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Review

A comprehensive review of deterministic models and applications for mean-variance portfolio optimization

Can B. Kalayci*, Okkes Ertenlice, Mehmet Anil Akbay

Pamukkale University, Faculty of Engineering, Department of Industrial Engineering, Kinikli, 20160, Denizli, Turkey

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ABSTRACT

Portfolio optimization is the process of determining the best combination of securities and proportions with the aim of having less risk and obtaining more profit in an investment. Utilizing covariance as a risk measure, mean-variance portfolio optimization model has brought a revolutionary approach to quantitative finance. Since then, along with the advancements in computational power and algorithmic enhancements, a lot of efforts have been made on improving this model by considering real-life conditions and solving model variants with various methodologies tested on various data and performance measures. A comprehensive literature review of recent and novel papers is crucial to establish a pattern of the past, and to pave the way on future directions. In this paper, a total of 175 papers published in the last two decades are selected within the scope of operations research community and reviewed in detail. Thus, a comprehensive survey on the deterministic models and applications suggested for mean-variance portfolio optimization in which several variants of this model as well as additional real-life constraints are studied. The review classifies the approaches according to exact and approximate attempts and analyzes the proposed algorithms based on various data and performance indicators in depth. Areas of future research are outlined.

Contents

* Corresponding author.
E-mail address: cbkalayci@pau.edu.tr (C.B. Kalayci).

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1. Introduction

Individual investors, brokers and fund managers invest billions of dollars in various sectors every year. Therefore, proper security selection for financial investment comes into prominence since generating profit throughout all market climates and minimizing losses during market downturns are desired. The most common investment strategy is building a portfolio consisting of different securities in order to spread the risk. Traditional portfolio analysis requires the evaluation of return and risk conditions of individual securities and may not provide success due to its subjective nature. In 1952, performing an analysis of the impact of risk, Markowitz presented a revolutionary approach for portfolio theory called Mean-Variance (MV) model (Markowitz, 1952) and initiated the era of modern portfolio theory. Using covariance as a risk measure is the key of this revolution since it was a spark that triggered quantitative finance. Following this milestone, the MV model has been a standard decision-making approach to structure and measure the performance of portfolios (Rubinstein, 2002) that quantitatively focus on the investment alternatives utilizing the covariance between securities based on return-risk trade-off (Kolm, Tutuncu, & Fabozzi, 2014). Thanks to his pioneering works in finance theory, in 1991, Markowitz was awarded the Nobel Prize for economics. Along with the developments in computational power, a growing number of researchers from not only financial fields, but also computer scientists and mathematicians have engaged a great attention to portfolio optimization (PO), evident by the vast number of publications in scientific journals to deal with mean-variance portfolio optimization (MVPO). New constraints, objectives, and solution approaches have been developed to address shortcomings of the early MV model (Konno & Yamazaki, 1991; Rockafellar & Uryasev, 2000; Young, 1998).Thus, a significant number of academic papers has been reached by accumulation of successive additions to MV model.

Over the last decade, researchers have analyzed the current trends and future research directions on PO (Table 1). In this context, Azmi and Tamiz (2010) reviewed lexicographic, weighted, minmax and fuzzy goal programming models and discussed the issues concerning multi-period returns, extended factors and measurement of risk. Metaxiotis and Liagkouras (2012) and Ponsich, Jaimes, and Coello (2013) analyzed the current state of research in portfolio optimization with a focus on Multi Objective Evolutionary Algorithms in which the lack of many real-life constraints as well as ineffectiveness of Pareto ranking schemes in the presence of many objectives are indicated. Mansini, Ogryczak, and Speranza (2014) focused on linear programming solvable models in the portfolio optimization classifying the models according to decision variables used in the integration of real features. Kolm et al. (2014) discussed practical advances in MVPO and pointed out new research directions such as diversification methods and multi-period optimization. Aouni, Colapinto, and La Torre (2014) reviewed the lexicographic, weighted, polynomial, stochastic and fuzzy goal programming models and pointed out the lack in developing computerized decision support systems to accomplish a helpful tool to facilitate the decision-making process in portfolio optimization. Doering, Juan, Kizys, Fito, and Calvet (2016) focused on recent contributions of metaheuristics in the sense of an introduction to this topic supported with a numerical example. Masmoudi and Abdelaziz (2018) focused on deterministic and stochastic multi-objective programming models comparing the different assumptions and proposed solutions in portfolio optimization. Zhang, Li, and Guo (2018) reviewed various extensions of Markowitz's MV model such as dynamic, robust, fuzzy portfolio optimization with practical factors and pointed out that combined forecasting theory with portfolio selection would be a promising future research direction to deal with uncertainty. Aouni, Doumpos, Pérez-Gladish, and Steuer (2018) reviewed multiple criteria decision aid methods for portfolio selection with a focus on exact solution methods on the construction and optimization of portfolios as well as on the analysis and the evaluation of specific securities.

The primary purpose of this paper is to deeply analyze the publications based on deterministic models and applications in the MVPO literature. This paper classifies the scientific literature presenting a taxonomy of solution techniques on solving MVPO with the aim of answering the following five research questions: (*i*) Which deterministic models are mostly investigated? (*ii*) What practical constraints have been introduced for portfolio optimization? (*iii*) How have researchers handled problem constraints? (*iv*) Which solution techniques have been employed to solve MVPO at what rate? (*v*) Which data sets and performance measures have been used to test the algorithms designed?

Section 2 clarifies the applied research methodology while Section 3 is dedicated to the deterministic models for MVPO as well as problem types and additional constraints. Section 4 describes that data while performance measures utilized to test the proposed algorithms are investigated in Section 5. Section 6 provides a detailed look on the attempts of developing solution approaches for MV model while Section 7 concludes the paper and discusses future research directions.

2. Applied research methodology

Content analysis and description of research methodology are summarized in four categories: material collection, descriptive analysis, category selection and material evaluation (Govindan, Soleimani, & Kannan, 2015; Özceylan, Kalayci, Güngör, & Gupta, 2018).

2.1. Material collection

The material for the literature review is detailed in this section. The study was conducted by covering the journal papers, book chapters and proceedings written in English language published from 1998 to 2018.

The search terms were identified through several trial and error attempts according prior experience of the authors and the keywords utilized in various papers. A keyword structure (Table 2) that initially aims to reach a broad range of search for capturing various publications in MVPO literature is carried out. Level 1 defines the main search context while level 2 indicated various alternatives of an author's approach. Level 3 focused on mean-variance and finally, Fuzzy and Robust keywords are excluded since the models dealing with uncertainty and robust portfolio optimization are not within the scope of this study with level 4. Utilizing the "title, abstract, keywords" search in Google Scholar database

Table 1
Previous reviews on portfolio optimization.

Year	Publication	Perspective	Focus
2010	Azmi and Tamiz (2010)	Goal Programming	Lexicographic/weighted/minmax/fuzzy goal programming models
2012	Metaxiotis and Liagkouras (2012)	Multi-objective optimization	Multi-objective Evolutionary Algorithms
2013	Ponsich et al. (2013)	Multi-objective optimization	Multi-objective Evolutionary Algorithms
2014	Mansini et al. (2014)	Linear programming	Linear programming solvable portfolio optimization models
2014	Kolm et al. (2014)	Practical challenges	Practical advances in MVPO
2014	Aouni et al. (2014)	Goal programming	Lexicographic/weighted/polynomial/stochastic/fuzzy goal programming models
2016	Doering et al. (2016)	Computational analysis	Metaheuristics
2017	Masmoudi and Abdelaziz (2018)	Programming models	Deterministic and stochastic multi-objective programming models
2017	Zhang, Li and Guo (2018)	Uncertainty	Dynamic/robust/fuzzy portfolio optimization with practical factors
2018	Aouni et al. (2018)	Multiple criteria decision aid methods	Exact methods for portfolio selection possessing multiple criteria
	This study	Computational analysis	Exact and approximate attempts on deterministic models of MVPO

Table 2
The proposed keyword combination structure.

Level	Search terms				
1	Portfolio				
	AND				
2	Selection	OR	Management	OR	Optimization
	AND				
3	Mean-variance				
	AND NOT				
4	Fuzzy	OR	Robust		

which covers more publications than the Web of Science and Scopus databases, initially 34,100 publications are reached with the search. In order to obtain relevant publications about deterministic models and applications of MVPO from an operations research perspective, 175 papers are hand-selected, reviewed, classified and saved in a spreadsheet for a deeper analysis and evaluation.

2.2. Descriptive analysis

The publishing trend using the number of publications in a given year is demonstrated in Fig. 1. A total number 175 publications (20 book chapters, 56 proceedings and 99 articles) are reviewed. This significant growth in the number of publications is noticeable after 2009.

The publications and distribution of the journals, proceedings and book chapters are presented in Fig. 2, Fig. 3 and Fig. 4, respectively. Fig. 2 shows that among the journals, Expert Systems with Applications is dominant representing 15% of all published articles. In Fig. 3 and Fig. 4, it is shown that 88% of proceedings are published by IEEE while 95% of book chapters are published by Springer.

2.3. Category selection

The categorization applied in this review is formed based on different properties of deterministic models and applications on MVPO. The categories are formed according to the following criteria: models, constraints, constraint handling, solution techniques, performance measures and data. The main categories used to classify the publications are shown in Fig. 5 and are described below:

2.4. Material evaluation

To enhance the credibility of the research, during the validation stage, Microsoft Excel spreadsheet and Endnote reference manager software are also applied to evaluate, analyze and reduce errors. Other databases such as Web of Science and Scopus are used to enrich the study by adding those papers not found in the initial stage. An independent working strategy of authors is carried out to adequately investigate publications via a series of search and cross-check activities.

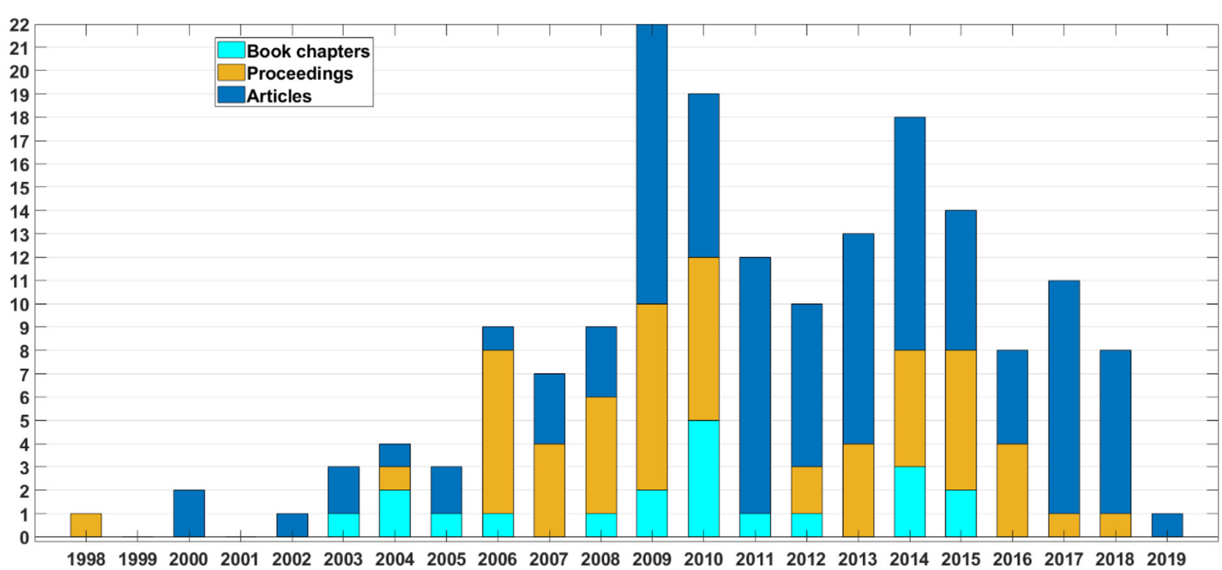

Fig. 1. Distribution of publications per year.

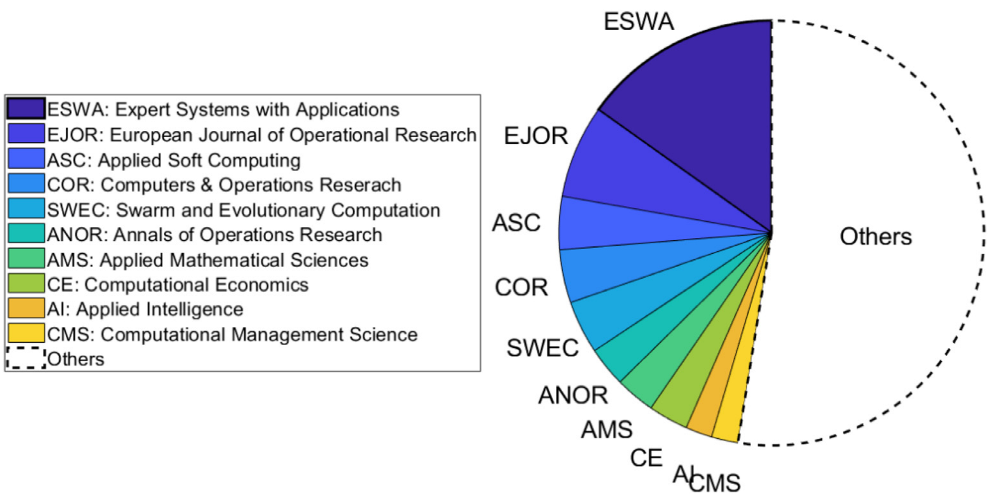

Fig. 2. Distribution of publications based on various journals (99 papers: 1998–2019).

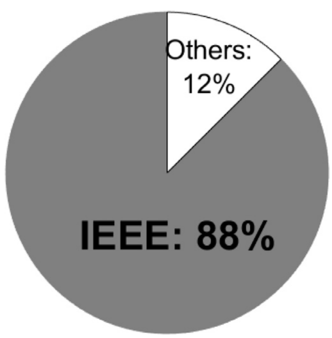

Fig. 3. Distribution of proceedings (46 proceedings: 1998–2018).

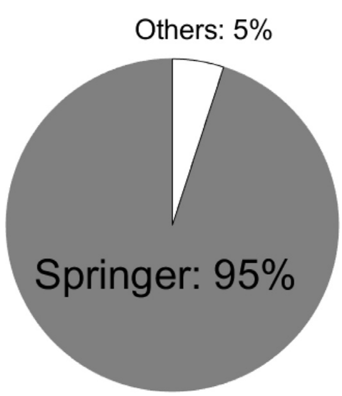

Fig. 4. Distribution of book chapters (36 book chapters: 1998–2018).

3. MVPO model

3.1. Single-objective MVPO model

The original MV model which aims to minimize risk (variance) for the desired level of return is a single-objective model.

Parameters

N	The number of assets available
μ_i	The expected return of asset i
σ_{ij}	The covariance between assets i and j
R^*	Desired expected return

Decision variables

w_i	The proportion held of asset

$$\begin{cases} \min \ \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij} & (1.1) \\ \textit{Subject to}: & \\ \sum_{i=1}^{N} w_i \mu_i = R^* & (1.2) \\ \sum_{i=1}^{N} w_i = 1 & (1.3) \\ 0 \le w_i \le 1, \qquad i = 1, \ \ldots, N & (1.4) \end{cases} \tag{1}$$

The objective function given in Eq. (1.1) aims to minimize risk while Eq. (1.2) guarantees to obtain returns at the desired return level. The investment of total budget is ensured by Eqs. (1.3) and (1.4) does not allow short sales. The original single objective MV model can also be rewritten as to maximize the return for a given level of risk. A portfolio obtained by solving model (1) by taking into consideration of minimum risk for a given level of return or a maximum return for a given level of risk is called efficient portfolio. However, to find an efficient portfolio, it is necessary to know either the level of risk that the investor can endure, or the desired return defined by the investor. In fact, it may not be quite possible in real world cases. So, to find the efficient portfolio among various combinations of assets in the solution space, instead of considering a single objective, researchers must consider all objectives at once. Therefore, the researchers transformed the single-objective model into a multi-objective model.

3.2. Multi-objective MVPO model

According to Zitzler (1999), the multi-objective mathematical model can be written as follows:

$$\begin{cases} \min \boldsymbol{f}(\boldsymbol{x}) = (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}) \ldots, f_p(\boldsymbol{x})) \\ \text{subject to: } \boldsymbol{e}(\boldsymbol{x}) = (e_1(\boldsymbol{x}), e_2(\boldsymbol{x}) \ldots, e_m(\boldsymbol{x})) \le \boldsymbol{0} \\ \text{where: } \boldsymbol{x} = (x_1, x_2, \ldots, x_n) \in \boldsymbol{X} \end{cases} \tag{2}$$

Where the constraints $\boldsymbol{e}(\boldsymbol{x}) \le 0$ determine the set of feasible solutions, $\boldsymbol{x} = (x_1,\ldots, x_n)$ is the vector of decision variables (parameters) and $\boldsymbol{X}$ is the decision space, p is equal to 1 in single-objective models and p is larger than 1 in multi-objective models.

Unlike single-objective optimization, a solution to a multi-objective problem is more of a concept than a definition (Marler & Arora, 2004). Therefore, it is significant to go through basic frameworks of this concept. Based on the structure defined by

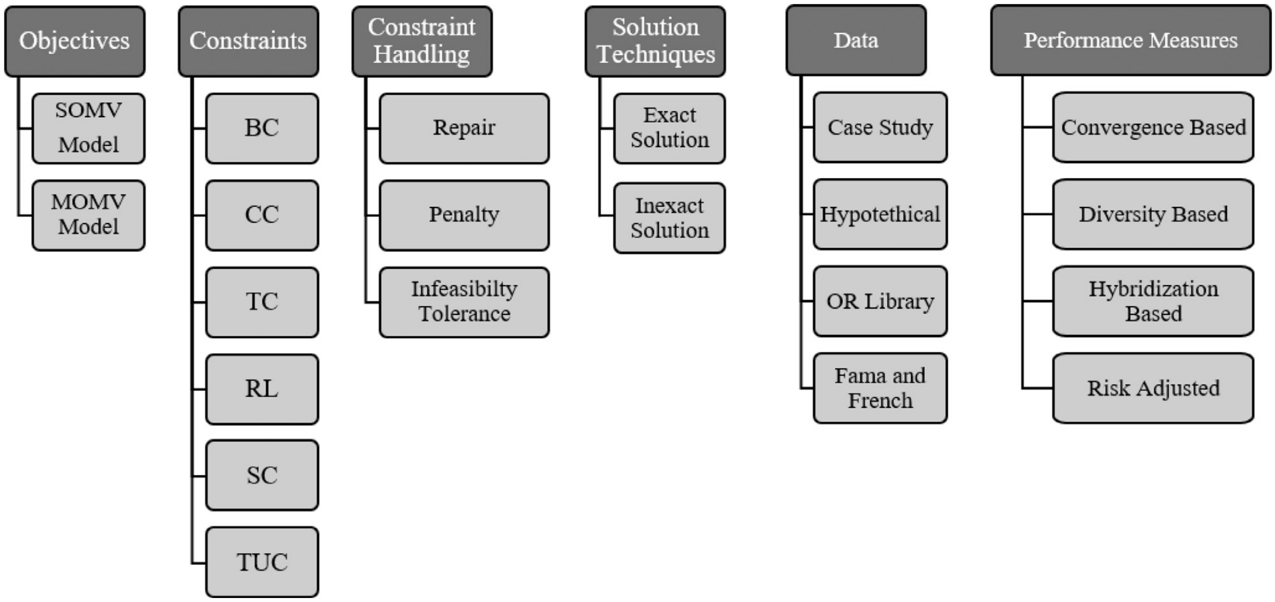

Fig. 5. Classification of models and applications on MVPO.
Single-objective MV (SOMV); Multi-objective MV (MOMV); Boundary Constraints (BC); Cardinality Constraints (CC); Transaction Costs (TC); Roundlot Constraints (RL); Sector capitalization Constraints (SC); Turnover Constraints (TUC); Methodologies to deal with various constraints on MVPO (Constraint handling); Various performance indicators to test the efficiency of proposed algorithms (Performance Measures);.

Zitzler (1999), the concepts of Feasible Set, Pareto Dominance, Pareto Optimality, Nondominated Sets are defined as follows:

Feasible Set

The feasible set $\boldsymbol{X_f}$ is defined as the set of decision vectors $\boldsymbol{x}$ that satisfy the constraints $\boldsymbol{e}(\boldsymbol{x})$.

$$\{\boldsymbol{X_f} = \{\boldsymbol{x} \in \boldsymbol{X} | \boldsymbol{e_i}(\boldsymbol{x}) \preccurlyeq \boldsymbol{0},\ \boldsymbol{i} = \boldsymbol{1}, \ldots, \boldsymbol{m}\} \tag{3}$$

The image of $\boldsymbol{X_f}$ denoted as $f(\boldsymbol{X_f}) = \bigcup_{\boldsymbol{x} \in \boldsymbol{X_f}} \{f(\boldsymbol{x})\}$ is the feasible region in the objective space.

Pareto Dominance

In model (4), concept of domination may be described as follows (Deb, 2001):

For any two decision vectors $\boldsymbol{u}$ and $\boldsymbol{v}$,

$$\begin{cases} \boldsymbol{u} \prec \boldsymbol{v} \text{ } (\boldsymbol{u} \text{ dominates } \boldsymbol{v}) \text{ if and only if } \boldsymbol{f}(\boldsymbol{u}) \prec \boldsymbol{f}(\boldsymbol{v}) \\ \boldsymbol{u} \preccurlyeq \boldsymbol{v} \text{ } (\boldsymbol{u} \text{ weakly dominates } \boldsymbol{v}) \text{ if and only if } \boldsymbol{f}(\boldsymbol{u}) \preccurlyeq \boldsymbol{f}(\boldsymbol{v}) \\ \boldsymbol{u} \sim \boldsymbol{v} \text{ } (\boldsymbol{u} \text{ is indifferent to } \boldsymbol{v}) \text{ if and only if } \boldsymbol{f}(\boldsymbol{u}) \not\preccurlyeq \boldsymbol{f}(\boldsymbol{v}) \text{ and } \boldsymbol{f}(\boldsymbol{u}) \not\succcurlyeq \boldsymbol{f}(\boldsymbol{v}) \end{cases} \tag{4}$$

Pareto Optimality

A decision vector $\boldsymbol{x} \in \boldsymbol{X_f}$ is said to be nondominated regarding a set $\boldsymbol{A} \subseteq \boldsymbol{X_f}$ if and only if there does not exist $\boldsymbol{u} \in \boldsymbol{A}$: $\boldsymbol{u} \prec \boldsymbol{x}$. $\boldsymbol{x}$ is set to be Pareto optimal if and only if $\boldsymbol{x}$ is nondominated regarding $\boldsymbol{X_f}$. The entire set of all Pareto-optimal solutions is called the Pareto-optimal set and the corresponding objective vectors form the Pareto-optimal front (Zitzler, 1999).

Nondominated Sets

Among a set of solutions $\boldsymbol{A}$, the nondominated set of solutions are those that are not dominated by any member of the set $\boldsymbol{A}$.

Because of the fact that addressing the MVPO by using a single objective problem-solving structure has several difficulties due to real-world conditions, multi-objective approaches have been applied. While solving single objective optimization model, it is possible to find a global and unique optimal solution, multi objective approach gives a set of optimal solution which is called Pareto optimal solutions. Single objective model may be defined in two different ways such as aiming risk minimization or return maximization. The multi-objective models on the other hand, are based on the idea of simultaneously optimizing conflicting objectives.

3.2.1. Methods for handling multi-objective MVPO

In multi-objective models, it may not be possible to optimize all objective functions at once, that's why, it is needed to give priority to some objectives over another by using methods such as weighted sum method or apply dominance-based approaches to tackle this issue.

Weighted sum approach

In the weighted sum method (model 5), a set of objectives are combined into a single objective by assigning an associated weight to prioritize one over another. Thus, it simply relaxes a constraint into a combined single objective. Because of its simple structure and ease of implementation, in addition to the fact that it is the most widely used classical approach for multi objective optimization problems (Deb, 2005), weighted sum approach is the most popular solution approach for MVPO as well. Nevertheless, in spite of its simplicity, there is a major difficulty in obtaining Pareto optimal solutions by this approach for multi-objective optimization problems having a non-convex Pareto-optimal front. Therefore, the main disadvantage of weighted sum approach is that it cannot generate all Pareto optimal solutions with non-convex trade-off surfaces (Zitzler, 1999).

$$\begin{cases} \min \sum_{i=1}^{p} \lambda_i f_i(x) \\ \textit{subject to}: x \in X_f \end{cases} \tag{5}$$

where λ_i is the weight of objective function f_i.

MOMV model can be written as follows using the weighted sum method (Chang, Meade, Beasley, & Sharaiha, 2000):

$$\begin{cases} \min \quad \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}\right] - (1-\lambda)\left[\sum_{i=1}^{N} w_i \mu_i\right] & (6.1) \\ \textit{Subject to}: & \\ \sum_{i=1}^{N} w_i = 1 & (6.2) \\ 0 \le w_i \le 1 \qquad i = 1, \ldots, N & (6.3) \end{cases}$$

As seen in Eq. (6.1), the two conflicting objectives (risk minimization, return maximization) are weighted by a parameter (λ).

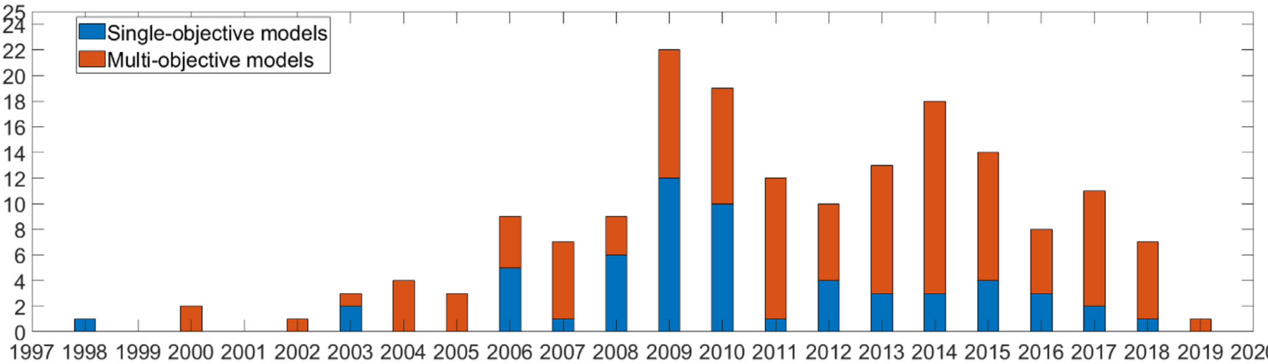

Fig. 6. Distribution of studies on single-objective and multi-objective models according to years.

The λ weighting parameter is assigned different values between 0 and 1. When the $\lambda = 0$, the objective function of model seeks the maximum return, while when $\lambda = 1$, the objective function seeks the minimum risk, and the λ parameter achieves a trade-off between risk and return for $0 < \lambda < 1$.

Pareto-based approaches

Pareto-based approaches can handle large search spaces and multiple alternative trade-offs in a single optimization run (Zitzler, 1999). However, in contrast to weighted sum approach converting the multi-objective structure into a single objective concept, there is no single criterion to assess the quality of a trade-off front; quality measures are relatively difficult to define.

In Pareto based approaches, typically, a strategy of solution ranking based on Pareto optimality concept is used (Horn, Nafpliotis, & Goldberg, 1994). Many of multi-objective algorithms are based on Pareto ranking, yet several variations are available such as dominance depth (Deb, Pratap, Agarwal, & Meyarivan, 2002), and dominance count (Zitzler et al., 2001).

Based on the concept given by Lwin, Qu, and Kendall (2014), multi-objective MV model can also be written as follows:

$$\begin{cases} \min\left[\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}\right] \text{and } \max\left[\sum_{i=1}^{N} w_i \mu_i\right] & (7.1)\\ \textit{Subject to}: & \\ \sum_{i=1}^{N} w_i = 1 & (7.2)\\ 0 \le w_i \le 1 \qquad i = 1, \ldots, N & (7.3) \end{cases}$$

As seen in Eq. (7.1), the two conflicting objectives (risk minimization, return maximization) are independently evaluated to achieve an optimization for obtaining the Pareto front.

3.3. Single vs. Multi objective MV model

It is assumed that the investors are aware of the risk or return levels they desire in single objective models. But in real life, this assumption is not always true. So, multi-objective models turn out to be more realistic. Multi-objective MVPO models are increasingly used in the literature as against single-objective models (Fig. 6).

Table 3 presents the classification of publications according to their objective type (multi objective and single objective) and generation methods (weighted-sum methods and Pareto based methods).

Table 3 clearly shows that in the literature, multi objective models are often preferred by the operations research community over single objective models. While weighted sum method is the most used, Pareto/dominance-based approaches has gained an increasing attention in recent years.

3.4. Consideration of real-world constraints

Despite all the advantages of the original MV model, it falls short in real world applications. The original MV model considers only one hard constraint, setting the sum of asset weights to one meaning that sum of invested amounts must be equal to the total budget. Therefore, the MV model needs additional constraints to solve realistic PO problems. The real-world constraints that have been added to the MV model are summarized in Table 4.

Table 5 lists the classification of publications according to constraint types and Fig. 7 demonstrates the distribution of additional constraints investigated with MV models showing that boundary constraints and cardinality constraints are highly dominant over others. Although transaction costs make more sense on multi-period portfolio optimization, researchers widely considered this constraint on single-period portfolio optimization for modelling purposes. If the selected portfolio is readjusted several times according to the determined investment horizon, TUC which is only valid for multi period portfolio optimization problems is often added into the model.

While the original MV model is presented with a quadratic objective function and linear constraints, several researchers added real life constraints which introduce non-linearity and non-convexity to MVPO. For example, *TC* may be a nonlinear and non-convex function of a difference in holdings of new and existing portfolio (Yoshimoto, 1996) which increases the complexity of the MVPO. However, *TUC* are to be formulated as a linear equation, the problem can still be solved by QP (Yoshimoto, 1996). On the other hand, *CC* together with *BC* leads to a non-convex search space (Xidonas & Mavrotas, 2014). Therefore, QP cannot be efficiently utilized and hence, researchers often head towards to inexact techniques in realistic cases.

4. Data

Researchers test the performance of their proposed algorithms developed to solve the MVPO problem using several different data sets in the literature. Table 6 lists and Fig. 8 demonstrates the distribution of data sets used in MVPO literature. Most of the researchers used real data to test their algorithms. Portfolio optimization test problems provided in OR-Library (Beasley, 1990) are popular benchmark datasets in the MVPO literature used for comparing algorithms. The data refer to the weekly stock prices from March 1992 to September 1997 for the indexes: Hang Seng with 31 assets, Dax 100 with 85 assets, FTSE 100 with 89 assets, S&P 100 with 98 assets and Nikkei with 225 assets. In addition, Kalayci, Ertenlice, Akyer, and Aygoren (2017) introduced new benchmarking data which is extracted from daily prices between May 2013 and April 2016 from XU030 and XU100 indices to further extend the

Table 3
Classification of publications based on problem objective types.

Problem objective type	Generation method	Publications
Multi objective	Weighted sum	(Ackora-Prah, Gyamerah, & Andam, 2014;Ackora-Prah, Gyamerah, Andam, & Gyamfi , 2014; Anagnostopoulos et al., 2010; Bacanin & Tuba, 2014; 2015; Bacanin et al., 2014; Baykasoglu et al., 2015; Busetti, 2006; Cesarone et al., 2013; Chang et al., 2000; Chang et al., 2009; Chen et al., 2013; Chen et al., 2012; Chen et al., 2008; ChiangLin, 2006; Cura, 2009; Deng & Lin, 2010a, b; Deng et al., 2012; Farzi et al., 2013; Fernandez & Gomez, 2007; Gaspero et al., 2011; Golmakani & Alishah, 2008; Hadi et al., 2016; Hao & Liu, 2009; Kalayci et al., 2017; Kamili & Riffi, 2015, 2016; Kao & Cheng, 2013; Koshino et al., 2007; Li et al., 2010; Lin, Li, & Li, 2005; Lu & Wang, 2013; Lwin & Qu, 2013; Maringer & Kellerer, 2003; Moral-Escudero et al., 2006; Mozafari et al., 2011; Ni et al., 2017; Niu et al., 2010; Niu et al., 2009; Pai & Michel, 2009; Peng et al., 2011; Pouya et al., 2016; Qu et al., 2017; Rong et al., 2009; Sabar & Song, 2014; Sadigh et al., 2012; Schaerf, 2002; Suganya & Vijayalakshmi Pai, 2009; Sun et al., 2011; Suthiwong & Sodanil, 2016; Tan et al., 2013; Tan et al., 2014; Tuba & Bacanin, 2014a; b; Tuba et al., 2014; Wang et al., 2015; Wang et al., 2011, 2012; Woodside-Oriakhi et al., 2011; Xia et al., 2000; Xu et al., 2010; Yaakob & Watada, 2010; Yin, Ni, & Zhai, 2015a; b; Zhu et al., 2010; Zhu et al., 2011)
	Pareto-based	(Anagnostopoulos & Mamanis, 2010, 2011a; b; Arkeman et al., 2013; Bevilacqua et al., 2011; Branke et al., 2009; Chen & Zhou, 2018; Chen et al., 2017; Chiam et al., 2007; Chiam et al., 2008; Dreżewski & Doroz, 2017; Duran et al., 2009; Eftekharian et al., 2017; Ehrgott et al., 2004; Fieldsend et al., 2004; Garcia et al., 2012; Jalota & Thakur, 2018; Kumar & Mishra, 2017; Liagkouras & Metaxiotis, 2014, 2017, 2018; Liang & Qu, 2013; Lwin et al., 2014; Lwin et al., 2013; Lwin et al., 2017; Macedo et al., 2017; Mishra et al., 2016; Mishra et al., 2014a; b; Mishra et al., 2009; Ong et al., 2005; Ruiz-Torrubiano & Suárez, 2007; Sen et al., 2015; Skolpadungket et al., 2007; Streichen & Tanaka-Yamawaki, 2006; Streichert et al., 2004a; b; Zhou & Li, 2014)
Single objective		(Abbas & Haider, 2009; Aranha & Iba, 2009; Ban et al., 2018; Bonami & Lejeune, 2009; Cao & Tao, 2010; Cesarone et al., 2015; Chang & Chen, 2008; Chang & Hsu, 2007; Chen & Cai, 2008; Chen et al., 2006; Chen & Zhang, 2010; Corazza et al., 2012a; 2013; Coutino-Gomez et al., 2003; Crama & Schyns, 2003; Cui et al., 2014; Cui et al., 2013; Dehghan Hardoroudi et al., 2017; Fasheng & Wei, 2006; Freitas et al., 2009; Gao & Chu, 2009; Golmakani & Fazel, 2011; He & Qu, 2016; Hoklie & Zuhal, 2010; Hong-mei et al., 2010; Hu & Zhangy, 2010; Huang & Shen, 2010; Huang, 2012; Jiang et al., 2014; Jiang et al., 2008; Kumar & Bhattacharya, 2012; Lai et al., 2006; Lean et al., 2008; Li et al., 2006; Lin & Liu, 2008; Loukeris et al., 2009; Mayambala et al., 2015; Reid & Malan, 2015; Ruiz-Torrubiano & Suarez, 2010; 2015; Sadjadi et al., 2012; Shaikh & Abbas, 2009; Shaw et al., 2008; Shoaf & Foster, 1998; Soleimani et al., 2009; Strumberger et al., 2017; Talebi et al., 2010; Tang et al., 2009; Thomaidis, 2010; Tian et al., 2016; Tuba et al., 2013; Wang et al., 2009; Xu & Chen, 2006; Xu et al., 2007; Yu et al., 2009; Zaheer & Pant, 2016; Zhang et al., 2010)

Table 4
Constraints for realistic portfolio optimization.

Boundary constraints (BC)	impose lower and/or upper bounds on the values of each asset weight, also known as *buy-in threshold* constraint.
Cardinality constraints (CC)	related to the number of assets invested in the portfolio, may be fixed to a certain value, may also ensure that the number of assets is between the desired range.
Transaction costs (TC)	investors pay a fee called transaction costs when they sell or buy stocks influencing the total profit
Roundlot (minimum lots) constraint (RL)	ensure that the amount invested in a security is multiples of the minimum transaction lot.
Sector capitalization constraints (SC)	impose the assets which belong to the sector with more capitalization value to have more shares in the final portfolio.
Turnover constraint (TUC)	sets the turnover rate of an asset from current period to next period which is especially useful in multi period portfolio optimization models.

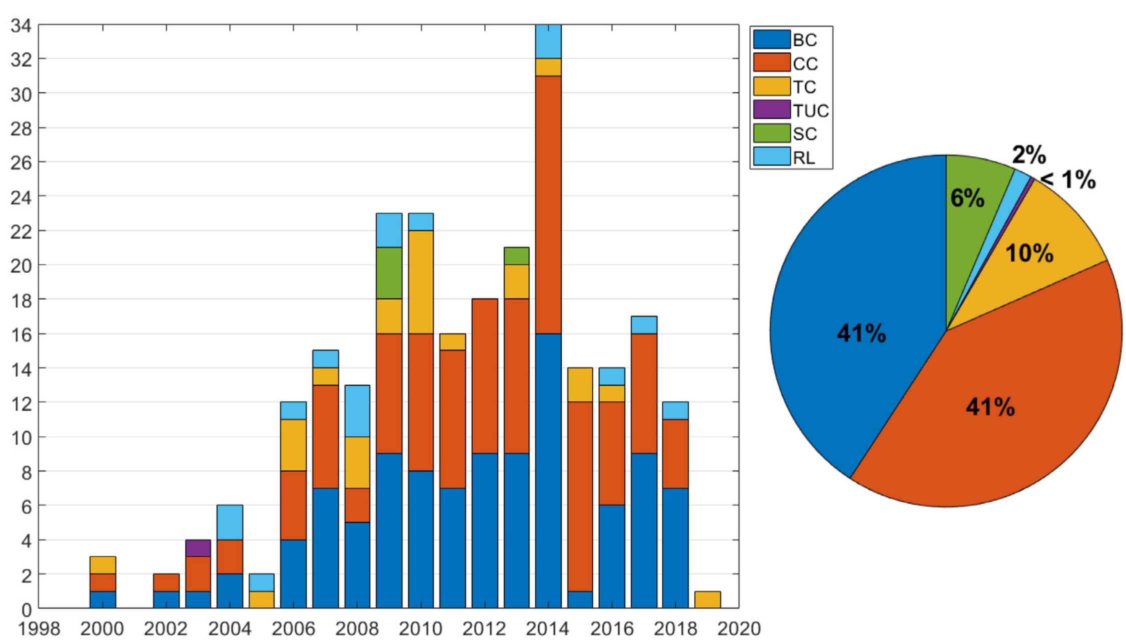

Fig. 7. Distribution of additional constraints used with MV model.

Table 5
Classification of publications according to constraint types.

Constraint type	Publications
BC–CC	(Ackora-Prah, Gyamerah & Andam 2014; Ackora-Prah, Gyamerah, Andam, & Gyamfi, 2014; Anagnostopoulos & Mamanis, 2010, 2011a; b; Anagnostopoulos et al., 2010; Bacanin & Tuba, 2014; 2015; Bacanin et al., 2014; Baykasoglu et al., 2015; Busetti, 2006; Cesarone et al., 2013; 2015; Chang et al., 2000; Chang et al., 2009; Chen et al., 2013; Chen et al., 2012; Chen et al., 2017; Chiam et al., 2007; Corazza et al., 2012a; 2013; Cui et al., 2014; Cui et al., 2013; Cura, 2009; Deng & Lin, 2010a, b; Deng et al., 2012; Eftekharian et al., 2017; Farzi et al., 2013; Fernandez & Gomez, 2007; Garcia et al., 2012; Gaspero et al., 2011; Golmakani & Alishah, 2008; Golmakani & Fazel, 2011; Hadi et al., 2016; Jalota & Thakur, 2018; Jiang et al., 2014; Jin et al., 2015; Kalayci et al., 2017; Kamili & Riffi, 2015, 2016; Kao & Cheng, 2013; Kırış & Ustun, 2012; Koshino et al., 2007; Kumar & Mishra, 2017; Kumar & Bhattacharya, 2012; Liagkouras, 2018; Liagkouras & Metaxiotis, 2014, 2018; Lwin & Qu, 2013; Lwin et al., 2013; Mansour et al., 2007; Mayambala et al., 2015; Mishra et al., 2016; Mishra et al., 2014a; b; Moral-Escudero et al., 2006; Mozafari et al., 2011; Ni et al., 2017; Ruiz-Torrubiano & Suarez, 2010; Ruiz-Torrubiano & Suárez, 2007; Sabar & Song, 2014; Sadigh et al., 2012; Sadjadi et al., 2012; Schaerf, 2002; Streichen & Tanaka-Yamawaki, 2006; Suthiwong & Sodanil, 2016; Tang et al., 2009; Tian et al., 2016; Tuba & Bacanin, 2014a; b; Tuba et al., 2014; Wang et al., 2015; Wang et al., 2011, 2012; Woodside-Oriakhi et al., 2011; Xu et al., 2010; Yaakob & Watada, 2010; Yin et al., 2015a; b)
TC	(Chen & Zhang, 2010; Huang & Shen, 2010; Li et al., 2010; Lu & Wang, 2013; Paiva et al., 2019; Peng et al., 2011; Tan et al., 2013; Xia et al., 2000; Zhang et al., 2010)
BC–CC–RL	(Chiam et al., 2008; Liagkouras & Metaxiotis, 2017; Lwin et al., 2014; Lwin et al., 2017; Skolpadungket et al., 2007; Streichert et al., 2004a; Streichert et al., 2004b)
TC–RL	(Chen et al., 2008; ChiangLin, 2006; Lin & Liu, 2008; Lin et al., 2005; Niu et al., 2010)
BC–CC–TC	(Brito & Vicente, 2014a; Gao & Chu, 2009; Hu & Zhangy, 2010; Ruiz-Torrubiano & Suarez, 2015)
CC	(Dehghan Hardoroudi et al., 2017; Maringer & Kellerer, 2003; Xu et al., 2011)
BC	(Abbas & Haider, 2009; Chang & Hsu, 2007; Jiang et al., 2008)
BC–TC	(Chen & Cai, 2008; Chen et al., 2006; Xu et al., 2007)
BC–CC–SC	(Pai & Michel, 2009; Tuba et al., 2013)
BC–RL	(Bonami & Lejeune, 2009; Zhou & Li, 2014)
BC–CC–SC–RL	(Soleimani et al., 2009)
BC–CC–TC–RL	(He & Qu, 2016)
BC–CC–TC–SC	(Suganya & Vijayalakshmi Pai, 2009)
BC–TC–TUC	(Crama & Schyns, 2003)

BC: Boundary constraints; CC: Cardinality constraints; TC: Transaction costs; RL: Roundlot constraint; SC: Sector capitalization constraints; TUC: Turnover constraint.

Table 6
Datasets used in MVPO literature.

Datasets	Publication
OR-Library	(Anagnostopoulos & Mamanis, 2010, 2011a; b; Bacanin & Tuba, 2014; 2015; Baykasoglu et al., 2015; Cesarone et al., 2013; 2015; Chang et al., 2000; Chang et al., 2009; Chen et al., 2013; Chen et al., 2012; Chen et al., 2017; Chiam et al., 2007; Chiam et al., 2008; Cui et al., 2014; Cura, 2009; Deng & Lin, 2010a, b; Deng et al., 2012; Fernandez & Gomez, 2007; Gaspero et al., 2011; Golmakani & Alishah, 2008; He & Qu, 2016; Jin et al., 2015; Kalayci et al., 2017; Kamili & Riffi, 2015, 2016; Kao & Cheng, 2013; Koshino et al., 2007; Kumar & Mishra, 2017; Liagkouras, 2018; Liagkouras & Metaxiotis, 2014, 2017; Lwin & Qu, 2013; Lwin et al., 2014; Lwin et al., 2013; Mayambala et al., 2015; Mishra et al., 2016; Mishra et al., 2014a; b; Mishra et al., 2009; Moral-Escudero et al., 2006; Mozafari et al., 2011; Ni et al., 2017; Ruiz-Torrubiano & Suarez, 2010; Ruiz-Torrubiano & Suárez, 2007; Sabar & Song, 2014; Sadigh et al., 2012; Sadjadi et al., 2012; Sen et al., 2015; Skolpadungket et al., 2007; Streichen & Tanaka-Yamawaki, 2006; Streichert et al., 2004a; b; Tian et al., 2016; Tuba & Bacanin, 2014a; b; Wang et al., 2015; Wang et al., 2011, 2012; Woodside-Oriakhi et al., 2011; Xu J. et al., 2011; Xu R.T. et al., 2010; Yin et al., 2015a; b; Zhang et al., 2018a)
Case study	(Abbas & Haider, 2009; Ackora-Prah, Gyamerah, Andam, 2014; Ackora-Prah, Gyamerah, Andam, & Gyamfi, 2014; Aouni et al., 2005; Aranha & Iba, 2009; Arkeman et al., 2013; Bacanin et al., 2014; Bevilacqua et al., 2011; Bonami & Lejeune, 2009; Branke et al., 2009; Brito & Vicente, 2014a; Busetti, 2006; Cao & Tao, 2010; Chang & Chen, 2008; Chang & Hsu, 2007; Chen & Zhou, 2018; Chen & Cai, 2008; Chen et al., 2008; Chen et al., 2006; Chen & Zhang, 2010; ChiangLin, 2006; Corazza et al., 2012a; Corazza et al., 2013; Crama & Schyns, 2003; Cui et al., 2013; Dehghan Hardoroudi et al., 2017; Drężewski & Doroz, 2017; Duran et al., 2009; Eftekharian et al., 2017; Ehrgott et al., 2004; Farzi et al., 2013; Fasheng & Wei, 2006; Fieldsend et al., 2004; Freitas et al., 2009; Gao & Chu, 2009; García et al., 2018; Garcia et al., 2012; Golmakani & Fazel, 2011; Hadi et al., 2016; Hao & Liu, 2009; Hoklie & Zuhal, 2010; Hong-mei et al., 2010; Hu & Zhangy, 2010; Huang & Shen, 2010; Huang, 2012; Jalota & Thakur, 2018; Jiang et al., 2014; Jiang et al., 2008; Kamali, 2014; Kırış & Ustun, 2012; Kocadağlı & Keskin, 2015; Kumar & Bhattacharya, 2012; Lai et al., 2006; Lean et al., 2008; Li et al., 2006; Li et al., 2010; Liagkouras, 2018; Liagkouras & Metaxiotis, 2018; Liang & Qu, 2013; Lin & Liu, 2008; Lin et al., 2005; Loukeris et al., 2009; Lu & Wang, 2013; Lwin et al., 2017; Mansour et al., 2007; Maringer & Kellerer, 2003; Niu et al., 2010; Niu et al., 2009; Ong et al., 2005; Pai & Michel, 2009; Paiva et al., 2019; Peng et al., 2011; Pouya et al., 2016; Qu et al., 2017; Reid & Malan, 2015; Rong et al., 2009; Ruiz-Torrubiano & Suarez, 2015; Schaerf, 2002; Shaikh & Abbas, 2009; Shaw et al., 2008; Shoaf & Foster, 1998; Strumberger et al., 2017; Suganya & Vijayalakshmi Pai, 2009; Sun et al., 2011; Suthiwong & Sodanil, 2016; Talebi et al., 2010; Tan et al., 2013; Tan et al., 2014; Tang et al., 2009; Thomaidis, 2010; Tuba et al., 2013, 2014; Wang et al., 2009; Xu & Chen, 2006; Xu et al., 2007; Yaakob & Watada, 2010; Yu et al., 2009; Zaheer & Pant, 2016; Zhang et al., 2010; Zhou & Li, 2014; Zhu et al., 2011)
Hypothetical	(Bacanin & Tuba, 2015; Ehrgott et al., 2004; Soleimani et al., 2009; Xia et al., 2000)

publicly available data sets to the attention of researchers, available on http://www.pau.edu.tr/portfolio/en. In addition to the dataset obtained from OR-Library, many researchers used case studies from various stock indices. Instead of testing and comparing the proposed solution approaches on publicly available data sets, studying on the data belonging to different financial markets is also valuable because of extended variety of available datasets. However, in this case, the computational comparison is not possible since datasets are not publicly available. Stock indices from China (Chen & Cai, 2008; Chen & Zhou, 2018; Chen, Xu, Yang, & Cai, 2008, Chen, Zhang, Cai & Xu et al. 2006, Jiang, Zhang, & Xie, 2008; Lai, Yu, Wang, & Zhou, 2006; Lean, Wang, & Lai, 2008; Liang & Qu, 2013; Lu & Wang, 2013; Niu, Tan, Xue, Li, & Chai, 2010; Qu, Zhou, Xiao, Liang, & Suganthan, 2017; Rong, Lu, & Deng, 2009; Xu, Lam, & Li, 2011; Yu, Wang, & Lai, 2009; Zhou & Li, 2014), United Kingdom (Brito & Vicente, 2014a; Brito & Vicente, 2014b; Corazza, Fasano, &

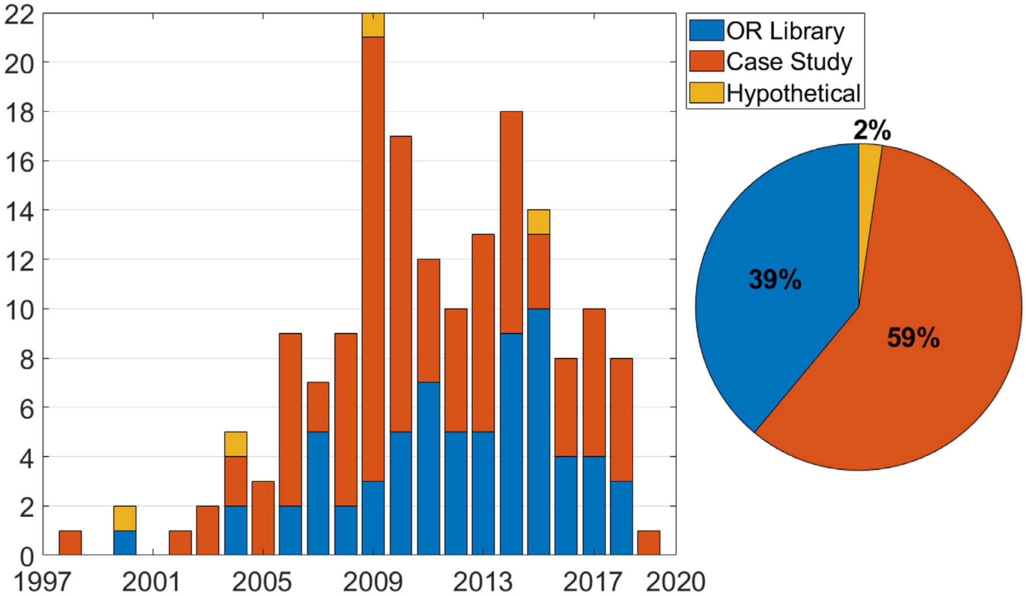

Fig. 8. Distribution of data sets.

Gusso, 2012a; Corazza, Fasano, & Gusso, 2012b; Eftekharian, Shojafar, & Shamshirband, 2017; Garcia, Quintana, Galvan, & Isasi, 2012; Jalota & Thakur, 2018; Kumar & Bhattacharya, 2012; Liagkouras & Metaxiotis, 2018; Loukeris, Donelly, Khuman, & Peng, 2009; Shaw, Liu, & Kopman, 2008), United States (Aranha & Iba, 2009; Bonami & Lejeune, 2009; Corazza, Fasano, & Gusso, 2013; Eftekharian et al., 2017; Ehrgott, Klamroth, & Schwehm, 2004; Fieldsend, et al., 2004; Lwin, Qu, & MacCarthy, 2017; Sun, Fang, Wu, Lai, & Xu, 2011; Xu, Chen, & Yang, 2007), Japan (Aranha & Iba, 2009; Eftekharian et al., 2017; Jalota & Thakur, 2018; Kumar & Bhattacharya, 2012; Pai & Michel, 2009; Suganya & Vijayalakshmi Pai, 2009), Hong Kong (Eftekharian et al., 2017; Jalota & Thakur, 2018; Jiang, Li, Gao, & Yu, 2014; Li, Sun, & Wang, 2006), India (Suganya & Vijayalakshmi Pai, 2009; Zaheer & Pant, 2016), Venezuela (Duran, Cotta, & Fernández, 2009), Ghana (Ackora-Prah, Gyamerah, & Andam, 2014; Ackora-Prah, Gyamerah, Andam, & Gyamfi, 2014), Portuguese (Freitas, De Souza, & de Almeida, 2009; Paiva, Cardoso, Hanaoka, & Duarte, 2019), Turkey (Kırış & Ustun, 2012; Kocadağlı & Keskin, 2015).

Indonesia (Hoklie & Zuhal, 2010), Pakistan (Abbas & Haider, 2009; Shaikh & Abbas, 2009), Thailand (Suthiwong & Sodanil, 2016), Taiwan (Chang & Chen, 2008; ChiangLin, 2006; Lin & Liu, 2008), Iran (Pouya, Solimanpur, & Rezaee, 2016; Talebi, Molaei, & Sheikh, 2010), Tunisia (Aouni, Abdelaziz, & Martel, 2005; Mansour, Rebai, & Aouni, 2007) and Poland (Dreżewski & Doroz, 2017) extracted by daily, monthly or yearly stock prices are extensively studied. Lastly, researchers tested performance of proposed solution approaches by using hypothetical datasets and benchmark functions in very limited studies.

5. Performance measures

Several performance metrics have been used for the comparison of different algorithms in the MVPO literature. Various indicators of MVPO literature can be categorized in four aspects of a solution set: convergence based, diversity based, hybridization based, and risk adjusted indicators.

Convergence based indicators: represent the closeness of the obtained approximation to the theoretical Pareto optimal front.

– Mean Euclidean Distance: refers to the average straight-line distance between each portfolio alternatives of the theoretical efficient frontier and the efficient frontier obtained (Cura, 2009).
– Variance of Return Error: The average value of all the errors which refers the horizontal distance corresponding a certain return level. (Fernandez & Gomez, 2007).
– Mean return error: The average value of all the errors which refers the vertical distance corresponding a certain risk(variance) level. (Fernandez & Gomez, 2007).
– Mean Percentage Error: shows the average of percentage errors (Chang et al., 2000).
– Median Percentage Error: The median value of all percentage errors (Chang et al., 2000).
– Generational Distance: measures the average distance between the non-dominated front obtained via the proposed algorithm and exact Pareto front (Van Veldhuizen & Lamont, 2000). If the generational distance is equal to zero, then all the solutions given by proposed algorithm are on the exact Pareto front. In other words, lower the generational distance value means better convergence ability and performance.
– Epsilon indicator: is a binary indicator that gives a factor by which an approximation set is worse than another considering all objectives (Zitzler, Thiele, Laumanns, Fonseca, & Da Fonseca, 2003) giving the idea about how two separate distributions of Pareto-fronts differ from each other according to their degree of positive or negative non-domination.
– Convergence metric: is used to compare the quality of two non-dominated sets without taking into consideration of the theoretical efficient frontier (Khare, Yao, & Deb, 2003).

Diversity based indicators: represent the uniformity of the distribution of the obtained solutions along the Pareto front.

– Spacing metric: defines the distribution characteristic of the solutions on the Pareto front of non-dominated solutions (Van Veldhuizen & Lamont, 2000). In other words, it shows how well non-dominated solutions scattered.
– Spread (diversity) metric: measures the extent of the spread i.e., how evenly the points are distributed among the approximation sets in objective space (Deb et al., 2002).

Hybridization based indicators: represent a combined indicator of convergence and diversity.

– Hypervolume indicator: measures the volume of the multi-dimensional region that is dominated by the set of non-dominated solutions provided by a multi-objective algorithm

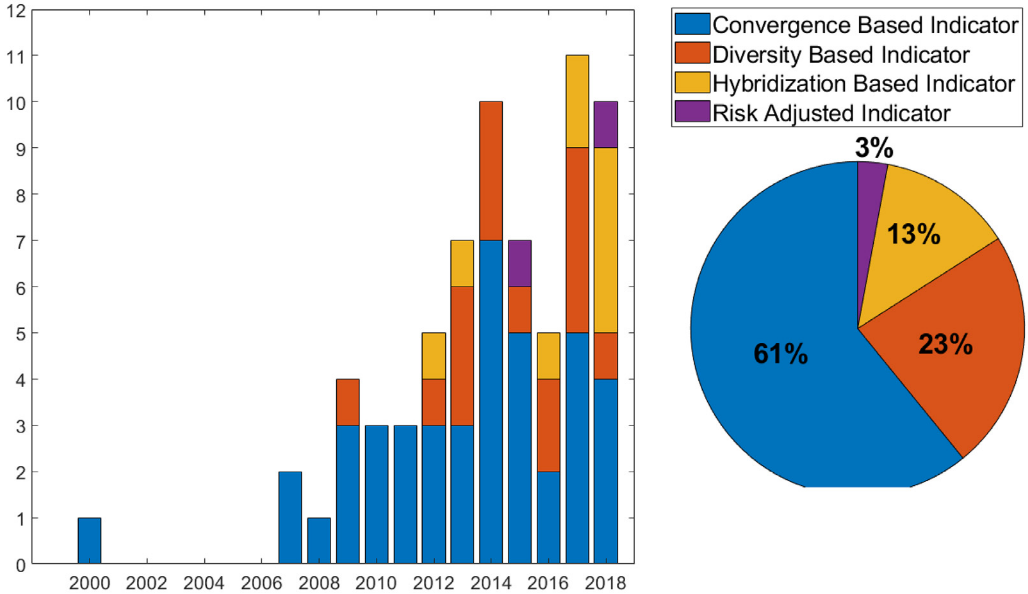

Fig. 9. Distribution of performance measures.

(Zitzler & Thiele, 1999). A higher hypervolume indicator value means better approximation of solution set.

- $D1_R$: gives information about both the average distance from the closest solution and convergence to the optimal Pareto front (Czyżżak & Jaszkiewicz, 1998).
- Inverted generational distance: as an improvement over the generational distance with a faster calculation advantage, is based on the idea of reversing the order of the fronts considered as input by the generational distance. In other words, while generational distance metric calculating the distance from the non-dominated solution front to reference front, inverted generational distance metric performs the calculation in a reverse order (Van Veldhuizen & Lamont, 2000).

Risk adjusted indicators: represent a risk-reward evaluation of a returns distribution which incorporates the beneficial impact of gains as well as the detrimental effect of losses.

- Sharpe ratio: is used for measuring of the risk adjusted return of an investment (Sharpe, 1966). In other words, by using sharp ratio performance metric, it can be calculated how well the portfolio return can compensate the risk taken by the investors. Higher Sharpe ratio value means better performance.
- Omega ratio: captures all the higher moment information in the returns distribution and also incorporates sensitivity to return levels while sharp ratio performance metric requires the assumption of mean-variance structure and normally distributed input data (Keating & Shadwick, 2002).

Fig. 9 demonstrates distribution of performance measures that used in MVPO literature.

The performance measures calculating the distance between the constrained efficient frontier obtained by the algorithm and the reference unconstrained efficient frontier, convergence-based performance indicators, are presented in Table 7. Diversity, hybridization based, and risk adjusted performance indicators utilized in MVPO literature is listed in Tables 8–10 respectively.

6. Applications on MVPO model

The MVPO problem has a quadratic structure, so exact solution algorithms such as quadratic programing can tackle MVPO. However, when additional constraints are added, or the problem dimension is increased, exact solution algorithms may face troubles while handling the MVPO problem. Therefore, many researchers have used inexact techniques to solve more realistic MVPO problems that incorporate non-convex constraints in the mathematical formulation, thus yielding the problem NP-hard (Moral-Escudero, Ruiz-Torrubiano, & Suarez, 2006). A broad taxonomy of solution techniques applied to PO based on MV model is given in Fig. 10. The following subsections provide a detailed review of solution techniques developed or adapted to solve MVPO.

6.1. Exact solution techniques

MVPO can be solved with some exact solution algorithms. The most popular of these is QP which is a particular type of nonlinear programming. Aouni et al. (2005) and Mansour et al. (2007) developed goal programming models for MVPO problem using QP. Hu and Zhangy (2010) compared the performance of PO models: MV, Mean Absolute Deviation, Conditional Value-at-Risk and Minimax model using linear programming. Peng, Kitagawa, Gan, and Chen (2011) proposed a MV model with transaction costs in quadratic form, thus, presented a model solved by QP. Brito and Vicente (2014b) developed a bi-objective model in which the first objective is minimizing the cardinality and second objective is maximizing return and minimizing risk using a derivative-free solver, based on direct multi-search reporting the solutions obtained by QP for several datasets. Mayambala, Rönnberg, and Larsson (2015) presented a new MV model, based on performing eigen decomposition of the covariance matrix and reported the performance of this model using QP. Qin (2015) introduced MV models for solving a hybrid portfolio selection problem: simultaneous presence of random and uncertain returns. The computational results obtained with QP indicate that the proposed models are meaningful and able to be applied.

Although the original MV model is a quadratic model, it is transformed into a nonlinear model when additional integer constraints are added. Hence, QP cannot tackle the nonlinear MV model but nonlinear programming can.

The researchers who solved the MVPO problem using the QP or nonlinear programming, mostly used CPLEX or MATLAB quadratic toolbox as the solver. Besides QP and nonlinear programming, Lagrange methods (Li et al., 2006; Shaw et al., 2008) and Branch & Bound algorithm (Bonami & Lejeune, 2009) were also applied to MVPO (Table 11).

Table 7
Convergence based performance indicators in MVPO literature.

Performance Measure	Publication
Mean Euclidean Distance	(Bacanin & Tuba, 2014; Baykasoglu et al., 2015; Chen et al., 2017; Cura, 2009; Jin et al., 2015; Kalayci et al., 2017; Kamili & Riffi, 2015, 2016; Kao & Cheng, 2013; Kumar & Mishra, 2017; Lwin et al., 2013; Mishra et al., 2016; Mishra et al., 2014a; b; Mozafari et al., 2011; Ni et al., 2017; Sadigh et al., 2012; Sen et al., 2015; Tuba & Bacanin, 2014a; Wang et al., 2011, 2012; Yin et al., 2015a)
Variance of Return Error and Mean Return Error	(Bacanin & Tuba, 2014; Baykasoglu et al., 2015; Cura, 2009; Fernandez & Gomez, 2007; Golmakani & Alishah, 2008; Kalayci et al., 2017; Kamili & Riffi, 2015, 2016; Kao & Cheng, 2013; Mishra et al., 2014a; Mozafari et al., 2011; Ni et al., 2017; Sadigh et al., 2012; Tuba & Bacanin, 2014a; Wang et al., 2011, 2012; Yin et al., 2015a)
Mean Percentage Error	(Baykasoglu et al., 2015; Chang et al., 2000; Cui et al., 2014; Deng & Lin, 2010a, b; Deng et al., 2012; Jalota & Thakur, 2018; Jin et al., 2015; Kalayci et al., 2017; Lwin & Qu, 2013; Pai & Michel, 2009; Sabar & Song, 2014; Tuba & Bacanin, 2014b; Woodside-Oriakhi et al., 2011; Xu et al., 2010)
Median Percentage Error	(Chang et al., 2000)
Generational Distance	(Lwin et al., 2017; Skolpadungket et al., 2007)
Epsilon indicator	(Liagkouras, 2018; Liagkouras & Metaxiotis, 2017, 2018)
Convergence metric	(Mishra et al., 2016; Mishra et al., 2014b; Mishra et al., 2009; Sen et al., 2015)

Table 8
Diversity based performance indicators in MVPO literature.

Performance Measure	Publication
Spacing metric	(Chen & Zhou, 2018; Eftekharian et al., 2017; Kumar & Mishra, 2017; Mishra et al., 2016; Mishra et al., 2009)
Diversity metric	(Chen et al., 2013; Chen et al., 2012; Chen et al., 2017; Liagkouras & Metaxiotis, 2014; Liang & Qu, 2013; Lwin et al., 2014; Lwin et al., 2013; Lwin et al., 2017; Mishra et al., 2016; Mishra et al., 2014b; Mishra et al., 2009; Sen et al., 2015; Suthiwong & Sodanil, 2016)

It is observed in the literature that, the number of publications that design the exact solution approaches for the MVPO problem is limited.

Table 9
Hybridization based performance indicators in MVPO literature.

Performance Measure	Publication
$D1_R$	(Chen et al., 2013; Chen et al., 2012; Suthiwong & Sodanil, 2016)
Inverted Generational Distance	(Liagkouras, 2018; Liagkouras & Metaxiotis, 2017, 2018; Lwin et al., 2017)
Hyper Volume	(Dreżewski & Doroz, 2017; Liagkouras, 2018; Liagkouras & Metaxiotis, 2017, 2018; Lwin et al., 2017; H. Zhang et al., 2018)

6.2. Inexact solution techniques

Approximation techniques have been extensively used in the literature since the MVPO problem is known to be NP-hard due to various real-life constraints. The approximation techniques are

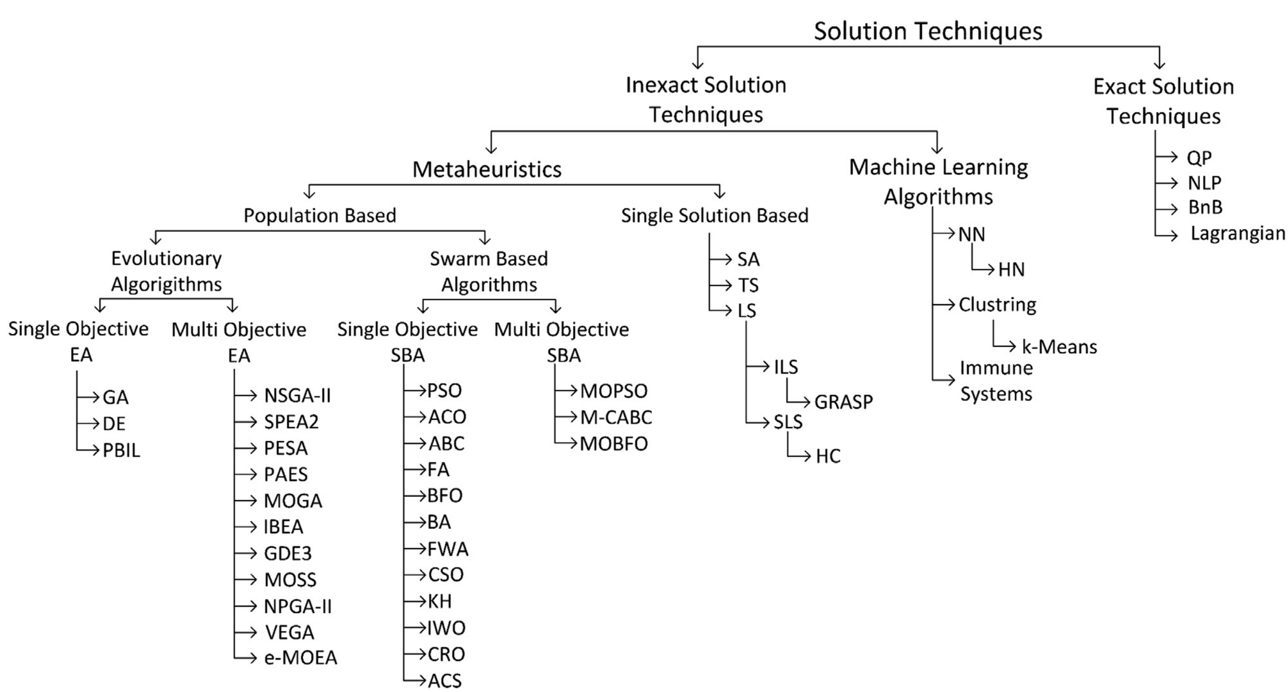

Fig. 10. A taxonomy of solution techniques applied to PO based on MV model.
Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Artificial Cooperative Search (ACS), Bat Algorithm (BA), Bacterial Foraging Optimization (BFO), Brunch & Bound, CRO (BnB), Chemical Reaction Optimization (CRO), Cat Swarm Optimization (CSO), Differential Evolutionary (DE), Firefly Algorithm (FA), Fireworks Algorithm (FWO), Genetic Algorithm (GA), Generalized DE3 (GDE3), Greedy Random Adaptive Search Procedure (GRASP), Guided LS (GLS), Hill Climbing (HC), Hopfield Network (HN), Indicator-Based Evolutionary Algorithm (IBEA), Invasive Weed Optimization (IWO), Iterated Local Search (ILS), Krill Herd (KH), Local Search (LS), Multi objective co-variance based ABC (M-CABC), Multi Objective GA (MOGA), Multi Objective PSO (MOPSO), Multi Objective Scatter Search (MOSS), Non-Linear Programing (NLP), Neural Network (NN), Niched Pareto GA 2 (NPGA-II), Non-dominated Sorting GA 2 (NSGA-II), Pareto Archived Evolution Strategy (PAES), Population Based Incremental Learning (PBIL), Pareto Envelope-based Selection Algorithm (PESA), Particle Swarm Optimization (PSO), Quadratic Programming (QP), Simulated Annealing (SA), Stochastic LS (SLS), Strength Pareto Evolutionary Algorithm 2 (SPEA-II), Tabu Search (TS), Vector Evaluated GA (VEGA), Variable Neighborhood Search (VNS).

Table 10
Risk adjusted performance indicators in MVPO literature.

Performance Measure	Publication
Sharpe ratio	(Ban et al., 2018; Ruiz-Torrubiano & Suarez, 2015)

examined in two categories: metaheuristics and machine learning algorithms.

6.2.1. Metaheuristics

Metaheuristics involve iterative high-level procedures guiding the sub-level heuristics designed for solving various optimization problems by performing search strategies in order to find near-optimal solutions in the vast solution space. In each iteration, metaheuristics may use a single solution or a population. Sub-level heuristics may be composed of a simple local search algorithm or a specific method developed to initialize a solution. In general, metaheuristics have two significant search mechanisms: exploration and exploitation. Exploration mechanism guides the main algorithm to discover new promising solution areas providing a less chance of getting trapped in a local optimum while exploitation mechanism examines the newly discovered solution space carefully to search for a better neighboring solution, hopefully global optimum. A balanced proportion and timing between these two mechanisms is crucial for an efficient and robust metaheuristic algorithm. Metaheuristic algorithms are classified in two categories: population-based algorithms and single solution-based algorithms.

6.2.1.1. Population based algorithms. Population based algorithms utilize the power of population during the search in the vast solution space. The population should be adequately diversified so that a larger area can be scanned. Population-based algorithms generate an initial population randomly or with heuristic support and follow the population improvement strategies in each iteration. Population-based algorithms can be examined in two categories according to the sources of inspiration: evolutionary algorithms and swarm-based algorithms.

Evolutionary algorithms:

The basic idea of evolutionary algorithms is to generate new solutions, represented by chromosomes, from a population of initial solutions utilizing the principles of natural selection and crossover or mutation strategies to create new offspring. The most popular evolutionary algorithm is genetic algorithm that is introduced by Holland (1975). Evolutionary algorithms applied to MVPO problem are summarized in Table 12.

Single objective evolutionary algorithms for MVPO:

Shoaf and Foster (1998) firstly applied genetic algorithm and Chang et al. (2000) adapted three algorithms including genetic algorithm to MVPO problem. Ehrgott et al. (2004) proposed a model for MVPO problem and designed three algorithms genetic algorithm, tabu search, simulated annealing for solving this model. Evaluation of algorithms in terms of utility value and standard deviation, genetic algorithm produced better results and turned out to be the most stable algorithm compared to the others. Busetti (2006) compared the performance of tabu search and genetic algorithm on MVPO and test results reported that genetic algorithm was both faster and more efficient. Lin and Liu (2008) proposed models for MVPO problem with minimum transaction lots and uses genetic algorithm to solve the models. The computational results showed that the genetic algorithm could obtain near-optimal solutions within a reasonably short time. Chang, Yang, and Chang (2009) reported that genetic algorithm can provide an efficient and convenient tool for investors by verifying that investors should not consider the number of assets to be held in the portfolio above one third of total assets since they are obviously dominated by portfolios with relatively less assets. Loukeris et al. (2009) compared genetic algorithm, differential evolution and particle swarm optimization, reporting that the differential evolution algorithm obtained the highest and most reliable results for different scenarios. Xu, Zhang, Liu, and Huang (2010) proposed a population based incremental learning algorithm and compared performance of the algorithm with genetic algorithm presented by Chang et al. (2000) and particle swarm optimization presented by Cura (2009). They reported that population based incremental learning algorithm obtained similar results with other algorithms. Woodside-Oriakhi, Lucas, and Beasley (2011) developed three algorithms (genetic algorithm, tabu search and simulated annealing) that outperform the algorithms designed by Chang et al. (2000) on all performance indicators tested such as mean percentage error and computation time for all data sets. Sadjadi, Gharakhani, and Safari (2012) presented a framework to efficiently solve cardinality constrained MVPO considering an uncertainty structure both independent and correlated by utilizing a genetic algorithm. Liu and Zhang (2015) proposed a multi period fuzzy PO model and adapted a genetic algorithm for solving the model.

Multi objective evolutionary algorithms for MVPO:

Fieldsend, Matatko, and Peng (2004) applied multi objective evolutionary algorithm firstly to MVPO problem. Ong, Huang, and Tzeng (2005) proposed a PO model with three objectives, maximizing expected return, minimizing uncertainty risk and minimizing relation risk. They NSGA-II in order to solve the three objective model and reported that NSGA-II can provide flexible and accurate results. Skolpadungket, Dahal, and Harnpornchai (2007) applied various multi-objective evolutionary algorithms to solve MVPO problem with cardinality constraints and boundary constraints such as vector evaluated genetic algorithm, multi objective genetic algorithm, SPEA2 and NSGA-II. According to the test results, even though multi-objective genetic algorithms and SPEA2 required more complex structures, they outperformed the others. Anagnostopoulos and Mamanis (2010) proposed a tri-objective PO model: maximizing return, minimizing risk and minimizing number of assets held in the portfolio. They experimented with NSGA-II, Pareto envelope based selection algorithm and SPEA2 for finding approximation solutions and test results showed that SPEA-II obtained the best results. Anagnostopoulos and Mamanis (2011a) presented five multi-objective evolutionary algorithms a single objective evolutionary algorithm for solving MVPO problem. The

Table 11
Publications that applied exact solution techniques to solve MVPO problem.

Technique	Publications
QP	(Abbas & Haider, 2009; Aouni et al., 2005; Baykasoglu et al., 2015; Brito & Vicente, 2014a; Cesarone et al., 2013; 2015; Cui et al., 2014; Cui et al., 2013; Gaspero et al., 2011; Hu & Zhangy, 2010; Jiang et al., 2014; Jin et al., 2015; Liagkouras & Metaxiotis, 2014; Mansour et al., 2007; Mayambala et al., 2015; Moral-Escudero et al., 2006; Peng et al., 2011; Ruiz-Torrubiano & Suarez, 2015)
Nonlinear Programming	(Kırış & Ustun, 2012; Kocadağlı & Keskin, 2015)
Branch & Bound	(Bonami & Lejeune, 2009; He & Qu, 2016)
Lagrangian	(Li et al., 2006; Shaw et al., 2008)

Table 12
Evolutionary algorithms applied to MVPO.

Evolutionary algorithm	Proposed by	Objective type
Genetic algorithm (GA)	Holland (1975)	Single objective
Differential evolution (DE)	Storn and Price (1997)	Single objective
Population based incremental learning (PBIL)	Baluja (1994)	Single objective
Non-dominated sorting genetic algorithm 2 (NSGA-II)	Deb et al. (2002)	Multi objective
Strength Pareto evolutionary algorithm 2 (SPEA2)	Zitzler et al. (2001)	Multi objective
Pareto envelope-based selection algorithm (PESA)	Corne et al. (2000)	Multi objective
Pareto archived evolution strategy (PAES)	Knowles et al. (2006)	Multi objective
Indicator based evolutionary algorithm (IBEA)	Zitzler and Künzli (2004)	Multi objective
Multi objective genetic algorithm (MOGA)	Fonseca and Fleming (1993)	Multi objective
Niched Pareto genetic algorithm 2 (NPGA-II)	Erickson et al. (2001)	Multi objective
Generalized differential evolution 3 (GDE3)	Kukkonen and Lampinen (2005)	Multi objective
Multi objective scatter search (MOSS)	Glover et al. (2000)	Multi objective
Vector evaluated genetic algorithm (VEGA)	Schaffer (1985)	Multi objective
e-multi objective evolutionary algorithm (e-MOEA)	Hanne (2007)	Multi objective

computational results report that, firstly, all multi-objective evolutionary algorithms outperform the single-objective ones in all problem instances on epsilon performance indicator and performed faster, secondly, NSGA-II and SPEA2 are best performing algorithms among the algorithms in terms of convergence capability. Liagkouras and Metaxiotis (2014) proposed a probe guided mutation operator and compared their proposed operator with a classical mutation operator embedded into NSGA-II and SPEA2 algorithms in terms of performance metrics such as hypervolume, epsilon indicator and the spread of solutions Results confirmed the superiority of the probe guided mutation operator. Lwin et al. (2014) proposed a learning guided multi-objective evolutionary algorithm for MVPO problem and compared their proposed algorithm performed well on diversity and hypervolume performance indicators, especially on large sized data sets. Macedo, Godinho, and Alves (2017) compared two multi-objective evolutionary algorithms on hypervolume performance indicator and technical analysis based strategies reporting that, NSGA II outperformed SPEA2 and SPEA2 frontiers presenting a lesser extent than those of the NSGA II. Evolutionary algorithms applied for MVPO problem are shown in Table 13.

While GA is the most preferred evolutionary algorithms in the MVPO literature so far, in recent years the attention has been given to MOEAs.

Swarm based algorithms:

Swarm based algorithms are based on the study of computational systems inspired by behaviors of animals living in herds in their natural lives. Swarms such as schools of fish, flocks of birds, colonies of ants and bees liaise for their natural activities (mostly hunting). Swarm based algorithms are born as a reflection of this cooperation to computational systems. The most popular swarm based algorithm is particle swarm optimization that introduced by Kennedy and Eberhart (1995). The swarm-based algorithms are examined in two categories: single objective swarm-based algorithm and multi objective swarm-based algorithm. Swarm based algorithms applied to MVPO problem are showed in Table 14.

Single objective swarm-based algorithms for MVPO:

Chen et al. (2006) was first to apply particle swarm optimization to MVPO problem. Cura (2009) developed a particle swarm optimization algorithm for MVPO with boundary constraints and cardinality constraints and compared to genetic algorithm, tabu search and simulated annealing (Chang et al., 2000) reporting that none of the four algorithms had clearly outperformed the others, however, the particle swarm optimization obtained best solutions on low risk levels on performance indicators such as Euclidian distance, contribution percentage, variance of return error and mean return error criteria. Deng and Lin (2010a) was first to apply ant colony optimization to MVPO problem and compared results with particle swarm optimization showing the robust and effective performance of the algorithm, especially for low-risk investments. Hong-mei, Zhuo-fu, and Hui-min (2010) was first to apply artificial bee colony algorithm to MVPO problem and noted the algorithm as a useful approach for MVPO problem. Zhu, Chen, and Wang (2010) proposed two swarm-based algorithms: ant colony optimization and particle swarm optimization. Computational results showed that ant colony optimization performed better than particle swarm optimization in small-scale and large-scale portfolios, however in the medium-scale portfolio turned out to be the opposite utilizing Sharpe ratio performance indicator. Golmakani and Fazel (2011) compared particle swarm optimization with genetic algorithms reporting the achievement of finding better solutions within a less amount of time. Xu et al. (2011) proposed chemical reaction optimization by adding a super molecule to the evolutionary process on performance indicators such as Sharpe ratio and execution time showing the improvement on the original algorithm. Deng, Lin, and Lo (2012) designed a particle swarm optimization algorithm with a mutation operator and compared against genetic algorithms, tabu search and simulated annealing algorithms (Chang et al., 2000) reporting the superiority of the algorithm on mean percentage error performance indicator. Chen, Liang, and Liu (2013) proposed an artificial bee colony algorithm with two phase encoding in which selection of stocks is determined in the first part of the encoding while investment percentage is determined in the second part of encoding. Kao and Cheng (2013) applied bacterial foraging optimization to MVPO problem and compared with genetic algorithms, tabu search and simulated annealing algorithms (Chang et al., 2000) and particle swarm optimization (Cura, 2009) claiming the superior performance of their algorithm against others in terms of solution quality and time. Tuba, Bacanin, and Pelevic (2013) was first to apply firefly algorithm to MVPO problem and reported that the algorithm has a potential for solving this problem. Bacanin, Tuba, and Pelevic (2014) compared the artificial bee colony algorithm with genetic algorithm and firefly algorithm and reported that their algorithm performed best on variance and return error performance indicators. Tan, Niu, Wang, Huang, and Duan (2014) proposed a bacterial foraging optimization algorithm with neighborhood learning for dynamic MVPO problem and showed its performance against the original algorithm. Test results showed that proposed algorithm was superior than original BFO. Tuba and Bacanin (2014b) proposed a firefly algorithm based solution approach by introducing a more intensive exploitation mechanism in the late iterations of algorithm's run. On mean and median percentage error performance indicators, they reported that proposed algorithm outperformed the original version of the algorithm. Chen (2015) developed an artificial bee colony algorithm to solve MVPO by

Table 13
Publications that applied evolutionary algorithms to solve MVPO problem.

Category	Evolutionary algorithm	References
SOEA	GA	(Ackora-Prah et al., 2014a; Aranha & Iba, 2009; Busetti, 2006; Chang et al., 2000; Chang et al., 2009; Chen et al., 2008; ChiangLin, 2006; Corazza et al., 2012a; Coutino-Gomez et al., 2003; Dreżewski & Doroz, 2017; Ehrgott et al., 2004; García et al., 2018; Hadi et al., 2016; Hao & Liu, 2009; Hoklie & Zuhal, 2010; Huang & Shen, 2010; Huang, 2012; Kamali, 2014; Lai et al., 2006; Lean et al., 2008; Lin & Liu, 2008; Lin et al., 2005; Loukeris et al., 2009; Lu & Wang, 2013; Moral-Escudero et al., 2006; Pai & Michel, 2009; Rong et al., 2009; Ruiz-Torrubiano & Suarez, 2010; 2015; 2007; Sabar & Song, 2014; Sadjadi et al., 2012; Shaikh & Abbas, 2009; Shoaf & Foster, 1998; Soleimani et al., 2009; Talebi et al., 2010; Thomaidis, 2010; Woodside-Oriakhi et al., 2011; Xia et al., 2000; Yu et al., 2009)
	DE	(Loukeris et al., 2009; Lwin & Qu, 2013; Zaheer & Pant, 2016)
	PBIL	(Jin et al., 2015; Lwin & Qu, 2013; Xu et al., 2010)
MOEA	NSGA & NSGA-II	(Anagnostopoulos & Mamanis, 2010, 2011a; Anagnostopoulos & Mamanis, 2011b; Arkeman et al., 2013; Branke et al., 2009; Chen & Zhou, 2018; Chiam et al., 2007; Chiam et al., 2008; Duran et al., 2009; Fieldsend et al., 2004; Garcia et al., 2012; Liagkouras, 2018; Liagkouras & Metaxiotis, 2014; Lwin et al., 2014; Macedo et al., 2017; Mishra et al., 2016; Mishra et al., 2014a; Mishra et al., 2009; Ong et al., 2005; Qu et al., 2017; Sen et al., 2015; Skolpadungket et al., 2007; Streichen & Tanaka-Yamawaki, 2006; Streichert et al., 2004a; Streichert et al., 2004b)
	SPEA2	(Anagnostopoulos & Mamanis, 2010, 2011a; Anagnostopoulos & Mamanis, 2011b; Chen & Zhou, 2018; Duran et al., 2009; Garcia et al., 2012; Liagkouras, 2018; Liagkouras & Metaxiotis, 2014; Lwin et al., 2014; Macedo et al., 2017; Mishra et al., 2016; Mishra et al., 2014a; Mishra et al., 2009; Skolpadungket et al., 2007)
	PESA & PESA2	(Anagnostopoulos & Mamanis, 2010, 2011a; Anagnostopoulos & Mamanis, 2011b; Lwin et al., 2014; Mishra et al., 2014a)
	PAES	(Lwin et al., 2014)
	MOGA	(Bevilacqua et al., 2011; Skolpadungket et al., 2007)
	IBEA	(Duran et al., 2009)
	GDE3	(Garcia et al., 2012)
	MOSS	(Lwin et al., 2013)
	NPGA-II	(Anagnostopoulos & Mamanis, 2011a)
	VEGA	(Skolpadungket et al., 2007)
	e-MOEA	(Anagnostopoulos & Mamanis, 2011a)
	Co-EMOA	(Dreżewski & Doroz, 2017)
	MODE-GL	(Lwin et al., 2017)
	MOEA/D-C	(Zhang et al., 2018a)

DE: Differential Evolutionary, GA: Genetic Algorithm, GDE3: Generalized DE3, MOGA: Multi Objective GA, MOPSO: Multi Objective PSO, MOSS: Multi Objective Scatter Search, NPGA-II: Niched Pareto GA 2, NSGA-II: Non-dominated Sorting Genetic Algorithm II, PAES: Pareto Archived Evolution Strategy, PBIL: Population Based Incremental Learning, PESA: Pareto Envelope-based Selection Algorithm, SPEA-II: Strength Pareto Evolutionary Algorithm 2, VEGA: Vector Evaluated GA.

Table 14
Swarm based algorithms applied to MVPO problem.

Swarm based algorithm	Proposed by	Objective type
Particle swarm optimization (PSO)	Kennedy and Eberhart (1995)	Single objective
Ant colony optimization (ACO)	Dorigo et al. (1996)	Single objective
Artificial bee colony (ABC)	Karaboga (2005)	Single objective
Firefly algorithm (FA)	Yang (2010b)	Single objective
Bacterial foraging optimization (BFO)	Passino (2002)	Single objective
Bat algorithm (BA)	Yang (2010a)	Single objective
Fireworks algorithm (FWA)	Tan and Zhu (2010)	Single objective
Cat swarm optimization (CSO)	Chu and Tsai (2007)	Single objective
Krill herd (KH)	Gandomi and Alavi (2012)	Single objective
Invasive weed optimization (IWO)	Mehrabian and Lucas (2006)	Single objective
Chemical reaction optimization (CRO)	Lam and Li (2010)	Single objective
Artificial cooperative search (ACS)	Civicioglu (2013)	Single objective
Multi objective particle swarm optimization (MOPSO)	Coello et al. (2004)	Multi objective
Multi objective co-variance based artificial bee colony (M-CABC)	Kumar and Mishra (2017)	Multi objective
Multi objective bacterial foraging optimization (MOBFO)	Panigrahi et al. (2011)	Multi objective

introducing a chaotic initialization approach and a hybridization with particle swarm optimization. Kamili and Riffi (2015) applied cat swarm optimization to MVPO with boundary and cardinality constraints. Kamili and Riffi (2016) published a comparative study on MVPO problem by using particle swarm optimization, cat swarm optimization and bat algorithms. The results claim that the three algorithms have obtained similar results. Ni, Yin, Tian, and Zhai (2017) proposed a particle swarm optimization with dynamic random population topology strategies and reported that the computational results demonstrate that the proposed dynamic random population topology could improve the performance of the original algorithm. Kalayci et al. (2017) proposed an artificial bee colony algorithm with feasibly enforcement and infeasibility toleration procedures for MVPO with boundary and cardinality constraints achieving much stronger performance than the original version of the algorithm as well as demonstrating the superiority against other algorithms such as genetic algorithms, tabu search and simulated annealing algorithms (Chang et al., 2000), (Deng et al., 2012), population based incremental learning approach (Lwin & Qu, 2013), GRASP-QP (Baykasoğlu, Avci, & Burcin Özsoydan, 2016) on various convergence metrics in the literature.

Multi objective swarm-based algorithms for MVPO

Mishra, Panda, and Meher (2009) applied multi objective particle swarm optimization to MVPO problem and compared with

Table 15
Publications that applied swarm-based algorithm to solve MVPO problem.

Category	Swarm based algorithms	References
SOSBA	PSO	(Abbas & Haider, 2009; Cao & Tao, 2010; Chang & Chen, 2008; Chang & Hsu, 2007; Chen & Cai, 2008; Chen et al., 2006; Chen & Zhang, 2010; Corazza et al., 2012a; 2013; Cui et al., 2014; Cura, 2009; Deng & Lin, 2010b; Deng et al., 2012; Farzi et al., 2013; Fasheng & Wei, 2006; Gao & Chu, 2009; Golmakani & Fazel, 2011; Kamali, 2014; Kamili & Riffi, 2016; Koshino et al., 2007; Li et al., 2010; Loukeris et al., 2009; Mozafari et al., 2011; Ni et al., 2017; Niu et al., 2010; Niu et al., 2009; Pouya et al., 2016; Reid & Malan, 2015; Sadigh et al., 2012; Sun et al., 2011; Talebi et al., 2010; Tang et al., 2009; Thomaidis, 2010; Wang et al., 2015; Wang et al., 2009; Xu & Chen, 2006; Xu et al., 2007; Yaakob & Watada, 2010; Yin et al., 2015a; Yin et al., 2015b; Zhang et al., 2010; Zhu et al., 2010; Zhu et al., 2011)
	ABC	(Bacanin et al., 2014; Chen et al., 2013; Chen et al., 2012; Hong-mei et al., 2010; Kalayci et al., 2017; Suthiwong & Sodanil, 2016; Tuba & Bacanin, 2014a; Wang et al., 2011, 2012)
	ACO	(Deng & Lin, 2010a; Zhu et al., 2010)
	FA	(Bacanin & Tuba, 2014; Tuba & Bacanin, 2014a; b; Tuba et al., 2013)
	BFO	(Kao & Cheng, 2013; Tan et al., 2013; Tan et al., 2014)
	BA	(Kamili & Riffi, 2016; Strumberger et al., 2017)
	FWA	(Bacanin & Tuba, 2015)
	CSO	(Kamili & Riffi, 2015, 2016)
	KH	(Tuba et al., 2014)
	IWO	(Pouya et al., 2016)
	CRO	(Xu et al., 2011)
	ACS	(Kumar & Bhattacharya, 2012)
MOSBA	MOPSO	(Chen & Zhou, 2018; Garcia et al., 2012; Lwin & Qu, 2013; Mishra et al., 2016; Mishra et al., 2014a; Mishra et al., 2009; Qu et al., 2017; Sen et al., 2015; Zhou & Li, 2014)
	MOABC	(Kumar & Mishra, 2017)
	MOBFO	(Mishra et al., 2014b)

NSGA-II, SPEA2 and parallel single front genetic algorithm and experimental results showed that their proposed algorithm significantly outperforms its counterparts in all experiments based on diversity performance indicators. Garcia et al. (2012) proposed a robust approach for MVPO and tested through experimentation using four multi objective algorithms (NSGA-II, SPEA-II, multi-objective particle swarm optimization and generalized differential evolution algorithms). According to comparative test results, multi-objective particle swarm optimization outperformed others. Mishra, Panda, and Majhi (2014b) proposed multi objective bacterial foraging optimization to MVPO problem with boundary and cardinality constrains and compared with three multi-objective evolutionary algorithms performing superior against other algorithms. Mishra, Panda, and Majhi (2016) proposed a prediction based MV model and implemented three multi objective algorithms (multi-objective particle swarm optimization, NSGA-II and SPEA2) reporting that multi-objective particle swarm optimization provided the best Pareto optimal solutions among all. Kumar and Mishra (2017) proposed a multi objective co-variance based artificial bee colony to tackle two conflicting objectives simultaneously validating the performance of their proposed algorithm for MVPO problem. Swarm based algorithms applied for MVPO problem are summarized in Table 15.

As shown in Table 15, particle swarm optimization is the most popular swarm-based algorithm for MVPO problem since it is the oldest algorithm among other swarm-based algorithms and there is no need for a transformation for the MVPO problem, i.e., the original structure of the algorithm is continuous and has a direct fit into the problem domain. Despite the popularity of the particle swarm optimization algorithm, it appears that the artificial bee colony algorithm has attracted the researchers' interest with its superior performance and therefore, artificial bee colony algorithm may become more popular in the near future for the MVPO problem.

6.2.1.2. Single-solution-based algorithms. Algorithms working on single solution are called trajectory methods (Blum & Roli, 2003). Single solution-based algorithms focus on modifying and improving a single solution throughout the iterations. Although, they underutilize the power of population, they can get results very quickly since they improve a single solution instead of a population in each iteration. Single solution-based algorithms that applied to MVPO problem are summarized in Table 16.

Table 16
Single-solution-based algorithms applied to MVPO problem.

Single-solution-based algorithm	Proposed by	Objective type
Simulated annealing (SA)	Kirkpatrick et al. (1983)	Single objective
Tabu search (TS)	Glover (1986)	Single objective
Greedy randomize adaptive search procedure (GRASP)	Feo and Resende (1995)	Single objective
Hill climbing (HC)	Forrest and Mitchell (1993)	Single objective
Archived multi objective simulated annealing (AMOSA)	Bandyopadhyay et al. (2008)	Multi objective

Single-solution-based algorithms for MVPO

Chang et al. (2000) and Ehrgott et al. (2004) applied genetic algorithm, tabu search and simulated annealing and compared all by leaving a comment that no algorithm outperformed others. Anagnostopoulos, Šević, Chatzoglou, and Katsavounis (2010) designed a greedy randomized adaptive search procedure algorithm to solve MVPO problem confirming its potential on the problem. Woodside-Oriakhi et al. (2011) proposed three metaheuristics (genetic algorithm, tabu search and simulated annealing) to MVPO problem and compared their experimental results with results obtained by Chang et al. (2000) and obtained better solutions faster. Fastrich and Winker (2012) designed a hybrid heuristic algorithm integrating simulated annealing algorithm as a modification mechanism into the main solution approach. Ackora-Prah, Gyamerah, Andam and Gyamfi et al.(2014) applied pattern search originally proposed by Hooke and Jeeves (1961) to MVPO problem reporting the efficacy of pattern search. Sen, Saha, Ekbal, and Laha (2015) applied archive multi objective simulated annealing and compared with NSGA-II on diversity performance indicators and multi-objective particle swarm optimization algorithm reporting their algorithm's superiority against the others. Chen, Lin, Zeng, Xu, and Zhang (2017) introduced a local search based multi-objective optimization, a combination of a local search schema and

Table 17
Publications that applied single-solution-based algorithm to solve MVPO problem.

Single-solution-based algorithm	References
SA	(Busetti, 2006); Chang et al. (2000); Coutino-Gomez et al. (2003); Ehrgott et al. (2004); Fastrich and Winker (2012); (García et al., 2018); Li et al. (2009); Schaerf (2002); Thomaidis (2010); (Woodside-Oriakhi et al., 2011)
TS	(Chang et al., 2000; Coutino-Gomez et al., 2003; Crama & Schyns, 2003; Ehrgott et al., 2004; Maringer & Kellerer, 2003; Schaerf, 2002; Thomaidis, 2010; Woodside-Oriakhi et al., 2011)
GRASP	(Anagnostopoulos et al., 2010; Baykasoglu et al., 2015)
HC	(Coutino-Gomez et al., 2003; Gaspero et al., 2011; Schaerf, 2002)
AMOSA	(Sen et al., 2015)
LS Based MOEA	Chen et al. (2017)
PS	Ackora-Prah, Gyamerah, Andam, & Gyamfi. (2014)

Simulated Annealing (SA); Tabu Search (TS); Greedy Randomized Adaptive Search Procedures (GRASP); Hill Climbing (HC); Archive Multi Objective Simulated Annealing (AMOSA); Pattern Search (PS).

Table 18
Machine learning algorithms applied to MVPO problem.

Machine learning algorithm	Proposed by
Hopfield network (HN)	Hopfield (1984)
Artificial immune systems (AIS)	De Castro and Timmis (2002)
K-means clustering	Lloyd (1982)

Table 19
Publications that applied single-solution-based algorithm to solve MVPO problem.

Machine learning algorithm	References
Neural networks	(Fernandez & Gomez, 2007; Freitas et al., 2009; Suganya & Vijayalakshmi Pai, 2009)
Artificial immune systems	(Abbas & Haider, 2009; Golmakani & Alishah, 2008)
K-means clustering	(Jiang et al., 2014; Pai & Michel, 2009; Suganya & Vijayalakshmi Pai, 2009)

a farthest-candidate approach, to solve MVPO problem. Publications that applied single-solution-based algorithms for MVPO problem are summarized in Table 17.

As shown in Table 17, compared to population-based solution approaches, the single-solution-based algorithms have not drawn much interest to solve MVPO problem. In the MVPO problem, single-solution-based algorithms have a handicap of efficient exploration capability since it may be more difficult to efficiently explore the solution space with a single solution since the MVPO problem lies in a continuous domain instead of discrete domain.

6.2.2. Machine learning algorithms

Machine learning field is evolved from the study of pattern recognition and computational learning theory in artificial intelligence. Machine learning algorithms explore the problem data, make data-driven predictions operating a model from a training set of input observations in order to make decisions expressed as outputs, rather than strictly following static program instructions.

Machine learning algorithms applied to MVPO problem are showed in Table 18.

Fernandez and Gomez (2007) applied Hopfield network (HN) to solve MVPO problem and compared against GA, SA and TS (Chang et al., 2000) reporting HN's superior performance on bigger sized instances. Golmakani and Alishah (2008) proposed an artificial immune system algorithm and compared with genetic algorithm, tabu search and simulated annealing (Chang et al., 2000) and Hopfield network (Fernandez & Gomez, 2007) indicating that artificial immune system approach could achieve better results, yet performed not as fast as others. Suganya and Vijayalakshmi Pai (2009) designed an algorithm based on Hopfield network and employed k-means clustering analysis to tackle additional constraints in this algorithm. Publications that applied machine learning algorithms for MVPO problem are summarized in the Table 19.

6.3. A peek into the solution approaches for MVPO

The exact and the approximation techniques applied to the MVPO problem were described in Section 3.1 and Section 3.2, respectively. Among those solution techniques, the metaheuristics are commonly used to solve the MVPO problem (about 82% of all). The primary reason would be the NP-hard property of the special variants of MVPO when integer constraints are introduced to the problem. The distribution of solution techniques applied to the MVPO problem in the literature is given in Fig. 11.

One may easily conclude that well-known metaheuristics such as genetic algorithms and particle swarm optimization have drawn a great attention in MVPO literature. However, because of the fact that studies on GA and PSO have reached an adequate level of maturity and perhaps very limited improvement area has left, these two algorithms have lost researcher's interest in the past few years. Contrary to this, the artificial bee colony algorithm which is relatively a newer algorithm, may get a bigger slice from the cake due to higher performance against other algorithms reported by (Kalayci et al., 2017).

6.4. Hybridization techniques

Hybridization strategy may be defined as designing a better algorithm by combining favorable characteristics of different algorithms. Researchers, in the quest of designing more efficient algorithms for MVPO, used this strategy to benefit from the advantages of pure algorithms or to dismiss their drawbacks. Publications that used hybridization strategy to solve MVPO problem can classified as in Table 20.

Moral-Escudero et al. (2006) designed a hybrid strategy that combines evolutionary techniques with quadratic programming. Gaspero, Tollo, Roli, and Schaerf (2011) presented a hybrid technique that combines a local search metaheuristic, as a master solver, with a quadratic programming procedure, as a sub solver. Lwin and Qu (2013) proposed a hybrid algorithm by combining population-based incremental learning and differential evolution algorithms adapting a mutation and an elitist strategy to enhance the evolution over the search space. Tuba and Bacanin (2014a) presented a hybridization of the artificial bee colony with the firefly algorithm for MVPO problem in order to enhance the search capability of the artificial bee colony algorithm for a more effective trade-off between exploitation and exploration. They compare the proposed algorithm against genetic algorithm, tabu search and

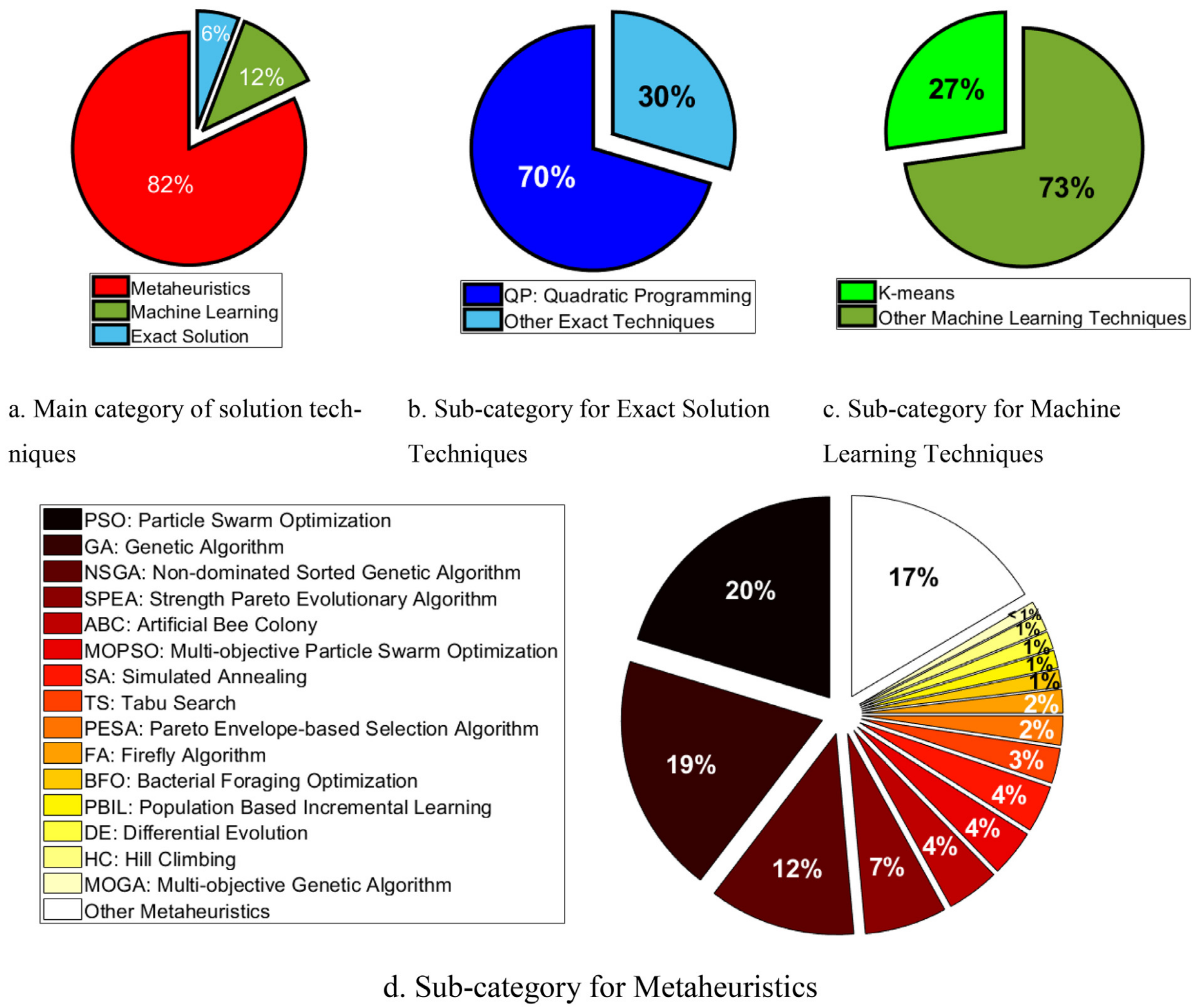

Fig. 11. Scatter chart of solution techniques applied MVPO problem.

Table 20
Hybrid algorithms developed to solve MVPO problem.

	Metaheuristic	**Exact**	**Machine learning**
Metaheuristic	(Lwin & Qu, 2013; Pai & Michel, 2009; Sadigh, et al., 2012; Tuba & Bacanin, 2014a; Yaakob & Watada, 2010)	(Baykasoglu, et al., 2015; Gaspero, et al., 2011; He & Qu, 2016; Jin, et al., 2015; Moral-Escudero, et al., 2006; Ruiz-Torrubiano & Suarez, 2015)	(Pai & Michel, 2009; Sadigh, et al., 2012)
Exact		N/A	N/A
Machine learning			(Suganya & Vijayalakshmi Pai, 2009)

simulated annealing (Chang et al., 2000) and particle swarm optimization (Cura, 2009) to confirm its performance. Ruiz-Torrubiano and Suarez (2015) proposed a hybrid approach that combines genetic algorithm and QP. Baykasoglu, Yunusoglu, and Ozsoydan (2015) developed a hybrid algorithm that selects a predetermined number of stocks with GRASP algorithm and finds the proportions of the selected stocks with QP.

6.5. Constraint handling methodology

In the MVPO literature, there are several methods to satisfy the constraints of the problem. Literature shows that constraint handling is done via a repair procedure, a penalty function or infeasibility tolerance. Fig. 12 demonstrates distribution of constraint handling techniques employed in MVPO literature.

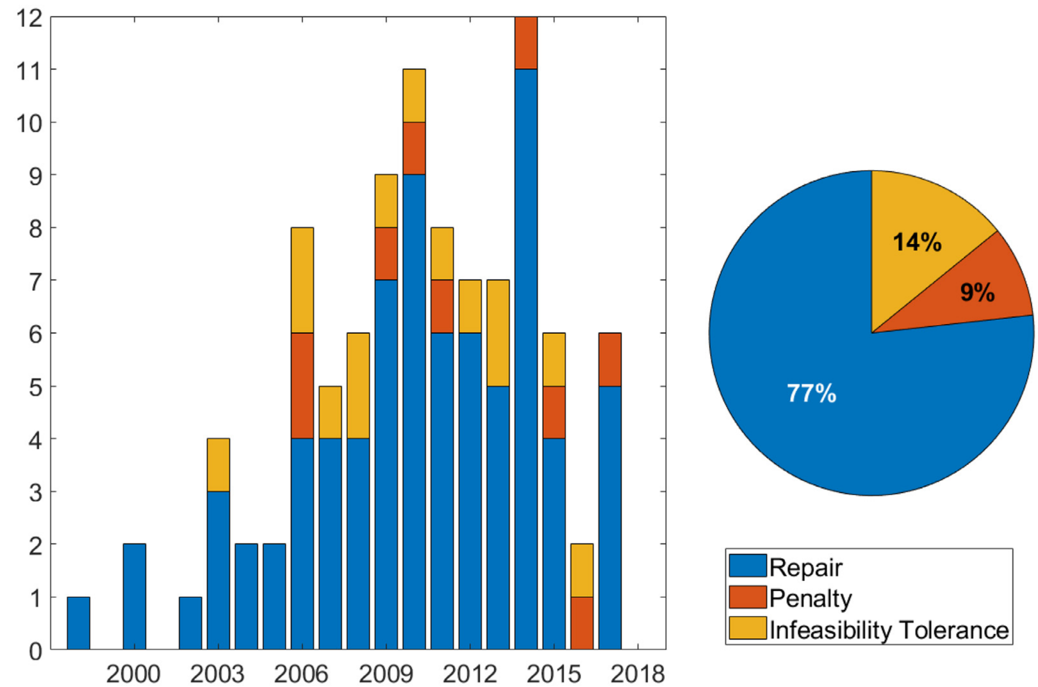

Fig. 12. Distribution of constraint handling techniques.

Table 21
Constraint handling techniques for MVPO problem.

Constraint handling technique	Publication
Repair procedure	(Anagnostopoulos & Mamanis, 2010, 2011a; b; Anagnostopoulos et al., 2010; Bacanin & Tuba, 2014; 2015; Bacanin et al., 2014; Branke et al., 2009; Chang et al., 2000; Chang et al., 2009; Chen et al., 2013; Chen et al., 2012; Chen et al., 2017; Chiam et al., 2007; Chiam et al., 2008; ChiangLin, 2006; Coutino-Gomez et al., 2003; Crama & Schyns, 2003; Cui et al., 2014; Cura, 2009; Deng & Lin, 2010a, b; Deng et al., 2012; Eftekharian et al., 2017; Fernandez & Gomez, 2007; Garcia et al., 2012; Golmakani & Alishah, 2008; Hao & Liu, 2009; Huang & Shen, 2010; Jiang et al., 2014; Jiang et al., 2008; Kalayci et al., 2017; Kamili & Riffi, 2015; Kao & Cheng, 2013; Koshino et al., 2007; Kumar & Mishra, 2017; Kumar & Bhattacharya, 2012; Lai et al., 2006; Lean et al., 2008; Liagkouras & Metaxiotis, 2014; Lin et al., 2005; Lwin & Qu, 2013; Lwin et al., 2014; Lwin et al., 2013; Lwin et al., 2017; Maringer & Kellerer, 2003; Mishra et al., 2014a; Moral-Escudero et al., 2006; Mozafari et al., 2011; Ong et al., 2005; Pai & Michel, 2009; Reid & Malan, 2015; Ruiz-Torrubiano & Suarez, 2010; Sabar & Song, 2014; Sadigh et al., 2012; Schaerf, 2002; Shoaf & Foster, 1998; Skolpadungket et al., 2007; Streichen & Tanaka-Yamawaki, 2006; Streichert et al., 2004a; b; Talebi et al., 2010; Tang et al., 2009; Thomaidis, 2010; Tuba & Bacanin, 2014a; b; Tuba et al., 2013; Wang et al., 2012; Woodside-Oriakhi et al., 2011; Xia et al., 2000; Xu J. et al., 2011; Xu R.T. et al., 2010; Yin et al., 2015a; Yu et al., 2009; Zhou & Li, 2014; Zhu et al., 2011)
Penalty function	(Chen & Cai, 2008; Chen et al., 2006; Chen & Zhang, 2010; Corazza et al., 2012a; Corazza et al., 2013; Crama & Schyns, 2003; Golmakani & Fazel, 2011; Lean et al., 2008; Lu & Wang, 2013; Moral-Escudero et al., 2006; Pouya et al., 2016; Reid & Malan, 2015; Rong et al., 2009; Xu et al., 2007)
Infeasibility tolerance	(Anagnostopoulos & Mamanis, 2010; Fasheng & Wei, 2006; Kalayci et al., 2017; Mishra et al., 2016; Mishra et al., 2014b; Reid & Malan, 2015; Soleimani et al., 2009; Wang et al., 2011; Xu & Chen, 2006)

Repairing an infeasible solution to get into feasible region is the most popular methodology for constraint handling when MVPO problem is solved. Many researchers (Babaei, Sepehri, & Babaei, 2015; Chen et al., 2013; Chen et al., 2017; Deng & Lin, 2010a, 2010b; Lwin & Qu, 2013; Lwin, Qu, & Zheng, 2013; Mishra, Panda, & Majhi, 2014a; Pai & Michel, 2009; Schaerf, 2002; Vijayalakshmi Pai & Michel, 2013; Woodside-Oriakhi et al., 2011) used the repair procedure suggested by Chang et al. (2000) to satisfy cardinality and boundary constraints at once. Crama and Schyns (2003) proposed specific approaches to deal with each specific class of constraint, either by explicitly restricting the portfolios to remain in the feasible region or by penalizing infeasible portfolios. Golmakani and Fazel (2011) and Corazza et al. (2013) used penalty functions for constraint handling. Some researchers have applied the selection rules proposed by Deb (2000) to deal with infeasibility. These selection rules can be summarized as follows: (*i*) If a solution is feasible and the other solution is infeasible, select the feasible one, (*ii*) if the both solutions are infeasible, select the solution with less violation, (*iii*) if both solutions are feasible, select the solution that has a better objective function value. Kalayci et al. (2017) used this infeasibility toleration technique to satisfy binary constraints and repair procedure to satisfy cardinality constraints in their proposed artificial bee colony algorithm reporting the superior performance against the repair procedure suggested by Chang et al. (2000). Table 21 shows the classifications of studies according to utilized constraint handling methodologies.

7. Conclusion and discussion

This paper provided a comprehensive survey of deterministic models and applications on MVPO. Analyzing the literature confirmed the growing interest in search of the new trends, developments and practical factors on portfolio optimization as the research in MVPO continues to be very active.

A taxonomy of applications based on models, constraints, constraint handling techniques, various solution approaches along with the performance indicators are presented. The vast majority of the presented work focused on employed exact and heuristic attempts for solving MVPO problem. The main research lines for this research area was devoted to the deterministic models with classical formulations including realistic features and the adaptation of various algorithms with a computational analysis utilizing difference performance indicators.

Although the original mean-variance model had single objective, multi-objective variants that simultaneously or independently consider minimized risk and maximized return turned out to be more popular as years pass since in practice, investors may not be aware of the risk and returns levels they desire. In order to tackle the multi-objective nature of the problem, the majority of researchers had either focused on weighted sum approach that systematically prioritizes objectives or dealt with efficiency and non-dominance rules to obtain Pareto optimal solutions forming the efficient frontier.

In the pursuit of a realistic portfolio management, various studies increasingly incorporated additional constraints such as cardinality, threshold, transaction costs, round lots, sector capitalization and turnover constraints to the original model. Because of the integer constraints, the classical convex quadratic programming problem with a polynomial worst-case complexity bound had been transformed into a mixed integer quadratic programming problem which introduced the problem to the class of NP-Complete problems. Therefore, the majority of researchers had employed approximate algorithms rather than exact algorithms to overcome computational complexity of the problem where solution time greatly matters in the financial business. Metaheuristics are by far the most preferred approximation algorithms adapted to solve MVPO. Although evolutionary and swarm intelligence algorithms utilizing the power of a population of solutions had drawn a great attention so far, other successful metaheuristic algorithms such as single-solution-based algorithms may get a bigger slice from the cake in the near future.

In the quest of precise optimization, researchers have employed various hybridization strategies to benefit from the advantages of different algorithms or to dismiss some drawbacks. Although an exact algorithm may be inadequate to reach optimal solutions alone in a reasonable time, literature analysis revealed that hybridizations of exact and metaheuristic algorithms had shown superior performance against other competing algorithms. This may trigger the design and implementation of mat-heuristics for MVPO variants.

Constraint handling, a requirement for constrained portfolio optimization, was done via repair procedures, penalty functions or temporarily tolerating infeasibility in the literature. Although a complete repair procedure was widely preferred in the literature, comparative results showed that a partial repair mechanism might enhance the algorithms with a dramatic effect on the performance.

Considering the intense competition in financial markets to provide a better portfolio optimization, developing new methodologies to efficiently solve portfolio optimization is a matter of great importance. Publicly available benchmark instances for portfolio optimization enable the computational comparison of the proposed algorithms in the literature. Solution approaches racing on the benchmarking platform would serve to the future of financial decision making with the help of algorithmic enhancements. Most of the studies are either based on some case studies or publicly available benchmarking datasets of limited variety and quantity. The future of financial decisions relies on algorithmic performances which can only be validated on various large-scale datasets gathered from complex environments and global markets.

Despite all the efforts made to present a complete review on MVPO based on the applied research methodology, assuming that the risky security returns obey normal distribution, it has some limitations. The review of powerful approaches for optimization under uncertainty, robust, fuzzy and dynamic optimization was out of the scope of this study.

The analysis of the literature revealed a number of open research fields requiring an in-depth discussion to guide researchers for future research directions in the light of the findings based on the solution approaches developed for MVPO. It is evident that the field presents significant research opportunities both for academics and practitioners. The identified gaps in literature for the future research opportunities are as follows:

- It is also worthy to note that the lack of multiple constraints in the problem formulation that the real-life portfolio managers deal with limits the methodologies' usefulness to academic purposes. Therefore, to reduce the gap between the academia and the real-world, the incorporation of additional real-life constraints is still a challenge to be answered.
- Further research is always required towards the design of new algorithmic enhancements on solving portfolio optimization variants.
- Because of the fact that different financial markets have different dynamics and features, extensions of the common datasets would undoubtfully be an important future direction in order to provide an opportunity for testing new solution methodologies and algorithms in various market conditions. New performance measures would also serve a better race platform for future algorithmic studies on testing the performance
- It appears that most of the researchers focus on the computational aspects of the problem and overlook its profitability in practice. A potential path of future research would be to analyze the performance of securities on investment horizons in dynamic real-world environment. Therefore, solution approaches should also be of interest in incorporating multi-period portfolio optimization since decision support systems in financial optimization rely on algorithmic decisions in consecutive phases.
- The decision-making process involved in portfolio optimization is extremely complex and difficult to automate. Therefore, to extend the capabilities of efficient algorithms to trade execution, the design of interactive and automated algorithms for the portfolio optimization problem promises a potential area for future research.
- Today the race is on financial trading. The investigation of performing short-term forecasting of stock prices with heuristics is a topic worth exploring that can provide trading decision models. Furthermore, combing forecasting theory with portfolio optimization is another promising research direction.
- In spite of the fact that uncertainty in MVPO was not within the scope of this study, it is evident from the uncertain characteristics of the financial data, making the model dynamic and robust may ensure a more consistent estimation. That's why, a detailed analysis on MVPO including uncertainty and robustness would be very helpful for the researchers and practitioners.
- As financial systems can be affected by various conditions such as social-fact events, politics and investor behaviors, data mining and big data analysis come into prominence for enhanced decision support systems.

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