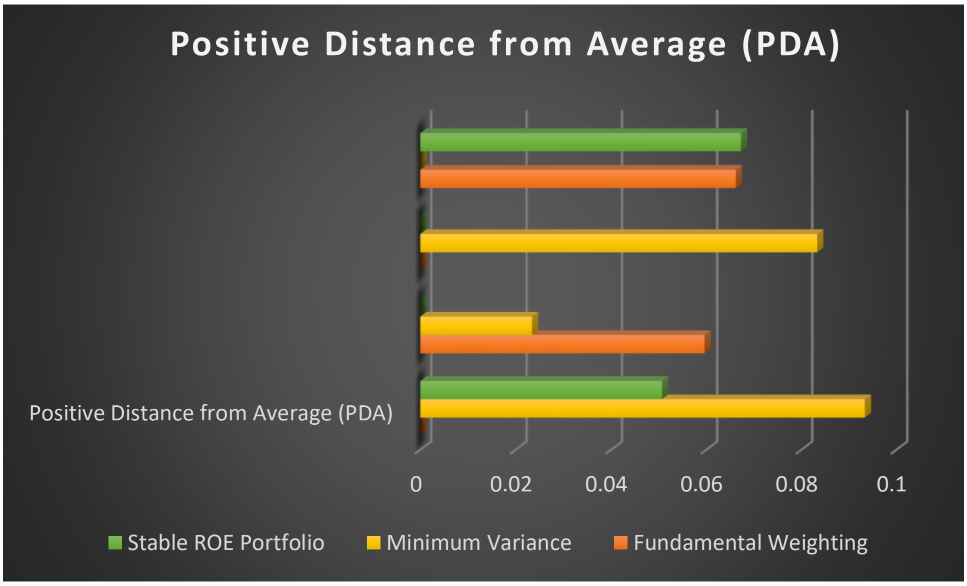

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TABLE 3. Negative Distance from Average (NDA)

	Negative Distance from Average (NDA)			
Fundamental Weighting	0.144067	0	0.002731	0
Minimum Variance	0	0	0	0.133504
Stable ROE Portfolio	0	0.083056	0.080612	0

Table 3 shows the Negative Distance from the Average (NDA) in a Security Analysis and Portfolio Management using the Analysis method in EDAS. Fundamental Weighting, Minimum Variance, Stable ROE Portfolio, Volatility, Sharpe Ratio, and Excess Return Over Benchmark are seen as all Maximum Values.

TABLE 4. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 4 shows the Weight used for the analysis. We took the same weights for all the parameters for the analysis.

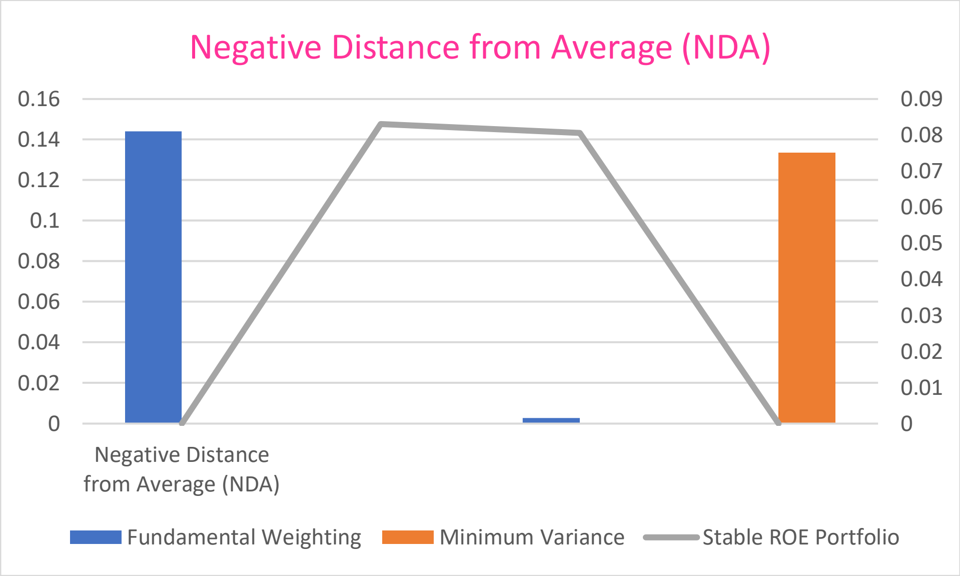

FIGURE 3. Negative Distance from Average (NDA)

Figure 3 shows the Negative Distance from the Average (NDA) in a Security Analysis and Portfolio Management using the Analysis method in EDAS. Fundamental Weighting, Minimum Variance, Stable ROE Portfolio, Volatility, Sharpe Ratio, and Excess Return Over Benchmark are seen as all Maximum Values.

TABLE 5. Weighted PDA SPi

	Weighted PDA				SPi
Fundamental Weighting	0	0.014907	0	0.016551	0.031458
Minimum Variance	0.023343	0.005857	0.020836	0	0.050036
Stable ROE Portfolio	0.012674	0	0	0.016825	0.029499

Table 5 shows the Weighted PDA SPi in the Security Analysis and Portfolio Management using the Analysis method in EDAS Analysis is shown the Table 2 and Table 4 in Multiple Value. Fundamental Weighting, Minimum Variance, Stable ROE Portfolio, Volatility, Sharpe Ratio, and Excess Return Over Benchmark is seen in all Multiple Value.

TABLE 6. Weighted NDA, SNI

	Weighted NDA				SNi
Fundamental Weighting	0.036017	0	0.0007	0	0.0367
Minimum Variance	0	0	0	0.0334	0.0334
Stable ROE Portfolio	0	0.0208	0.0202	0	0.0409

Table 6 shows the Weighted PDA SPi in the Evaluation of Security Analysis and Portfolio Management using the Analysis method in EDAS Analysis is shown in Table 3 and Table 4 in Multiple Value. Fundamental Weighting, Minimum Variance, Stable ROE Portfolio, Volatility, Sharpe Ratio, and Excess Return Over Benchmark is seen in all Multiple Value.

TABLE 7. Final Result of the Security Analysis and Portfolio Management

	SPi	SNi	ASi	Rank
Fundamental Weighting	0.6287	0.1031	0.3659	2
Minimum Variance	1	0.1843	0.5921	1
Stable ROE Portfolio	0.5896	0	0.2948	3

Table 7 shows the Final Result of the Security Analysis and Portfolio Management using the Analysis for the EDAS Method. Minimum Variance has the highest rank whereas Stable ROE Portfolio has the lowest rank.

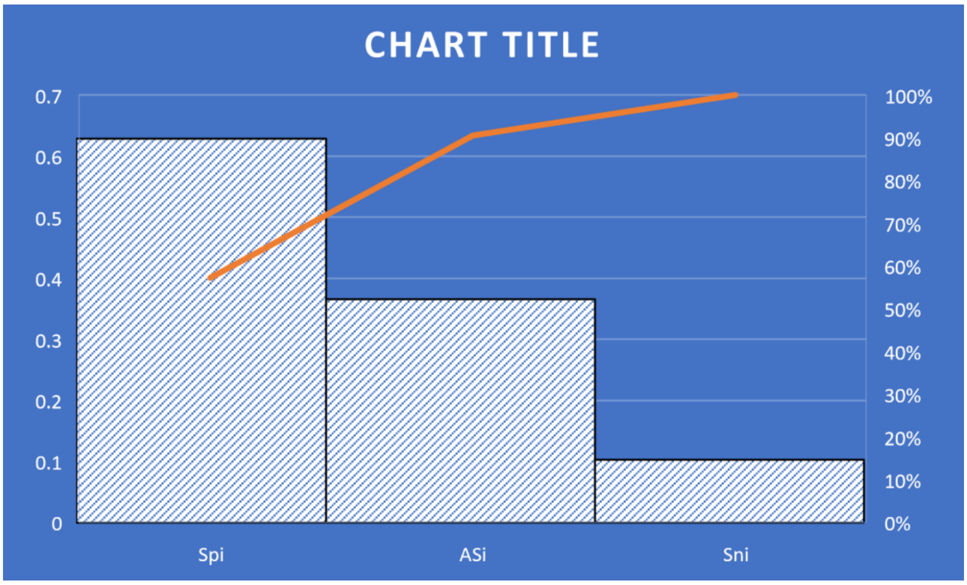

FIGURE 4. Final Result of the Security Analysis and Portfolio Management

Figure 4 shows the Final Result of Security Analysis and Portfolio Management using the Analysis for EDAS Method. Minimum Variance has the highest rank whereas Stable ROE Portfolio has the lowest rank.

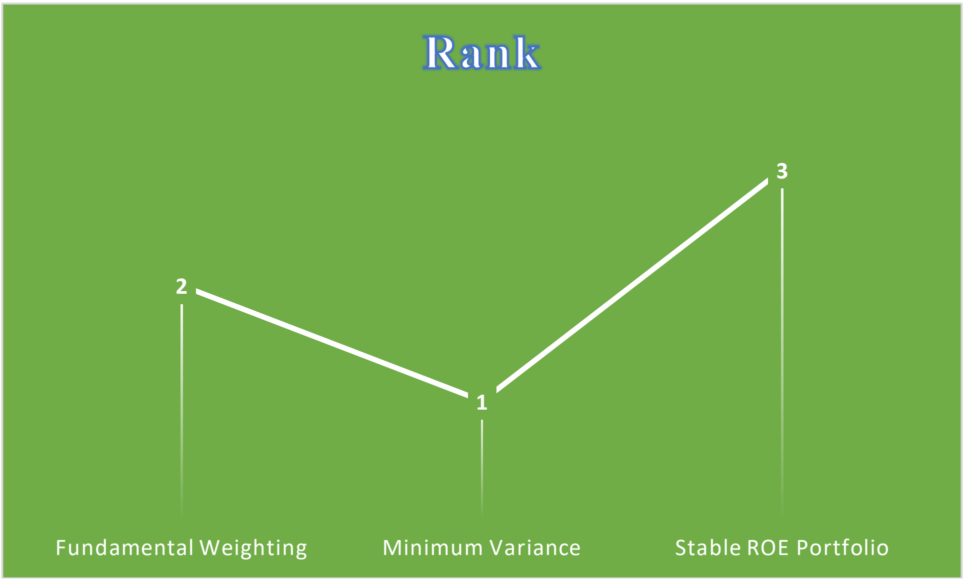

FIGURE 5. Show the Rank

Figure 5 shows the Ranking for Minimum Variance has the highest rank whereas Stable ROE Portfolio has the lowest rank.

Conclusions

According to us, the primary function of financial modeling is to assist in individual decision-making while taking into account the particulars of the actual issue at hand and reaping the potential benefits of any financial theory findings. It entails three steps: (1) investigating a range of various decision-making procedures; (2) defining the connections between decision alternatives and their (potential) results; and (3) looking for an appropriate (set) of decision alternatives. Our notion of financial modeling is illustrated using a comprehensive framework for portfolio management that can help with investment decision-making. The organization is goal-oriented. To accommodate any kind of investor is quite general. Because it takes into account the many circumstances of the portfolio management problem, the framework is particularly specific. Without asking the investor to create a comprehensive predicted return-covariance structure of future returns, it makes an effort to use all available information. The occupational area of security analysis and portfolio management combines technical analysis with the influence of related factors. As a result, increasingly complex methodologies are always needed for the technical analysis of securities, their allocation in portfolios, portfolio distribution, and analysis of relevant factors. These incorporate deep learning, sentiment analysis, and statistical learning applications. The technical analysis of securities uses artificial intelligence, machine learning, and deep learning algorithms to build more precise predictive models, analyze market sentiments, assess the impact of sentiments related to specific security, build portfolios for maximum predictive gain, and optimize portfolios. It aids in a variety of financial operations, including trade execution, regulatory compliance, potential fraud identification, potential market vulnerability detection, and many more. The usage of artificial intelligence and machine learning in the financial services sector is increasingly being driven by expanding data sets and current developments in the field of artificial intelligence. In contrast, even when the fundamental idea is accepted, university professors, administration, and society have trouble securing funding for initiatives, for example. This is because they do not grasp the vital requirement to provide a balance between theory and practise. The goal of this study is to encourage the expansion of investment funds at public and private institutions across the country.

References

[1]. Lei, Adam YC, and Huihua Li. "Using Bloomberg terminals in a security analysis and portfolio management course." *Journal of Economics and Finance Education* 11, no. 1 (2012): 72-92.

[2]. Markese, John D. "Applied security analysis and portfolio management." *Journal of Financial Education* (1984): 65-67.

[3]. Reilly, Frank K., and Keith C. Brown. *Investment analysis and portfolio management*. Cengage Learning, 2011.

[4]. Burns, William, and Michele Burns. "The use of a portfolio management simulation as a learning device." *Journal of Financial Education* (1982): 79-82.

[5]. Fu, Tak-Chung, Chi-Pang Chung, and Fu-Lai Chung. "Adopting genetic algorithms for technical analysis and portfolio management." *Computers & Mathematics with Applications* 66, no. 10 (2013): 1743-1757.

[6]. Spronk, Jaap, and Winfried Hallerbach. "Financial modeling: Where to go? With an illustration for portfolio management." *European Journal of operational research* 99, no. 1 (1997): 113-125.

[7]. Cunningham, Ward. "The WyCash portfolio management system." *ACM SIGPLAN OOPS Messenger* 4, no. 2 (1992): 29-30.

[8]. Treynor, Jack L., and Fischer Black. "How to use security analysis to improve portfolio selection." *The journal of business* 46, no. 1 (1973): 66-86.

[9]. Riley, William B., and Austin H. Montgomery. "The Use of Interactive Computer Programs in Security Analysis and Portfolio Management." *Journal of Financial Education* (1980): 89-92.

[10]. Morrison, Russell J. "Securities Analysis and Portfolio Management as Art Forms." *Financial Analysts Journal* (1987): 6-70.

[11]. Gautam, Bhavna, Sanjiv Gupta, and Suvigya Awasthi. "Securities Analysis and Portfolio Management using Artificial Neural Networks." *Available at SSRN 3332162* (2019).

[12]. Lawrence, Edward C. "Learning portfolio management by experience: University student investment funds." *Financial Review* 25, no. 1 (1990): 165-173.

[13]. Bear, F. Thomas, and G. Michael Boyd. "An applied course in investment analysis and portfolio management." *Journal of Financial Education* (1984): 68-71.

[14]. Pandya, Falguni H. *Security analysis and portfolio management*. Jaico Publishing House, 2013.

[15]. Carter, Richard B., and Howard E. Van Auken. "Security analysis and portfolio management: a survey and analysis." *Journal of Portfolio Management* 16, no. 3 (1990): 81.

[16]. Elton, Edwin J., and Martin J. Gruber. "Optimum centralized portfolio construction with decentralized portfolio management." *Journal of Financial and Quantitative Analysis* 39, no. 3 (2004): 481-494.

[17]. Black, Fischer. "Implications of the random walk hypothesis for portfolio management." *Financial Analysts Journal* 27, no. 2 (1971): 16-22.

[18]. Soman, Siddhesh. "TLP for Security Analysis & Portfolio Management 2020-2021." (2020).

[19]. Jarrow, Robert A. "Active portfolio management and positive alphas: fact or fantasy?." *The Journal of Portfolio Management* 36, no. 4 (2010): 17-22.

[20]. İlhan, Emirhan. "FIN3702: Investment Analysis and Portfolio Management." (2023).

[21]. Balasubramanian, P. R., Tomas Isakowitz, Rob Kauffman, and Raghav K. Madhavan. "Exploiting hypertext valuation links for business decision making: a portfolio management illustration." (1991).

[22]. Fuller, Russell J., Raife Giovinazzo, and Yining Tung. "The Stable ROE Portfolio: An alternative equity index strategy based on common sense security analysis." *The Journal of Portfolio Management* 40, no. 5 (2014): 135-145.

[23]. Mennis, Edmund A. "An integrated approach to portfolio management." *Financial Analysts Journal* 30, no. 2 (1974): 38-46.

[24]. Ferguson, Robert. "Active portfolio management: How to beat the index funds." *Financial Analysts Journal* 31, no. 3 (1975): 63-72.

[25]. Helliar, Christine V., R. Michaelson, D. M. Power, and C. D. Sinclair. "Using a portfolio management game (Finesse) to teach finance." *Accounting Education* 9, no. 1 (2000): 37-51.