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Review

Robust Portfolio Mean-Variance Optimization for Capital Allocation in Stock Investment Using the Genetic Algorithm: A Systematic Literature Review

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Abstract: Traditional mean-variance (MV) models, considered effective in stable conditions, often prove inadequate in uncertain market scenarios. Therefore, there is a need for more robust and better portfolio optimization methods to handle the fluctuations and uncertainties in asset returns and covariances. This study aims to perform a Systematic Literature Review (SLR) on robust portfolio mean-variance (RPMV) in stock investment utilizing genetic algorithms (GAs). The SLR covered studies from 1995 to 2024, allowing a thorough analysis of the evolution and effectiveness of robust portfolio optimization methods over time. The method used to conduct the SLR followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines. The result of the SLR presented a novel strategy to combine robust optimization methods and a GA in order to enhance RPMV. The uncertainty parameters, cardinality constraints, optimization constraints, risk-aversion parameters, robust covariance estimators, relative and absolute robustness, and parameters adopted were unable to develop portfolios capable of maintaining performance despite market uncertainties. This led to the inclusion of GAs to solve the complex optimization problems associated with RPMV efficiently, as well as fine-tuning parameters to improve solution accuracy. In three papers, the empirical validation of the results was conducted using historical data from different global capital markets such as Hang Seng (Hong Kong), Data Analysis Expressions (DAX) 100 (Germany), the Financial Times Stock Exchange (FTSE) 100 (U.K.), S&P 100 (USA), Nikkei 225 (Japan), and the Indonesia Stock Exchange (IDX), and the results showed that the RPMV model optimized with a GA was more stable and provided higher returns compared with traditional MV models. Furthermore, the proposed method effectively mitigated market uncertainties, making it a valuable tool for investors aiming to optimize portfolios under uncertain conditions. The implications of this study relate to handling uncertainty in asset returns, dynamic portfolio parameters, and the effectiveness of GAs in solving portfolio optimization problems under uncertainty, providing near-optimal solutions with relatively lower computational time.

Keywords: robust portfolio; mean-variance; stock; literature review; genetic algorithm

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1. Introduction

Robust portfolio mean-variance (RPMV) is a method of portfolio management that combines the principles of mean-variance (MV) with the elements of uncertainty or market fluctuations [1]. This method focuses on portfolio optimization to achieve an optimal balance between expected return (mean) and risk as measured by variance or standard deviation. In the context of an MV portfolio, the main goal is to develop a portfolio that provides maximum returns at a certain level of risk or, vice versa, reduces risk at a certain level of return [2,3]. However, financial markets often experience fluctuations and uncertainty capable of significantly affecting portfolio performance. RPMV addresses this uncertainty by considering variations in the parameters used in MV analysis, such as expected returns and covariance among assets in a portfolio. Therefore, RPMV focuses on developing a portfolio that is more resistant to market fluctuations and provides consistent results in different conditions with due consideration for uncertainty. This shows that the method is very important for investors to manage risk better and achieve investment goals.

A heuristic method often used in portfolio optimization is the genetic algorithm (GA). It was developed by Holland [4] based on the principles of natural selection and genetic theory. Arnone et al. introduced the use of the GA in dealing with portfolio optimization problems [5]. Some studies, including Chang et al. [6], Soleimani et al. [7], and Chang et al. [8], reported the ability of the method to achieve optimal solutions. Furthermore, a more flexible stock portfolio was proposed with a focus on using the GA for optimization in the RPMV model.

The investment in shares has a potential for high profits and commensurate risks. Despite the high risks, it has attracted the interest of several investors because of the possibility of high returns in the long term. The information presented in Table 1 shows that three past studies only discuss robust portfolios [9,10], while one focuses exclusively on MV and the GA [11]. Another study also discusses MV [12], while one focuses on RPMV in stock investment without paying attention to the GA [13]. This shows the need for a Systematic Literature Review (SLR) considering the significant growth of studies related to RPMV in stock investment in recent years.

Table 1. The differences among the relevant previous SLRs and the current study.

No	Paper	Content Analysis?	Article Period	Robust Portfolio?	MV?	GA?
1	[9]	✔	1991–2021	✔	-	-
2	[10]	✔	1995–2019	✔	-	-
3	[11]	✔	1998–2016	-	✔	✔
4	[12]	✔	1998–2019	-	✔	-
5	[13]	✔	2002–2015	✔	✔	-
6	Present study	✔	1995–2024	✔	✔	✔

This study aims to perform an SLR on the topic of RPMV in stock investment using the GA as an addition to the body of existing reviews summarized in Table 1. For example, Mandal and Thakur formulated a portfolio model with a focus on returns and other higher-order moments in the stochastic environment to explain robust optimization [12]. Xidonas. et al. also showed that robust strategies were favored over classical ones because of their superior stability in portfolio returns and enhanced out-of-sample performance [10]. The trend showed that robust mathematical programming could be a valuable asset in several other financial domains. Moreover, Kalayci. et al. [12] reviewed the implementation of GAs in mean-variance portfolio optimization (MVPO) and identified three types of problems, including unconstrained and cardinality-constrained portfolio optimizations as well as transaction costs. This led to a review of MVPO based on three categories, including metaheuristics at 82%, machine learning at 12%, and exact solutions at 6% [12]. Zhang. et al. [13] also reviewed several factors that significantly enhanced the performance of the MVPO model, including dynamic robust, and fuzzy portfolio optimization as well as the incorporation of practical factors. It was reported that a robust portfolio directly considered estimation errors during the decision-making process. Furthermore, robust optimization typically aims to identify optimal solutions for specific problems while accounting for uncertain input parameters.

This study is organized into four sections. The second section outlines the SLR method adopted. The third section starts with an analysis of the objectives and methodologies used in past studies along with the applications for capital allocation in stock investment and the proposed solutions discussed. The discussion ends with a summary of the identified study gaps. The fourth section explores potential future directions, and the fifth section concludes the entirety of this study.

2. Materials and Methods

2.1. Selection Method

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were used to conduct the SLR [14]. The method was selected because it offered clear instructions for performing an SLR [15] and improved both the methodological rigor and the precision of reporting. The stages of the PRISMA method are presented in Figure 1.

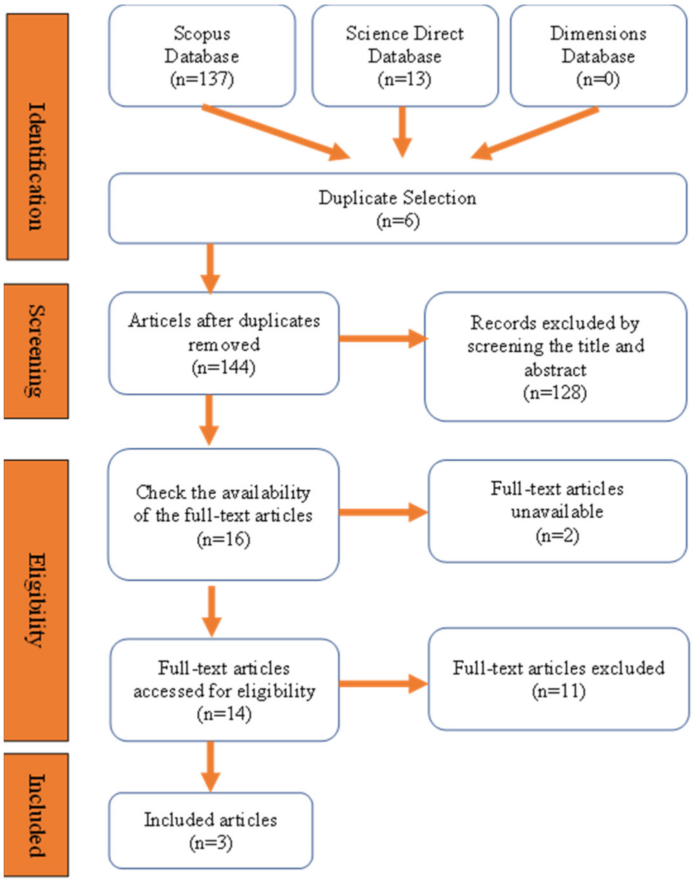

Figure 1. PRISMA stages.

2.1.1. Identification Stage

The Scopus, Science Direct, and Dimensions databases were used for the search with a focus on the following criteria:

(i) Articles;
(ii) Journal sources;
(iii) Written in English;
(iv) Published between 1995 and 2024;
(v) Related to robust portfolios;
(vi) MV or Markowitz;
(vii) Stocks;
(viii) GAs;
(ix) Published in Scopus.

Although Scopus and ScienceDirect are Elsevier products, each database caters to different aspects of the research process, which is why their approaches to literature selection differ. Scopus provides a broad, inclusive overview of academic research through abstracts and citations, while ScienceDirect offers detailed, full-text access to specific articles and book chapters published by Elsevier. This is reflected in the search results for the same keywords in Table 2, where the number of articles from the Scopus and ScienceDirect databases is different.

Table 2. Number of articles retrieved from Scopus, ScienceDirect, and Dimensions.

Code	Keyword	Number of Articles			Total
		Scopus *	**Science Direct ****	**Dimensions *****	
A	("robust portfolio")	2825	433	324	3582
B	("robust portfolio") AND ("mean-variance" OR "Markowitz")	1.338	226	66	1630
C	("robust portfolio") AND ("mean-variance" OR "Markowitz") AND ("stocks")	814	142	20	976
D	("robust portfolio") AND ("mean-variance" OR "Markowitz") AND ("stocks") AND ("genetic algorithm")	137	13	0	150
	Total	5114	814	410	6338

* sourced from https://www.scopus.com/. ** sourced from https://www.sciencedirect.com/. *** sourced from https://www.dimensions.ai/.

The titles, abstracts, and keywords of the articles were examined using specified search terms in order to ensure that the fifth through eighth criteria were satisfied. The keywords used during the search identification phase included ("robust portfolio") AND ("mean-variance" OR "Markowitz") AND ("stocks")" AND ("genetic algorithm"), as presented in Table 2. This led to the retrieval of 150 articles, including 137 from Scopus, 13 from ScienceDirect, and 0 from Dimensions. All the articles were evaluated, and six duplicates were removed, leaving 144 for subsequent use in the screening stage.

2.1.2. Screening Stage

During the screening phase, two co-authors independently reviewed the titles and abstracts of the 144 identified articles to ensure they were relevant to robust portfolios (the fifth criterion), MV or Markowitz (the sixth criterion), stocks (the seventh criterion), and the GA (the eighth criterion). To reduce subjectivity, the following process was used: an article advanced to the next phase if both co-authors agreed on its inclusion. If only one co-author included an article, they discussed it to reach a decision. If they could not agree, the lead author independently reviewed the abstract and made the final decision. This phase resulted in the retention of 16 articles.

2.1.3. Eligibility Stage

During the eligibility phase, we initially excluded two articles because their full texts were unavailable. Then, three co-authors independently reviewed the remaining 14 articles (referred to as Dataset 1) to determine whether they met the criteria related to robust portfolios (the fifth criterion), MV or Markowitz (the sixth criterion), stocks (the seventh criterion), and the GA (the eighth criterion). The same exclusion procedure used in the screening phase was applied here, but this time, it was based on the full texts. The 14 articles included 13 from Scopus and one from ScienceDirect. Following this, a bibliometric analysis was conducted on Dataset 1, leading to the complete list, full-text selection, and reference relevance, as presented in Table 3. At this stage, an article advanced to the next phase if all three co-authors agreed on its inclusion. If only two co-authors included an article, the lead author made the final decision. As a result, we retained a total of 3 articles (referred to as Dataset 2) for the SLR analysis.

Table 3. Summary of Dataset 1 based on accessibility and relevance of full texts and references.

No	RQ1	RQ2	RQ3	RQ4	RQ5	Description	Ref
1	Develop a novel portfolio modeling strategy considering data uncertainty using robust optimization methods.	New portfolio modeling with uncertain data and robust optimization methods.	GA.	Five indices from global capital markets (1992–1997).	To address the problem with a practical level of perturbation.	Reference Paper	[14]
2	Examine high- and low-return stocks, evaluate portfolio risk through fund standardization, and design a low-risk, stable-reward portfolio.	Fund standardization.	GA, Sharpe ratio.	*Taiwan Economic Journal* (2010–2016).	Precisely develop a portfolio that minimizes risk while maximizing rewards.	Not Suitable	[15]
3	Investigate portfolio problems with asymmetric distributions and uncertain parameters.	Robust multi-objective portfolio models with higher moments.	Multi-objective particle swarm optimization.	Ten Chinese stocks (2006–2010).		Not Suitable	[16]
4	Introduce a novel method for calculating relative-robust portfolios.	Relative-robust portfolios based on minimax regret.	GA.	DAX index (1992–2016).	Calculation of the proposed robust portfolios for the minimax regret solutions.	Reference Paper	[17]
5	Introduce a new decision-making framework for stock portfolio optimization using hybrid meta-heuristic algorithms.	The MV method has the followingrisk levels: mean absolute deviation (MAD), semi-variance (SV), and variance with skewness (VWS).	Electromagnetism-like Algorithm (EM), Particle Swarm Optimization (PSO), GA, Genetic Network Programming (GNP), and Simulated Annealing (SA).	Tehran Stock Exchange.	-	Not Suitable	[18]
6	Develop portfolio selection models offering limited assets to minimize costs and remain robust.	Sparse and robust portfolios.	L 2 -Norm regularization and worst-case optimization.	Kenneth French's 49 industry portfolios (1975–2014).	-	Not Suitable	[19]
7	Enhance the efficiency of a diversified stock portfolio using a grouping GA.	MVPO with four fitness functions and a trading mechanism.	GA.	Taiwan Stock Exchange (2010–2014).	To address the GSP (Group Stok Portfolio) optimization problem.	Not Suitable	[20]
8	Introduce methods to optimize the variance and covariance of asset returns without expected return estimates.	Global minimum variance portfolio, robust optimization	-	Euro Stoxx50 index (1992–2016).	-	Not Suitable	[21]

Table 3. *Cont.*

No	RQ1	RQ2	RQ3	RQ4	RQ5	Description	Ref
9	Examine the MV portfolio optimization model under specific constraints in uncertain conditions.	Cardinality constraints mean-variance (CCMV) and robust counterpart.	-	S&P 500 Communication Service.	-	Not Suitable	[22]
10	Develop Data Envelopment Analysis (DEA) models consistent with diversification and study parameter uncertainty effects.	DEA under the MV framework; parameter uncertainty.	-	Thirty American industry portfolios.	-	Not Suitable	[23]
11	Address potential estimation inaccuracies in MVPO.	Conventional multi-objective evolutionary algorithms.	-	Comprehensive financial indices (2006–2020).	-	Not Suitable	[24]
12	Analyze clustering outcomes to select top-performing stocks using a GA for portfolio weighting.	Self-Organizing Maps (SOMs), MV.	GA.	LQ45 shares (2018–2019).	To obtain the best offspring to produce the optimal solution for the problems at hand.	Not Suitable	[25]
13	Develop a more aggressive robust Omega portfolio.	Robust Omega Portfolio.	GA.	The dataset of 30 U.S. industry portfolios was sourced from Kenneth R. French's website.	To solve the mixed-integer programming problem suggested in the preselection.	Not Suitable	[26]
14	Improve MVPO considering integer transaction lots and robust covariance matrix estimators.	Markowitz portfolio, transaction lots, robust estimation	GA.	Six stocks in the Indonesia Stock Exchange. Distribution with contamination.	To complete integer optimization.	Reference Paper	[27]

The following study questions (RQs) were previously determined to ensure easy analysis of the gaps in Dataset 1:

RQ1: What goals were intended to be achieved in the portfolio?

RQ2: What methods were used to obtain maximum portfolio returns?

RQ3: What methods were used to solve portfolio selection problems under . . .. . . conditions of uncertainty?

RQ4: What types of stocks were used in the simulation?

RQ5: What was the role of the GA in solving portfolio problems with an element of . . .. . . uncertainty?

The rationale for selecting RQ1 through RQ5 can be explained as follows:

(a) RQ1: This question assisted in identifying the primary objectives that the portfolio aims to achieve. Understanding these goals is essential as it guides the entire analysis and strategy formulation in portfolio management, ensuring that the research outcomes are aligned with the intended objectives.
(b) RQ2: This question assisted in determining and evaluating the methods employed to maximize portfolio returns. By exploring the strategies used, this research can assess the effectiveness of different investment approaches within the context of this study.
(c) RQ3: Given that uncertainty is a key factor in investment decisions, this question focuses on the methods used to address portfolio selection challenges under uncertain conditions. Understanding these methods is vital in analyzing how risks are managed and how investment decisions are made in unpredictable environments.
(d) RQ4: This question aims to clarify the types of stocks included in the simulation. Knowing the stock types helps contextualize the research findings and ensures that the selected stocks are representative of relevant market conditions.
(e) RQ5: This question explores the role of genetic algorithms (GAs) in solving portfolio problems involving uncertainty. By addressing this question, this research can evaluate the effectiveness of the GA as an optimization technique in complex and uncertain scenarios.

Collectively, these research questions are designed to provide a comprehensive understanding of the goals, methods, assets, and techniques involved in the study of portfolios, particularly in managing uncertainty.

2.1.4. Inclusion Phase

The information presented in Table 3 provides insights into the evolution of study themes across different time frames, emphasizing the emergence, development, and interplay of key thematic areas within the analyzed literature. The analysis led to the conclusion that Dataset 2, consisting of one article from ScienceDirect and two from Scopus, was obtained using Dataset 1, covering 2012 to 2023. This was based on the content, which focused on a robust mean-variance portfolio and later developed with a GA over time, followed by a detailed explanation in the Results Section. Refined Dataset 2 was subsequently subjected to further analysis, and the results from the selection process are presented in Table 4.

Table 4. The number of articles selected based on the PRISMA framework.

Database	Data Code D	Duplicate		Abstract and Title		Full Text	
		I	E	I	E	I	Ex
Scopus	137	137	0	13	124	2	13
ScienceDirect	13	7	6	1	0	1	0
Dimensions	0	0	0	0	0	0	0
Total	150	144	6	14 *	124	3 **	13

* Dataset 1 for bibliometric analysis, ** Dataset 2 for the literature review, E = Excluded, I = Included.

2.2. Bibliometric Analysis

Bibliometric analysis was applied to Dataset 1. This method has been frequently used in literature reviews to determine a bibliographic overview of scientific selections from highly cited publications. The method has the capacity to generate lists of author contributions, national or subject bibliographies, and other subject-specific patterns [28]. The analysis in this study was conducted using resVOSviewer 1.6.19 and R-bibliometrix 4.2.3. VOSviewer 1.6.19 is a software program designed for bibliometric mapping [29], while R-bibliometrix 4.2.3 is an open-source R package with a Shiny web interface that enables comprehensive analysis and scientific mapping of data containing complete bibliographic information [30]. It is important to state that both tools offer distinct advantages for bibliometric analysis.

3. Results

3.1. Bibliometric Results

The results in this section are presented in four parts, including the following: (1) Most Globally Cited Documents in Dataset 1, (2) the Representation Network of Dataset 1, (3) Mapping the Themes in Dataset 1, and (4) the Theme Evolution of Dataset 1.

3.1.1. The Most Globally Cited Documents in Dataset 1

Figure 2 shows Dataset 1 based on the yearly publication frequency and number of citations, created using R-bibliometrix 4.2.3 software. The topic was observed to have been introduced in 2012 and gained traction, particularly in 2018 and 2019. Moreover, the results showed that the articles on RPMV were highly cited in 2019, with the highest recorded for Bavardsad Salehpoor, followed by Chen C [16] and another [14].

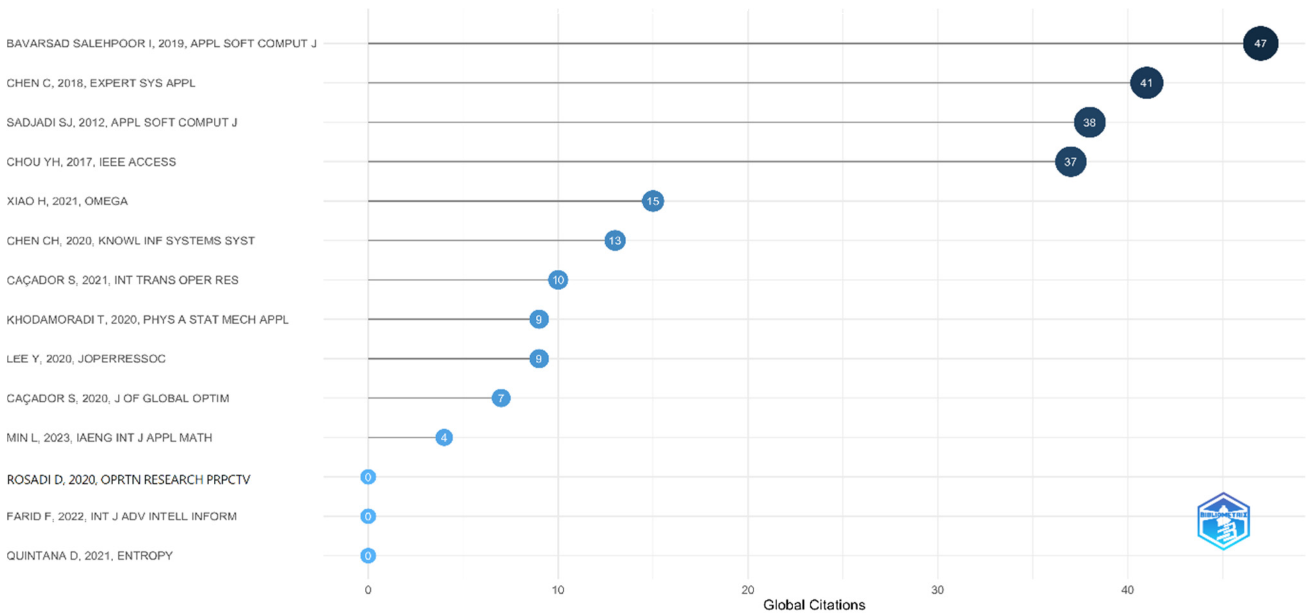

Figure 2. Categorization of Dataset 1 by publication year and citation counts. Sourced from https://www.r-project.org/.

3.1.2. The Representation Network of Dataset 1

The next stage was to identify the popular topics frequently covered in Dataset 1 based on the frequency of relevant words appearing across all the articles. The results are visually presented in Figure 3, created using VosViewer software version 1.6.18, with a focus on the associations among all the words. Moreover, only the words that appeared more than once are presented in order to simplify the figure.

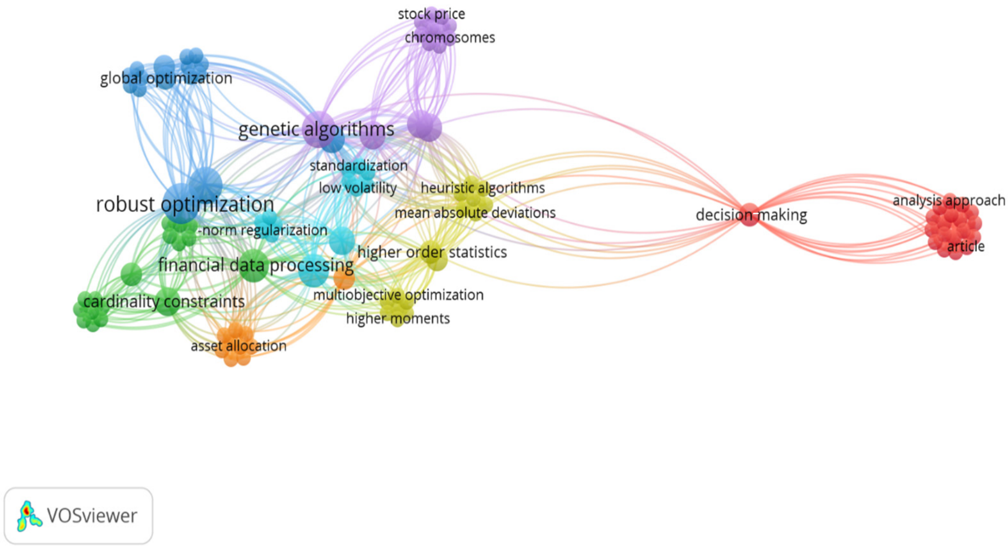

Figure 3. A representation of the commonly appearing words across Dataset 1. Sourced from https://www.vosviewer.com/.

The size of each circle shows the frequency of occurrence for the words in Dataset 1, where larger circles represent more frequent mentions, while smaller circles indicate fewer mentions. The lines connecting the circles symbolize relationships among words, and the existence of more lines suggests a higher level of association. Furthermore, the color of each circle represents a word cluster. and those with the same color belong to the same group. The distance between circles also signifies the intensity of the relationship among the words, such that closer circles are believed to have a stronger connection.

The circles labeled "robust optimization" and "genetic algorithms" in Figure 3 are large, have short connecting lines, and belong to different clusters. This shows that the two terms have a strong relationship and are among the fourteen most frequently discussed topics. Another set, "global optimization", "optimization modeling", "robust minimum variance", "expected utility", and "minimax regret", signifies the study goals. This shows that the models presented in the fourteen articles analyze the practical application and case studies in addition to the formulation of RPMV. Moreover, another group of terms, including "cardinality constraint", "financial data processing", "omega ratio", "model-independent", "non-Gaussians", "covariance matrix", and "data uncertainty," represents different robust optimization variables considered. There is also a group with terms such as "mean-variance", "semi-variance", "variance with skewness", and "mean absolute deviation", which were applied to show different portfolio optimization models aimed at achieving high returns. Finally, the circles containing "chromosomes," "fitness functions," "genetic operation", "grouping problem", "stock portfolio", and "stock price" show the different stages of implementing a GA.

3.1.3. Mapping the Themes in Dataset 1

Figure 4 shows the themes mapped from 2012 to 2023 using R-bibliometrix 4.2.3 software in order to visualize the distribution of the topics within Dataset 1 across different quadrants and clusters as well as offer a clear view of the development and relative position of each over the study period. From 2012 to 2023, all topics were observed across four quadrants and seven distinct clusters. The three most significant clusters were identified to be robust optimization and minimum variance, the GA and Sharpe ratio, as well as portfolio optimization and portfolio selection. These clusters were prominently situated in the first quadrant, showing strong internal relationships. Specifically, robust portfolio optimization with GA was the dominant topic within the portfolio optimization theme quadrant, thereby showing significant connections with other clusters during the period.

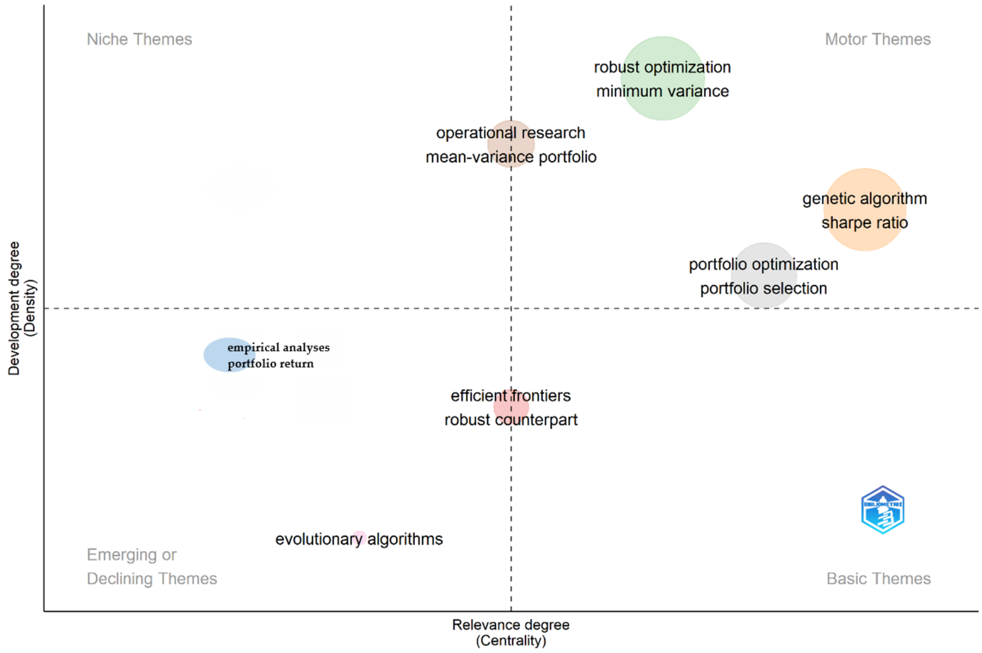

Figure 4. Mapping of the themes. Source from https://www.r-project.org/.

3.1.4. The Theme Evolution of Dataset 1

The evolution of themes in Dataset 1 was analyzed through the application of the Keywords Plus parameter to track thematic shifts. The parameter required a minimum cluster frequency of five and two labels. Two intersection points as foundational elements were identified. Moreover, the thematic evolution was delineated across three distinct periods, including 2012–2017, 2018–2020, and 2021–2023, represented by 1, 2, and 3, respectively, as presented in Figure 5. These divisions facilitated detailed observations of the change and development in the themes over the specified intervals. This offered a comprehensive view of the dynamics of primary themes under scrutiny in the literature.

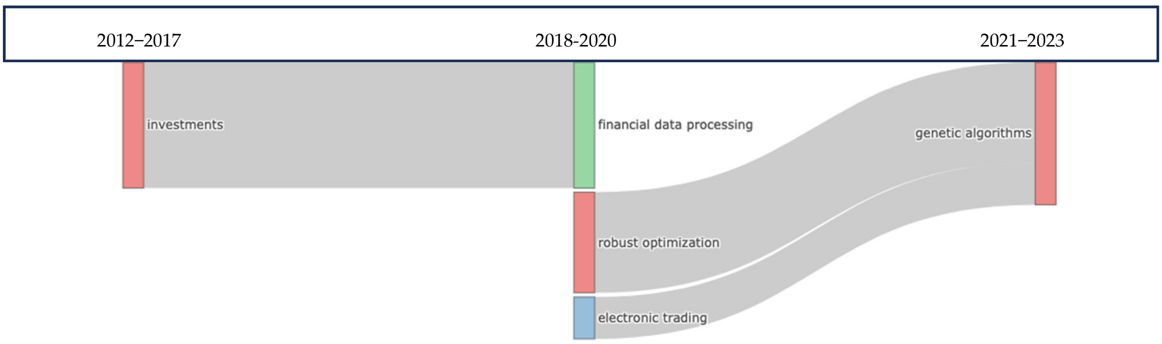

Figure 5. Visualization of the evolution of themes. Source from https://www.r-project.org/.

During period 1, the focal theme was solely investment, which later evolved in period 2 because of the incorporation of financial data processing, robust optimization, and electronic trading. Although the financial data processing that dominated period 2 did not advance further, robust optimization and electronic trading continued to develop, leading to the emergence of the GA in period 3. This evolution shows the ongoing relevance and potential for further exploration of topics related to robust optimization and GAs.

3.2. Results from SLR

The results presented in Tables 3 and 4 were used to analyze Dataset 2. The first part of this section discusses the identification of the study objectives in the articles. The second part discusses the methodology applied to obtain maximum portfolio returns. The third part explains the methodology used in the portfolios under uncertainty, and the final part discusses the types of stock used in the modeling data simulations.

3.2.1. RQ1: Study Objectives

According to Sadjadi et al., robust optimization is an established concept, but recent progress shows the challenges of handling uncertainty in optimization problems. It is widely acknowledged that the optimal solution to a linear programming problem is located at an extreme point or on the boundary of the feasible region. Therefore, their study aimed to introduce a new framework for formulating and solving cardinality-constrained portfolio problems under uncertainty using robust optimization methods, particularly emphasizing the D-norm, and to validate the results in real-world investment scenarios [14].

Cacador et al. emphasized that although empirical applications of relative-robust models in portfolio optimization theory are limited, the practical advantages are being investigated. Their study aimed to introduce a novel method for computing relative-robust portfolios through the minimax regret method [17]. Moreover, Rosadi et al. expanded the study on MVPO by integrating robust estimators for the covariance matrix with integer transaction lots. Their study focused on enhancing MVPO by considering integer transaction lots and using robust covariance matrix estimators to manage outliers and optimize portfolios with moderate lot sizes [17].

In summary, the main aim was to present a new portfolio model with cardinality constraints that considered uncertainty factors. The model used robust optimization methods with D-norm [14], minimax regret [17], and IoT transactions [27].

3.2.2. RQ2: Study Methodologies Used to Obtain Maximum Portfolio Return

The portfolio selection conundrum has garnered significant attention in the financial literature over the past few decades. The MV model is recognized for introducing portfolio selection as an optimization challenge. It concentrates on assessing the value and risk of portfolios rather than individual securities, commonly known as modern or Markowitz portfolio theory. The main benefit of the MV model is its ability to achieve diversified asset allocation. The following mathematical framework is often used to determine optimal asset allocation by balancing the trade-off between risk and return:

$$\begin{aligned} &\max z = \mu' x - \lambda x' \textstyle\sum x \\ &\text{subject to } \mathrm{x}' e = 1 \end{aligned} \tag{1}$$

where the set of asset allocations within a portfolio is $\mu \in \mathbb{R}^n$, associated with the vector of expected returns $\Sigma \in \mathbb{R}^{nxn}$ of the covariance matrix related to the asset returns. Moreover, vector e consists of all ones, and λ is a constant linked to the risk aversion level of the investor [31]. Sadjadi et al. reformulated the model of the cardinality-constrained portfolio problem as follows [14]:

$$\begin{aligned} \max w = \quad & w - \sum_{i=1}^{n} \hat{\mu}_i x_i + z\Gamma + \sum_{i=1}^{n} p_i \leq 0, \\ \text{subject to} \quad & \delta_i \sigma_i y_i \leq z + p_i,\ \forall i = 1, \ldots, n, \\ & -y_i \leq x_i \leq y_i, \forall i = 1, \ldots, n, \\ & \sum_{i=1}^{n} u_i = k, \\ & \sum_{i=1}^{n} x_i = 1, \\ & LB_i u_i \leq x_i \leq UB_i u_{i,}\ \forall i = 1, \ldots, n, \\ & u_i \in 0, 1,\ \forall i = 1, \ldots, n, \\ & z \geq 0, x_i \geq 0,\ y_i \geq 0, p_i \geq 0,\ \forall i = 1, \ldots, n. \end{aligned} \tag{2}$$

Model (2) is a refinement of model (1), which incorporates additional assumptions and initially considers the uncertain returns associated with each risky asset. For example, one study was focused on concurrently maintaining a fixed number, k, of these assets given a set of risky assets with uncertain returns $\tilde{r}_i$. For each risky asset, denoted as i, lower and upper bounds, LB_i and UB_i, respectively, were established with x_i used to represent the portion of the portfolio allocated to each asset. A binary variable, u_i, was introduced, which took the value of one when investment occurred in each asset and zero otherwise. Moreover, a fixed number of assets held, denoted as k, was stated, and short selling was prohibited to enhance the realism of the problem. In the robust formulation, the parameter p_i was essential to maintain system convexity while Γ regulated the likelihood of constraint violation and degradation of the objective function, referred to as the "price of robustness" by Bertsimas and Sim [32]. Γ assumed any real value between 0 and the number of uncertain data points in each constraint, denoted as $|j_i|$. When $\delta = 0$, the nominal solution was produced, but $\delta = n$ represented the worst-case scenario, where uncertainty existed across all input parameters. Furthermore, Cacador et al. introduced the problem of maximizing the expected utility of portfolio as follows:

$$\begin{aligned} &\max E = \left[u\left(W\left(1 + r^p_{t+1}\right)\right)\right] \\ &\text{subject to } \mathrm{x} \in \mathrm{X} \end{aligned} \tag{3}$$

where W denotes the total wealth invested across a collection of N stocks and $x \in \mathbb{R}^N$ represents the vector determining the weight combination for portfolio of investors. At period $t + 1$, r^p_{t+1} is the portfolio return, u denotes the utility function, and X represents the feasible solutions set. To characterize the preferences of the investor, used the power utility function, reflecting Constant Relative Risk Aversion (CRRA) preferences regarding wealth, with a CRRA parameter ($\gamma \in \mathbb{R}^+ \setminus \{1\}$) defined as [17]:

$$u\left(1 + r^p_{t+1}\right) = \frac{\left(1 + r^p_{t+1}\right)^{1-y}}{1 - y} \tag{4}$$

In the empirical application, adopted CRRA preferences and used the power utility function that was previously discussed [17]. Moreover, uncertainty was integrated into both the asset returns vector and the returns covariance matrix. A unified uncertainty set for the uncertain parameters was established based on the method described in [33]. The weight combination vector corresponding to the minimax regret solution, denoted as x, was also determined by solving the relative-robust optimization model:

$$\min_{x \in X} \max_{s \in U} E\left[u^s\left(1 + r^p_{t+1}\right)\right] - E\left(u^s\left(1 + r^p_{t+1}\right)(x)\right) \tag{5}$$

where each s_i is defined as follows (for brevity, the index i was omitted in the definition):

$$s = \left(\mu^s, \sum s\right) \tag{6}$$

$$\mu^s = \begin{bmatrix} \frac{1}{J} \sum_{j=z(s)}^{z(s)+J-1} r_{j1} \\ \vdots \\ \frac{1}{J} \sum_{j=z(s)}^{z(s)+J-1} r_{jN} \end{bmatrix} \tag{7}$$

$$\sum^{s} = \frac{1}{J-1} \sum_{j=z(s)}^{z(s)+J-1} \left(r^s_j - \mu^s\right)\left(r^s_j - \mu^s\right)^T \tag{8}$$

In the absolute-robust portfolio optimization method, the portfolio that maximized the minimum possible outcome or maximin solution was defined using the appropriate vector of weights, as presented in the following formula:

$$\min_{x \in X} \max_{s \in U} E\left[u^s\left(1 + r_{t+1}^p(x)\right)\right] \tag{9}$$

Rosadi et al. further presented robust covariance estimators as follows [27]:

$$\begin{aligned} &\min w = w^T \sum w \\ &\text{subject to } \sum_{i=1}^{n} k x_i c_i \leq b \\ &w_j = \frac{c_j x_j}{\sum_{i=1}^{n} x_i c_i}, j = 1, 2, \ldots, n, \\ &x \text{ is an integer} \end{aligned} \tag{10}$$

where b is assumed to represent the capital to be invested in n available shares at time t. Suppose c_i is the price per share of the ith share and k represents the number of shares per lot and assume that Σ denotes the variance–covariance matrix estimated using previous data. Then, the weight of the ith asset, w_i, and the number of lots of the ith asset, $\mathrm{x_i}$, can be determined by solving the following optimization problem (assuming the short sale is prohibited). Therefore, Rosadi et al. defined the modified weight after lot calculation as follows [27]:

$$w_j = \frac{c_j x_j}{\sum_{j=1}^{n} x_j c_j}, j = 1, 2, \ldots, n, \tag{11}$$

The modified weight included in the weight vector, w, was used in the fitness function as follows:

$$F = w^T \sum w - \in \left| b - \sum_{j=1}^{n} c_j x_j \right| \tag{12}$$

In the above function, the second term acted as a penalty to ensure that the total investment amount remained close to the total available capital b. Moreover, by adjusting the value of ε, the algorithm is allowed to determine the portfolio where the total value closely matches b. Essentially, this allows the investor to allocate nearly all of the available capital when desired. In summary, the portfolio was maximized by initially applying the MV portfolio method, which was adapted to incorporate the uncertainty associated with returns on risky assets [14], incorporating the power utility function to reflect CRRA preferences concerning wealth [17] and adjusting the weight w using the fitness function [27].

3.2.3. RQ3: Study Methodologies for Portfolios under Uncertainty

Sadjadi et al. developed a traditional GA method to produce high-quality and efficient solutions for the cardinality-constrained portfolio problem. In response to the lack of feasible solutions for robust portfolio optimization, specifically under increasing uncertainty, a straightforward GA method was introduced to identify near-optimal solutions. Sadjadi et al. also adopted several norms in the proposed methods, and the preliminary results showed that the D-norm performed better than the LP-norm by achieving relatively lower CPU times [14].

The relative-robust optimization problem (5) using the GA toolbox in Matlab R2018a after determining the optimal solutions for each scenario S within the uncertainty set U [17]. An initial population of randomly generated feasible solutions was used with the application of several options from the GA toolbox, including uniform mutation with a probability rate of 0.15. A similar procedure was followed to compute the absolute-robust portfolio with an uncertainty set U constructed from each estimation subsample, as previously explained. After computing the S scenarios, the maximin solution was found by solving the problem (9) using the GA. In this case, the fitness function was defined as the minimum expected utility of the portfolio across all scenarios in U (inner maximization problem in (9)). Therefore, optimization was considered the worst-case performance across the entire uncertainty set. The initial population was made up of randomly generated feasible solutions, using the same GA options as in the relative-robust method. Each maximin solution was subsequently evaluated across the validation subsamples by calculating the expected utility for each validation subsample and identifying the lowest expected utility. The absolute-robust portfolio was later found as the solution with the best worst-case performance based on the highest minimum expected utility.

Applied a popular heuristic GA method commonly used in portfolio optimization to solve the problems identified in the model [27]. The method was initially proposed by Holland based on the principles of natural selection and genetic theory. In the GA, each potential solution was encoded as a chromosome, and the algorithm was initiated by generating an initial population of chromosomes followed by the selection of pairs known as "parents". The selected pair produced new chromosomes to present the next generation using crossover and/or mutation operators with specified probabilities. Moreover, a fitness function developed based on the objective function of the problem was used to assess the performance of each solution represented by the chromosomes. The cycle continued over several generations until a final termination condition was achieved. The fundamental steps of the GA developed by Chang et al. are stated as follows [8]:

1. Generate an initial population of multiple chromosomes.
2. Assess the fitness of each chromosome in the population.
3. Select "parents" from the population.
4. Form the next generation by combining parents through crossover and mutation.
5. Evaluate the fitness of the new generation.
6. Replace part or all of the current population with the new generation.
7. Repeat steps 3 to 6 until a satisfactory solution is achieved.

Arnone et al. pioneered the application of the GA to solve portfolio optimization problems, while several studies, such as Chang et al. [6], Soleimani et al. [7], and Chang et al. [18], showed its capability to determine near-optimal or even optimal solutions efficiently. In conclusion, the GA was found to be effective for tackling portfolio problems under uncertainty and in efficiently determining near-optimal or even optimal solutions. The method also showed relatively lower CPU times, with D-norm observed to have better results compared with LP-norm [14]. Furthermore, the GA was able to determine the optimal solution for each scenario within the uncertainty set U [17]. The robust estimator was also observed to perform better than classical maximum likelihood estimation when the data contained outliers and during several moderately sized instances [27].

3.2.4. RQ4: Types of Stocks

The necessary test data used by Sadjadi et al. [14] to solve numerical examples were sourced from the OR Library [34] or numerical examples. The first dataset included five indices from different global capital markets such as Hang Seng (Hong Kong), DAX 100 (Germany), FTSE 100 (UK), S&P 100 (USA), and Nikkei 225 (Japan). The focus was on mean, variance, and covariance values for 31, 81, 85, 98, and 225 assets, respectively, calculated from weekly stock prices spanning from March 1992 to September 1997. The resulting dataset was observed to be smaller than the actual index because of the exclusion of stocks with missing values. Meanwhile, the second portion of the data was subsequently generated randomly with future returns through a phenomenon referred to as the momentum effect [35].

For the empirical analysis, historical daily data from January 1992 to December 2016 (25 years) on stocks within the DAX index were collected from Thompson Reuters Datastream [17]. The adoption of historical windows of varying lengths enabled the authors to examine the impact of considering long-term versus short-term past data on defining the uncertainty set. Consequently, the method was used to investigate the influence of incorporating past long-term data on the predictive accuracy of the model. The results showed that past long-term returns, measured over extended periods, negatively correlated with future returns, a phenomenon known as the long-term reversal effect [36]. Meanwhile, short-term past returns, typically evaluated over the previous year, showed a positive correlation. Another study selected six stocks from the Indonesia Stock Exchange (IDX) and collected data spanning 20 months. The prices of all selected stocks ranged from IDR 3100 to IDR 9950. In summary, weekly or daily stock data was required to simulate a modified robust portfolio model. Stock data for analysis was sourced from the OR Library, while the DAX index was collected from Thomson Reuters DataStream and IDX.

3.2.5. RQ5: Role of GAs

Because of the absence of viable solutions for robust portfolio optimization, particularly under increasing uncertainty levels, a straightforward GA method to identify near-optimal solutions [14]. The process was initiated with the calibration of GA parameters using a full factorial analysis followed by the presentation of the results from both the GA and the exact solution. It was observed that the GA typically had superior performance when all input parameters were appropriately adjusted. Given the stochastic nature of any GA meta-heuristic method, statistical tests were required for validation. The phenomenon led to the observation of three key parameters requiring adjustment in the proposed GA, which included POP for the population size for each generation, RC for the crossover rate, and RM for the mutation rate.

The GA method was adopted in one study to compute the proposed robust portfolios, leading to the transformation of the three-level optimization problem into a two-level problem to achieve minimax regret solutions [17]. The results were analyzed by assuming different in-sample period lengths and varying values of the risk aversion parameter. Moreover, relevant conclusions were drawn about the real benefits of the proposed method from the perspective of the investors. Additional GA options used in this application included uniform mutation with a probability rate of 0.15 and tournament selection. Several authors have also reported the efficiency of GAs in addressing the challenges posed by computational complexity when solving portfolio optimization problems with future uncertainty. In the above study, the GA facilitated the simultaneous resolution of the second and third optimization levels, thereby reducing the computational effort required to determine robust solutions. The flexibility allowed the GA to identify portfolio opportunities that more traditional programming methods might not recognize.

Previous research shows that the GA is a heuristic method often used to solve integer problems [27]. It was used by Rosadi et al. to determine the optimal weights in portfolios, assuming that short selling was prohibited. The method had the capacity to identify a near-optimal or even optimal solution for portfolio optimization problems. This was based on the ability of the GA to determine a nearly optimal solution by tuning the parameters using full factorial analysis, transforming the three-level optimization problem into a two-level optimization problem and determining the optimal weights in portfolios based on the assumption that short selling was prohibited.

Table 5 lists various modifications to RPMV referenced from studies in Dataset 2, including specific techniques and approaches applied in RPMV. It covers the inclusion of uncertainty parameters, such as returns and covariances, to enhance optimization robustness. The classic mean-variance approach aims to maximize the mean return for a given level of risk. Cardinality constraints limit the number of assets in the portfolio for practicality. General optimization constraints include budget limits and transaction costs. The risk-aversion parameter reflects the investor's tolerance for risk, influencing the risk–return trade-off. Strategies for relative and absolute robustness ensure stable portfolio performance under various scenarios and extreme conditions. Robust covariance estimators use statistical methods to mitigate the impact of outliers and estimation errors. Additionally, genetic algorithms, inspired by natural selection, are employed to find near-optimal solutions in complex and non-linear optimization problems. Sadjadi et al. discussed the consideration of uncertainty parameters, mean-variance optimization, cardinality constraints, and the use of genetic algorithms [14]. Cacador et al. included additional considerations from sadjadi et al. such as risk aversion and relative and absolute resilience parameters [17]. Rosadi et al. focused on mean-variance, optimization constraints, and robust covariance estimators, as well as genetic algorithm approaches [27].

Table 5. The various modifications to RPMV methods in Dataset 2.

Ref.	Uncertainty Parameters	MV	Cardinality Constraint	Optimization Constraint	Risk-Aversion Parameter	Relative and Absolute Robustness	Robust Covariance Estimators	GA
[14]	✔	✔	✔	-	-	-	-	✔
[17]	✔	✔	✔	-	✔	✔	-	✔
[27]	-	✔	-	✔	-	-	✔	✔

4. Discussion

The preceding section showed the three areas that the analysis identified as requiring further studies. The gaps and suggested directions are explained as follows:

4.1. Limitations in Handling Uncertainty

The robust optimization method was able to address uncertainty in asset returns, but this article did not explore the different types deeply, particularly the uncertainties considered non-linear or complex, affecting the final results [14]. Moreover, the minimax regret model was used to handle uncertainty, but the assumptions associated might not always be valid or optimal for all market situations. For instance, the model assumed that investors exhibited consistent utility behavior, and this might not accurately reflect the actual condition in real markets [17]. In addition, robust estimators could manage data with outliers, but the assumptions associated might not always be valid or optimal for all types of data or market conditions, potentially limiting the generalizability of the proposed method [27]. Therefore, further study is needed on uncertainty models in robust portfolios to address non-linearities and inconsistent investor behavior as well as incorporate additional assumptions to optimize robust estimators for different market conditions.

4.2. Simple Assumptions on Robust Portfolio Parameters

The proposed model assumed static portfolio parameters, such as asset returns and covariance matrices. In reality, these parameters might fluctuate over time, necessitating a more dynamic method to manage the changes effectively [14]. Moreover, the optimization models discussed compared the performance of relative-robust portfolios to non-robust portfolios, absolute-robust portfolios [17], and robust estimators [27] but did not include newer and potentially more effective methods. Some of these include machine learning [37], data-driven [38], portfolio optimization models for risk-averse investors [39], or other methods such as robust optimization models that consider risk tolerance and risk-aversion factors.

4.3. Limited Empirical Validation

The use of several benchmark datasets is insufficient for broad real-world validation [14]. Moreover, the empirical validation conducted using data from the DAX index over a specific period might not be representative enough to determine the effectiveness of the method across different stock markets with varying characteristics [17]. This limitation restricted the generalizability of the results to other market conditions. The same trend was also observed for the data from the IDX [27]. Therefore, a more comprehensive empirical test is necessary to ensure the effectiveness of the proposed method across diverse real market conditions.

5. Conclusions

In conclusion, this literature review evaluated several robust portfolio optimization methods during uncertainty. The analysis showed the modification of methods to consider uncertainty in risky asset returns. The improvements included using a power utility function to reflect the preference of CRRA for wealth and adjusting the weights through a fitness function. The GA was also proven to be effective in solving portfolio optimization problems under uncertainty because of its ability to determine near-optimal or even optimal solutions at relatively lower CPU time efficiency compared with the other methods. It also was observed to have shown good performance in overcoming robust estimator problems on data containing outliers. Furthermore, the empirical validation conducted using the data from the DAX index and the Indonesian Stock Exchange (IDX) showed that the results obtained might not be generalizable to other market conditions with different characteristics. This showed the need for more comprehensive empirical tests to ensure the effectiveness of the proposed method in different real market conditions. Moreover, weekly or daily data needed to simulate the modified robust portfolio model were obtained from the OR library, DAX index, and IDX, with a focus on several global indices as well as historical stock data. Overall, this study showed that although existing methods had great potential in robust portfolio optimization, there is a need to further test and develop new methods considered more adaptive to market uncertainty and variability.

The policy implications of this study are that policymakers should consider developing and implementing regulations that encourage the adoption of robust portfolio optimization techniques, such as those integrating GAs. This can help financial institutions and investors better manage risks associated with market uncertainties and asset return fluctuations. A second implication is that there should be a concerted effort to promote the use of advanced analytical and optimization tools in the financial sector. By integrating methods like robust portfolio mean-variance optimization with genetic algorithms, financial analysts and portfolio managers can achieve more stable and higher returns, thereby enhancing overall market efficiency. By focusing on these policy implications, policymakers can help create a more resilient financial system capable of withstanding uncertainties and providing stable returns to investors.

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