Decision Support Systems in Stock Investment Problems

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Abstract: - This study compiles decision support systems that aim to optimize financial decision processes by examining the literature studies targeting stock investments. The review encompasses a range of methodologies and applications, from traditional approaches such as Markowitz's Modern Portfolio Theory, Black-Litterman, and Single Index models to artificial intelligence-based techniques. In detail, the contributions of Decision Support Systems to stock portfolio construction and portfolio optimization processes along with comparative analyses between these systems are scrutinized. The review also aims to enable researchers and practitioners to be engaged in portfolio optimization with a framework for future investigations in areas such as historical data analysis, future price movement prediction, assessment of risk factors, and determination of optimal portfolio distribution. Furthermore, it seeks to enhance the understanding of decision support systems employed in portfolio optimization, facilitating a more comprehensive grasp of their utility within stock investments.

Key-Words: - Decision support systems, stock investment, portfolio optimization, modern portfolio theory.

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1 Introduction

Stocks are financial instruments that companies benefit from to meet their financial needs, [1]. A stock portfolio is a collection of specific stocks selected from many financial assets available in the market, [2]. While creating the portfolio, we decide which stocks will be chosen and how many shares will be allocated to these stocks. The financial value of the portfolio depends on the prices of the stocks it contains and can be continuously monitored by the investor. Portfolio optimization usually specifies the amount of investment that should be invested in selected stocks as a proportion of available resources, [3]. In this context, companies may need to choose among many parameters, such as risk tolerance, return expectations, liquidity needs, and other factors. In this process, investors aim to select an appropriate combination of the securities in which they invest. While making these combinations, investors should consider many factors, such as the number of companies invested in, the percentage of investment in which company, and the correlation between the invested companies.

Researchers usually try to solve this confusion using computer applications or mathematical models. However, the variety of investment strategies and the intricacy of investment choices have consistently grown over the past two decades. This rise has revealed the need for comprehensive and extensible financial decision support systems (DSS) that include the main approaches to investment decisions.

DSS is a computer-based tool used during the decision-making process for a company or user, [4]. DSS helps decision-makers in the decision-making process with its features, such as analyzing data by processing, modeling decisions in different scenarios, and predicting the consequences of future actions. These systems can collect data from various sources, such as business data, financial information, and market research results, and analyze this data to provide accurate information to decision-makers. DSS helps managers or investors make faster, more effective, and more informed decisions in the decision-making process.

The predominant DSS applications finance involves crafting choices for financial audit and project portfolios, overseeing fixed-income portfolios, handling credit risk within home mortgage portfolios, and refining investment policy and strategy optimization, [5]. Therefore, DSS is a helpful mechanism for choosing the most suitable portfolio according to the investor's sector among different portfolios. These systems determine an optimal asset allocation, considering an investor's risk tolerance, return targets, and other constraints. This type of optimization often requires statistical analysis of the returns and risks of assets in a particular portfolio. Using these systems can increase an investor's ability to maximize potential returns and minimize risk.

In this study, we examine the existing research in stock investments for portfolio optimization and place the focus on DSS structures aimed at optimizing financial decision processes. In Section 2, we summarize current research on creating an optimal portfolio for stock investments with an overview and present DSS studies aimed at optimizing financial decisions in this context. Section 3 outlines the objectives, methodologies, and advantages of DSS structures employed in portfolio optimization within the context of stock investments. Moreover, the pivotal role of DSS in formulating and managing stock investment portfolios is elaborated. DSS structures elucidate how researchers and practitioners can make more effective decisions in various domains, such as historical data analysis, forecasting future price movements, assessing risk factors, and determining optimal portfolio allocations. Additionally, we (or the authors/researchers/experts) expound upon the contributions of these structures to the financial decision-making process. In the Section "Analysis and Final Thoughts", the importance of using DSS is emphasized to create an optimal portfolio in stock investments. It also provides an overview of areas where future research could provide further understanding and in-depth analysis. The results show that DSS is an effective tool for optimizing financial decision processes and achieving better results.

2 Literature Survey Overview

Portfolio optimization is a process that assists individual or institutional investors in making optimal investment decisions by considering their risk and return expectations. In this process, investors must make a series of decisions to construct the most suitable portfolio among a set of financial instruments. These decisions include choosing which financial instruments to have, determining the allocation percentages, selecting the quantity of each tool, and deciding when to purchase and sell. In the pioneering studies, [6], and, [7], where portfolios are selected according to certain conditions, it has been argued that by researching the relationships between the returns of securities comprising an investment portfolio and combining securities in a portfolio that do not have a total positive correlation between their returns, non-systematic risk can be reduced without a decrease in expected return, [8]. The author also led the way in measuring security and portfolio risk using the statistical measure known as variance. In the mean-variance model, the objective function is determined to maximize the expected return for a certain risk level or to minimize the chance for a certain expected return level, [9]. The problem corresponds to a mathematically non-linear, multi-objective optimization problem with linear constraints and has more than one solution method, [10]. For the Markowitz mean-variance problem, which seeks a solution to a non-linear objective function with linear constraints, one solution is the Kuhn-Tucker method, which can be adapted to computer programming languages, [11], [12]. This method has been extensively studied in the portfolio optimization literature, [10], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22]. The portfolio selection, optimization, and management model has been rapidly developed based on the mean-variance model. In studies, [23], [24], [25], [26], [27], and

[28], the authors significantly developed the theory of portfolio selection and management by considering various factors that investors face in the real world. They have integrated real-life constraints into the model, such as the proportion of a portfolio comprised of risky assets that an investor decides upon, borrowing-lending situations, short sales, transaction costs, and taxation. In, [29], the author researched borrowing and lending rates, while the author in, [30], investigated personal taxation, uncertain inflation, and off-market assets. In, [31], and, [32], the authors developed the short-sale theme further. The single-index model and the Multi-Index Models address the complications brought by the increasing number of securities in determining the expected return and variance of optimal portfolios, [24], [33]. The Single Index Model developed by William Sharpe is a methodology employed to gauge the performance of risky assets within a portfolio. This model facilitates portfolio managers in quantifying the returns obtained relative to the risk undertaken. Often synonymous with the Sharpe Ratio, this metric delineates the relationship between the achieved return of a portfolio and its associated risk level. A higher Sharpe Ratio indicates superior risk management proficiency on the part of the portfolio manager, [34]. A mathematical model for the portfolio optimization problem was presented by the authors of the Black-Scholes model, which is famous for option pricing, [35].

Equity portfolio optimization aids investors in determining how to allocate their assets to maximize expected returns while minimizing risk. Monte Carlo simulations are commonly employed in solving these optimization problems. The Monte Carlo simulation is a statistical computation method that uses many random samples to achieve results. In this simulation, random weights are assigned to equity instruments, ensuring the total of the weights equals 1. The expected return and standard deviation are calculated and stored for each combination of these weights. Weights are then changed again, assigned randomly, and the process is repeated. This gives investors valuable insights into how their portfolios will perform under different scenarios, equipping them to make more informed investment decisions, [36]. Monte Carlo simulation methods continue to be developed in various DSS using other programming languages today, [22], [37], [38], [39], [40].

Studies on the mean-variance model have given rise to the Financial Asset Pricing Model, a progression that is both a mathematical and logical extension of the original model, [41]. To address some of the issues encountered in the mean-variance model, Black and Litterman made some improvements to this model and presented a model named after themselves. This model was first introduced in the 1990 article “Asset Allocation: Combining Investor Views with Market Equilibrium” by Black and Litterman and was expanded in subsequent studies in 1991 and 1992, [42], [43], [44]. The Black-Litterman approach lets investors modify the equilibrium returns of equities based on their perspectives, utilizing the Bayesian methodology. This model has two primary characteristics that set it apart from the traditional mean-variance method. One feature is that investors can specify their expectations on returns for any number of securities they desire. Second, investors take the equilibrium market returns as prior estimates of security returns and integrate investor views with this prior information set, [45]. "Numerous studies have been conducted from the past to the present on portfolio optimization with the Black-Litterman model, as well as comparisons of this model with Markowitz's model, [1], [9], [41], [45], [46], [47], [48], [49], [50]. In the literature, these models considered traditional methods, do not involve the direct use of a DSS. However, they have formed the basis for many studies related to portfolio optimization, where the DSS assists investors in the decision-making process.

The diversity in investment strategies and the growing intricacy of investment choices have persistently risen, necessitating robust and scalable financial decision support systems that cover the primary methodologies for making investment decisions. In three reviews conducted in, [51], [52] and, [53], the authors examined about 670 published DSS applications among the published applications, providing information about the types, purposes, sectors, and technologies of these applications. The researchers introduce DSS in general and address topics such as what these systems are, how they work, and what types of decisions they can be used for. Their reviews showed that DSS applications are used in various sectors, including finance, production, healthcare, education, and public administration. DSS applications’ most frequent decision processes were forecasting, planning, auditing, and management decisions. They concluded that the rate of DSS usage in the finance sector was progressing slower than in other industries and was around an average of 10%.

DSS uses mathematical models and algorithms to help investors optimally manage their portfolios. These models assist investors in making the best investment decisions by considering factors like risk tolerance, return expectations, and other criteria. Palma-dos-Reis and Zahedi (1999) have used DSS to explore and investigate the influence of investors' personal traits on their use of models when making investment decisions, [5]. In, [54], it is utilized the DSS by integrating decision analysis and investment evaluation techniques to assist investors. This system guides in constructing an investment model for the Shanghai Stock Exchange and making optimal decisions. In, [55], and, [56], different researchers introduced a DSS each had developed for portfolio optimization problems. The authors propose a multi-criteria decision-making model based on the PROMETHEE method to select superior stocks in the stock market and apply this model to the Tehran Stock Exchange as a real-world case in, [57]. As a stock selection strategy, it is developed two DEA models for the Taiwan Stock Exchange in, [58], while it is implemented a prototype named MISMIS for the Hang Seng Index in, [59]. The DSS introduced in, [60], is a design that transforms stock votes from online communities into investment decisions, and the portfolios created with this system clearly outperform the market benchmark and other funds in terms of performance over a specific observation period. In, [61], the authors developed an adaptive trading model that intelligently recognizes trading signals and aids investors in their decisions, utilizing techniques like neural networks, particle swarm optimization, and denoising. Simulations showed that traders could achieve higher returns using this decision support system, highlighting the advantages of incorporating adaptive and intelligent decision-making into forecasts. In the literature, many studies have been conducted using multi-criteria decision-making techniques such as AHP (Analytic Hierarchy Process), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), ELECTRE (Elimination and Choice Expressing Reality), and MOORA (Multi-Objective Optimization on the basis of Ratio Analysis), [62], [63], [64], [65], [66], [67], [68], [69].

In recent years, deep learning techniques such as Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), machine learning, and genetic algorithms have been applied to complex problems in financial markets, such as stock market investment. Thanks to their capabilities in processing large amounts of data and learning, these techniques have been used in predicting stock prices, portfolio management, and risk analysis. These approaches can potentially overcome challenges previously addressed by traditional financial models, [3], [47], [48], [60], [61], [70], [71], [72], [73], [74], [75].

The studies presented here provide only a few examples of the use of DSS in portfolio optimization. However, a wide array of approaches and models are available in this field, constantly evolving. The need to understand and address the complexity of financial analysis has led to a continuous increase in research within the literature. Future studies should delve more extensively into integrating DSS more effectively to achieve more accurate results and contribute to further enhancing portfolio management.

3 The Utilization of Decision Support Systems in Stock Market Scenarios

The portfolio optimization problem is one of the most studied classic topics in computational finance. This optimization process involves a series of mathematical models and methods investors use to decide how to allocate their portfolios most effectively. In particular, Harry Markowitz's Modern Portfolio Theory is considered one of the cornerstones in this field. The Single Index Model emerges as one of the fundamental building blocks of portfolio optimization, as does the Capital Asset Pricing Model (CAPM). On the other hand, more sophisticated approaches like the Black-Litterman model allow investors to make more customized portfolio forecasts, taking into account market equilibriums and specific views. This model is based on the fundamentals of Modern Portfolio Theory and combines market data with investors' risk tolerance and expectations to create the most optimized portfolios, [76]. Meanwhile, Monte Carlo simulations assist investors in testing various investment scenarios and risk levels. Accordingly, these simulations allow investors to simulate market conditions and investment scenarios for a particular period and subsequently optimize their portfolios.

With technological advancements, DSS used in portfolio optimization have diversified and evolved. Especially in recent years, technological innovations in this field have paved the way for the emergence of more complex and sophisticated decision mechanisms. A review of the literature reveals that numerous DSSs have been developed and utilized for portfolio optimization. These systems offer in-depth analyses to investors and portfolio managers, helping them find the most appropriate balance between expected returns and risk. These new approaches, which are far more advanced than traditional methods, integrate both financial and mathematical models to maximize the potential of portfolio management. In the following, we describe some prominent DSS found in the literature and review which methods and how these systems are used.

The authors conducted a study in which they developed a flexible and intelligent financial DSS design and examined the personalizing mechanisms of this system through laboratory experiments, [5]. The findings indicate that the user's characteristics (particularly risk aversion and gender) significantly influence the use of the DSS and model selection. However, the generalizability of these results could be improved, and further experiments with a larger sample size are planned. The research presents significant initial steps on how a financial DSS can be personalized based on user characteristics.

The author introduced an intelligent DSS that combines decision analysis with traditional investment evaluation procedures to assist decision-makers in making better investment decisions, [54]. The system offers tools like the influence diagram generator to help model the decision problem while providing personalized solutions considering the decision-maker's risk attitude and preferences. What sets this system apart is its ability to individualize traditional investment decisions and analyses by considering the decision maker's risk stance and preferences. Although the system has been tested on the Shanghai Stock Exchange, there is a need for extensive testing and evaluation of its adaptability to other stock markets.

In, [55], the authors present an information and knowledge exchange framework focused on how agents can exchange information and knowledge to solve common problems collaboratively. Specifically designed for stock trading, the Multi-Agent System for Stock Trading (MASST) system architecture employs an active blackboard to facilitate dynamic information exchange among agents. This structure ensures that agents use their resources efficiently while successfully responding to user requests and unforeseen situations.

In, [56], the authors designed a DSS using genetic algorithms to make the decision-making process in portfolio management easier and faster. This model presents investors with different scenarios derived from complex data. The decision support system, MISMIS was developed for financial data predictions, [59]. This system allows investors to create complex prediction models in a step-by-step manner. Results from each model can be used as inputs for the next one. This multi-level approach provides for breaking down complex models into more understandable sub-models, making it easier to detect and correct potential errors. Its effectiveness was demonstrated in an application on the Hong Kong Hang Seng Index, and financial consultants agreed that this system is an effective decision-support tool for stock market investments. In a system developed in, [60], the authors utilizes the crowd's wisdom, simulations have shown a 123% performance increase in investments, [60]. This proves that the system significantly outperforms market indices, offering investors the potential to harness crowd data effectively. In, [61], DSS methods for portfolio optimization using particle swarm optimization and artificial neural networks are developed, and multi-objective genetic algorithms and goal programming are employed in, [77], It is utilized multivariate linear regression in, [70], and the LightGBM machine learning model, it is applied the Capital Asset Pricing Model (CAPM) and PHP programming language in, [72], while it is adopted genetic algorithms in, [47].

The research in, [48], presents an algorithm for portfolio optimization as an information service. It compares three models: Black-Litterman, Markowitz, and equal-weighted, using a limited asset set and their historical returns. The Black-Litterman model, informed by historical data, is favored in simulations.

The authors propose a DSS for creating a portfolio with high return and low risk in the Singapore stock market, using the trend ratio assessment indicator and the global-best guided quantum-inspired tabu search algorithm (GNQTS) with a quantum-NOT gate in, [78]. It is proposed a comprehensive DSS focused on the three main aspects of stock market investment: stock price forecasting, stock selection, and portfolio optimization in, [3]. Artificial neural networks and fundamental analysis are used for price predictions; differential evolution is employed for stock selection; and genetic algorithms combined with statistical analysis are utilized for portfolio construction. Experiments were conducted on stocks within the S&P 500, and the results demonstrate that the proposed system outperforms existing methods in various scenarios. Another study showed a mean-variance portfolio investment problem in a stochastic environment was addressed in the same year, and a stochastic rule-based DSS was proposed to select the best portfolio without directly solving the optimization problem, [73].

In studies, [79], [80], [81], [82], the authors focus on the development of various expert systems that support the decision-making process for optimal portfolio selection. These studies indicate that these systems provide guidance to investors on how to optimize their portfolios, evaluate potential risks, and predict the possible returns of different investment scenarios.

The author conducted the first study using a large-scale predictive decision-making approach for cryptocurrency portfolio allocation in, [74]. The research treated price predictions as a time series forecasting problem and defined portfolio allocation as a Multiple Criteria Decision Making (MCDM) issue. The Prophet Forecasting Model (PFM) was employed to make time-series price predictions, and the CLUS-MCDA algorithm was expanded for the asset allocation phase. An experiment analyzing over 70 cryptocurrencies was conducted to verify the method's reliability, The results indicate that the proposed decision support system is a trustworthy tool for real-world big data challenges. Recommendations include verifying time series forecasting models, linking to a real-time database, incorporating natural language processing and semantic analysis into the methodology, and enhancing the algorithm with neural network inference for more accurate and realistic outcomes.

When examining the sources in the literature, we observe that a significant portion of the stock portfolio optimization problems use Multi-Criteria Decision-Making techniques as their DSS structures. These techniques enable investors to apply a scientific and systematic approach to complex investment decisions by considering different criteria and constraints. Specifically, decision-makers prefer the Analytic Hierarchy Process in the prioritization process between criteria; they use TOPSIS to determine the proximity of alternative stocks to the ideal solution, and they favor Vikor to reveal optimal compromise solutions. Methods like ELECTRE and PROMETHEE also stand out with their capacity to rank and eliminate investment alternatives. The integrated use of these multi-criteria methods allows investors and portfolio managers to make more informed decisions under different scenarios and variables.

Various software and package programs are utilized for the DSS structures used in stock portfolio optimization. Investors frequently prefer Microsoft Excel and its additional Solver tool for basic optimization tasks. MATLAB is employed to implement complex algorithms, while Python, enriched with libraries such as pandas and numpy, is becoming increasingly popular for financial analysis and optimization. The R language stands out for financial analysis with "Performance Analytics" packages. Eviews and Stata are commonly used for econometric analyses and time series. For large-scale optimization challenges, modeling systems like GAMS and AMPL are chosen, and MPT-based specialized software addresses tailored needs. Optimization solvers like CPLEX and Gurobi are employed to solve intricate portfolio optimization issues. These tools offer features that cater to the diverse aspects of portfolio management.

4 Analysis and Final Thoughts

The complexity and uncertainty of stock market investments force investors to make difficult decisions. However, the rising role of technology in the finance sector offers new methods with the potential to overcome these challenges. In particular, technologies such as natural language processing, machine learning, and big data analysis have significantly advanced financial data analysis and market movement predictions. Advanced techniques, such as evolutionary algorithms, simulations, and the Monte Carlo method, are used to predict the possible distributions of risk and return. Combined with classic models like Markowitz's Modern Portfolio Theory, these techniques provide investors with critical information to optimally allocate their portfolios. The Minimum Variability-Minimum Risk method aims to take on the least risk while minimizing portfolio volatility. The Sectoral Analysis strategy allows investors to diversify their risks by investing in different sectors. With the Factor Analysis method, investors can minimize risks by considering the factors in their portfolios.

DSS enables investors to utilize these techniques and strategies effectively. DSS guides investors in investing in the most suitable sectors and factor combinations. At the same time, integrating advanced methods such as decision tree analysis, multi-criteria decision-making, artificial neural networks, and genetic algorithms optimize the portfolio creation process for investors. The study in, [3], reveals that DSS provides investors the opportunity to make more informed and strategic decisions. With the rapid advancements in technology, research on portfolio optimization is continuously evolving and being updated.

Furthermore, the rise of crypto assets in financial markets necessitates the adoption of new approaches in portfolio optimization strategies. Risk assessment methods specially developed for these highly volatile assets enable investors to make their crypto-asset investments more informedly. Additionally, the growing popularity of sustainable investments has highlighted the integration of environmental, social, and governance criteria into portfolio optimization processes. These criteria allow investors to consider their social and environmental impacts while maximizing financial returns.

Studies indicate that these tools and methods offered by modern technology provide investors with the potential to make more informed and effective investment decisions. To keep pace with these rapid changes in the investment world, there is a need for continuously updated and adaptive methods.

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